A Meta-Analysis of Environmental Kuznets Curve Studies

Therese A. Cavlovic, Kenneth H. Baker, Robert P. Berrens, and Kishore Gawande

An understanding of the empirical relationship between income and environmental quality is evolving through recent studies investigating the *Environmental Kuznets Curve* (EKC). The EKC represents an inverted-U relationship between income and environmental degradation. However, studies may employ different methods, evaluate different environmental indicators, and use different data, resulting in a broad spectrum of findings and leading to sometimes conflicting interpretations. The purpose of this paper is to synthesize the results of existing EKC findings by conducting a statistical meta-analysis, and to predict new income turning points (ITP). Results indicate how both methodological choices and pollutant types affect ITPs. (JEL Q20).

Questions about the empirical relationship between income and environmental quality have prompted the recent emergence of a set of studies investigating whether an inverted-U relationship exists between income and environmental degradation. Following from the Kuznets Curve, an inverted-U relationship between economic development and income inequality (Kuznets 1955), this income-environment relationship has been coined the *Environmental Kuznets Curve* (EKC). However, various EKC studies have employed different methods, evaluated different environmental indicators, and used different data, resulting in a broad spectrum of findings. As suggested by van den Bergh and Button (1997), this has provided the ideal opportunity to use meta-analysis to synthesize the EKC literature.

The empirical EKC literature is controversial. Some view it as a kind of general evidence of the relationship between economic growth and the environment, and draw the broad policy conclusion that society is able to grow its way out of most environmental problems (e.g., Beckerman 1992). Others argue that the EKC relationship should not be interpreted as a substitute for environmental policy or institutional change (Arrow et al. 1995; Panayotou 1997; Selden et al. 1999). When present the EKC may only indicate that negative externalities are being shifted onto low income communities or countries, and may not necessarily hold in the future due to ecological thresholds and carrying capacities (e.g., Arrow et al. 1995). While the EKC appears to hold for some pollutants in some cases, it does not hold in all cases and its presence will likely depend on the scale of analysis and the type of environmental problem.

Conjectures and theoretical models explaining the EKC exist, yet the empirical models used to estimate the EKC generally are reduced form equations describing a net relationship between income and environmental problems. Suggested reasons for observed EKC results include: shiftable externalities (Arrow et al. 1995), industry composition (Grossman and Krueger 1996), technical efficiency (Grossman and Krueger 1996), environmental regulation (Grossman and Krueger 1996), net migration (Berrens et al. 1997; Bohara et al. 1999), and changes or differences in trade policy regimes (Lucas et al. 1992; Rock 1996).

The purpose of this study is to statistically summarize EKC findings using a meta-analysis. A meta-analysis is a statistical method of synthesizing results of similar empirical studies to determine whether credible conclusions about prior study results can be made (van den Bergh and Button 1997). While there are several insightful EKC reviews (e.g., Barbier 1997; Ekins 1997; Stern et al.

Therese A. Cavlovic and Kenneth H. Baker are graduate students, Robert P. Berrens and Kishore Gawande are assistant and associate professors, respectively, with the Department of Economics at the University of New Mexico.

Agricultural and Resource Economics Review 29/1 (April 2000) 32–42

1996), this is the first meta-analysis. A meta-analysis of 25 EKC studies (with over 120 observations) is used to explore the effects of different pollutants, methods, and research choices. Using the results from the meta-analysis, new income turning point (ITP) predictions are calculated for eleven different pollutants, which may be more reliable than ITP estimates obtained by any single study.

Selected Review of the EKC Literature

A variety of different models are used to analyze the inverted-U phenomenon, but they follow the general form:

$$(1) \qquad p_{it} = \beta_0 + \beta_1 y_{it} + \beta_2 y_{it}^2 + X\gamma + \varepsilon_{it},$$

where p_{it} represents the level of some pollutant or extent of environmental degradation for a geographical region i at time t, y_{it} represents some measure of per capita income for region i at time t, and X is a vector of factors chosen by the analyst that control for other influences on p_{it}. Such influences include (but are not limited to) population or population growth, trend or period effects, trade effects, geographic location or climate, and measures of manufacturing or industrial intensity of the area. The error term, ε_{it}, may be serially correlated across time and heteroscedastic across i. The signs and magnitude of β_1 and β_2 determine whether an ITP and corresponding EKC exists. An EKC exists if β_1 is positive, β_2 is negative, and $-\beta_1/2\beta_2$ is a small number, relative to mean per capita income levels of the region.

A review of some prominent EKC studies helps illustrate different methodological choices. In two important EKC studies, Grossman and Krueger (1993, 1995) investigate the relationship between a variety of environmental quality indicators and per capita income. They use available data in the Global Environmental Monitoring System's (GEMS) tracking of ambient urban air concentrations for various cities in developing and developed countries. Grossman and Krueger use reduced form equations that relate pollution levels in an air or water location to current and lagged per capita income and to site specific covariates as follows:

$$(2) \qquad p_{it} = \beta_0 + \beta_1 y_{it} + \beta_2 y_{it}^2 + \beta_3 y_{it}^3 + \beta_4 \bar{y}_{it} + \beta_5 \bar{y}_{it}^2 + \beta_6 \bar{y}_{it}^3 + X_{it}'\gamma + \varepsilon_{it},$$

where p_{it} and y_{it} are as defined for (1), and $\bar{y}_{it}$ is the average per capita GDP over the prior three years. X_{it} includes a set of site specific variables encompassing geographic features, climate, population, city structure (e.g., urban, rural, etc.), or nature of land use (e.g., commercial, residential, etc.) of location i. To capture possible improvements in environmental quality related to global advances in technology or increased awareness for environmental quality, they include a linear time trend as a separate regressor (Grossman and Krueger 1995). Grossman and Krueger find an EKC for most environmental indicators, and suggest that as incomes rise, societies begin to harness new technologies to conserve natural resources. However, the ITPs vary across types of pollutants.

Selden and Song (1994) hypothesize that the trend in pollution is likely the result of both market forces, such as the income elasticities of environmental quality and the composition of production and consumption, and changes in government policy, such as trade policy. They examine suspended particulate matter (SPM), SO_2 (both also examined by Grossman and Krueger), nitrogen oxides (NO_X), and CO_2. Whereas Grossman and Krueger (1993, 1995) use urban air quality data, Selden and Song use aggregate emissions data. They speculate that ITPs will be lower for urban air quality. Using GEMS data across country and time, they present pooled cross-section estimates for the relationship between environmental quality and per capita income from the following model:

$$(3) \qquad p_{it} = \beta_0 + \beta_1 y_{it} + \beta_2 y_{it}^2 + \beta_3 d_{it} + \varepsilon_{it},$$

where d_{it} controls for population density. Selden and Song expect population density to be negatively related with emissions since densely populated countries are likely to be concerned with reducing per capita emissions, or because these areas may have lower auto emissions. Selden and Song acknowledge that other exogenous factors, not included in their model, may influence emissions, and thus cause a correlation in error terms for a country across all periods. Hence, they estimate fixed and random effects models.

Selden and Song (1994) find that urban measures of pollution have lower ITPs. They identify the following factors as being responsible for the lower ITPs: (i) the immediacy of perceived health risks, for example the elimination of fecal coliform in drinking water, (ii) lower costs of local abatement, (iii) wealthier urban residents having positive income elasticities for environmental quality, for example in the regular disposal of garbage, and (iv) polluting industries relocating to areas where rents are lower (i.e., as urban areas develop, rents increase and as a result industries will relocate in a freely mobile world). Selden and Song speculate that globally dispersed pollutants with relatively high abatement costs, such as CO_2, will have higher ITPs. This is corroborated by Holtz-Eakin and Selden (1995), who find a positive relationship between income and CO_2 (the turning point does not occur until approximately $10 million, in 1992 U.S. dollars). Furthermore, Selden and Song find that turning point estimates are not necessarily robust across methods of estimation; random effects estimation tends to yield higher ITPs than fixed effects estimation.

Since EKC results usually are estimated from a reduced form equation, a variety of sometimes conflicting theoretical explanations may be consistent with the EKC. A case in point is the controversy over the relationship between trade openness and the environment. A central issue is whether trade policy reforms will lead to greater than optimal levels of environmental degradation or natural resource depletion (see Arrow et al. 1995; Grossman and Krueger 1993).

Rock (1996) presents empirical evidence demonstrating a positive relationship between trade openness and pollution intensities; that is, the more open a country, the higher its production of pollution per dollar of output. This result is inconsistent with the findings of Lucas et al. (1992) who find that closed, fast-growing economies shift production towards more toxic manufacturing structures while a negative relationship exists between fast-growing, open economies and industrial pollution intensity. Suri and Chapman (1998) find that trade activity increases ITPs for pollutant emissions related to energy use by examining the composition of trade imports and exports to domestic manufacturing production. Specifically, industrializing nations will experience greater export-manufacturing ratios and higher emissions as they strive for industrial tenacity, while industrialized nations experience reductions in emissions with increasing substitution towards importing manufactured goods. Thus, Suri and Chapman (1998) find that a structural shift towards manufacturing imports will lower an ITP.

Use of Meta-Analysis in Environmental Economics

Meta-analysis is the formal method of synthesizing the results of similar existing empirical studies in order to explain (in part) the systematic variation in explanatory variables and outcomes. Hunt (1997) describes meta-analysis as a way to: (i) combine the numerical results of studies with disparate, even conflicting research methods and findings; (ii) discover the consistencies in a set of seemingly inconsistent findings; and (iii) arrive at conclusions more accurate and credible than those presented in any one of the primary studies. Conducting a meta-analysis requires collecting all possible existing studies on a particular topic, developing some guidelines for structuring the problem, and then statistically evaluating the data in some fashion. While meta-analyses attempt to replace the subjectivity of literary reviews with a more rigorous synthesis, they inevitably still require some subjective choices in preparing the data and structuring the statistical investigation (van den Bergh and Button 1997).

Empirical models investigating a given relationship, such as the relationship between income and the environment, involve theory and the analyst's judgment (Smith and Kaoru 1990). This judgment comes in the form of testing a hypothesis or estimating parameters, using the best available data, selecting model specification, defining variable construction, and using information from the existing literature. A meta-analysis controls for these judgments by statistically summarizing the literature, and allows researchers to obtain new estimates for the underlying empirical values. Since these predictions are based on information from the complete existing literature, they are considered more reliable than any single estimate.

Although common in other social sciences, meta-analyses are only just emerging in the field of environmental economics (Loomis and White 1996; Smith and Huang 1995; Smith and Kaoru 1990; Smith and Osborne 1996; and Walsh et al. 1992). In one of the first meta-analyses in environmental economics, Smith and Kaoru (1990) examined 77 studies that used the travel cost method (TCM) to estimate demand for recreation sites. They found a systematic relationship between surplus estimates and features of the different models. That is, choices and assumptions made by each analyst, for example measuring the opportunity cost of time and inclusion of substitute price terms, significantly affected the size of the estimated surplus. Walsh et al. (1992) performed a meta-analysis on TCM and contingent valuation (CV) studies concerned with demand for outdoor recreation. In addition to finding a significant difference between TCM and CV surplus estimates, they also found that modeling choices significantly affected estimated surplus measures. Smith and Huang (1995) used a meta-analysis to investigate variations in hedonic property value models concerned with differences in marginal willingness to pay (MWTP) estimates for reducing particulate matter. Using 86 observations from 37 studies, they also found that choices of the analysts were significant determinants of variations in MWTP.

The common element across these studies is the attempt to explain the variations in the valuation measures obtained by each study. Meta-analyses improve understanding of economic behavior by identifying systematic patterns, and they illustrate how methodological choices may be affecting results; on both counts they can be an important touchstone for future research. Furthermore, by statistically synthesizing information from a set of common studies, a meta-analysis allows researchers to obtain new estimates of underlying empirical values (Smith and Huang 1995). For example, Smith and Huang (1995) predict new MWTP estimates for reducing particulate matter by drawing on information from the 37 studies. A similar approach is followed in this study to make new predictions of ITPs.

The meta-analysis in this study investigates whether a systematic relationship exists between income and specific measures of environmental quality. Specifically, this study controls for research choices and then predicts new ITPs for various environmental indicators. For example, do studies that examine the income-environment relationship for developed nations only find an EKC that is representative for developing nations? Or as Suri and Chapman (1998) find, does the composition of a nation's manufacturing imports and exports, which are generally proxied by income in reduced form equations, affect emission levels? This meta-analysis can provide a consistency check on modeling choices, and reduces the sensitivity to extreme results. The hypothesis is that methodological choices and pollutant types play an important role in the size of a predicted ITP.

Data and Development of Explanatory Variables

The data for this meta-analysis consists of 121 usable observations gathered from a set of 25 studies.[1] Definitions and descriptive statistics for the independent variables are presented in table 1. The independent variables are grouped and classified as either methodological variables, which capture choices made by the analysts, or pollutant categories, which divide different environmental indicators or types of pollutants into specific categories. An important feature from the summary of the EKC literature is the variation in study methods. Not only does the literature encompass a number of different pollutants, but also includes differences in pollutant measurements. Some studies measure pollutants in concentration levels, while others use emissions. Ambient concentrations measure the quantity of pollutants per unit area of volume without regard to the activity that emitted them. Emissions are defined as the amount of pollution generated by an economic activity without regard to the size of the area into which the pollutants are emitted, therefore emissions are not necessarily correlated with environmental degradation (Kaufman et al. 1998). Other common differences include controls for population effects, the countries used in the analysis, estimation differences (e.g., fixed versus random effects), trade policy, and whether panel or cross-sectional data were used in the analysis.

Nine variables are used to capture methodological factors: (i) whether the study included data from developed countries only (DEVELOP); (ii) the sample size used in an EKC study (SAMPLE); (iii) whether the pollutant was measured as ambient concentrations or as emissions (EMISSION); (iv) whether the study controlled for population effects (POP); (v) whether the study controlled for trade policy (TRADE); (vi) whether the study used random or fixed effects (RE); (vii) whether cross-sectional data were used (CROSSECT); (viii) whether the study controlled for socio-demographic characteristics (SOCIO); and (ix) whether the study controlled for the scale or composition of a region's economic activity (ECONACT). The effects of these variables on ITPs are not clear *a priori.*

The environmental indicators are divided into 11 categories, which could be supported by the data (i.e., contained multiple observations).[2] These categories include; toxic emissions (TOXIC), urban air quality (URBANAIR), deforestation (DEFOREST), heavy particulates (PARTIC), urban quality (URBANQ), water quality/pollution (H_2OPOLL), heavy metals (HMETALS), SO_2, combustion by-products (COMBUST), hazardous waste (HW), and CO_2. Some categories, such as URBANQ, contain several environmental indica-

[1] To be included in the sample, a study needed information on estimation results. Many studies presented results from multiple models from the same data. If there was no way to differentiate between models, only one observation was selected. The model selection criteria generally used was R^2.

[2] A detailed appendix defining the pollutant categories, and the pollutants contained within a category, is available from the lead author upon request.

Table 1. Variable Descriptions, Descriptive Statistics, and Expected Signs on Peak ITPs[a]

Name	Definition	Expected Sign on Peak ITPs	Mean (standard errors)
	Methodological Variables		
DEVELOP	Dummy variable - 1 indicates the study used developed countries only, 0 otherwise.	—	0.25 (0.43)
SAMPLE	The natural log of the sample size of a given observation.	—	5.59 (1.73)
EMISSION	Dummy variable - 1 indicates the pollutant was measured as emissions, 0 otherwise.	—	0.48 (0.50)
POP	Dummy variable - 1 indicates the study controlled for population, 0 otherwise.	—	0.30 (0.46)
TRADE	Dummy variable - 1 indicates the study controlled for trade policy, 0 otherwise.	—	0.19 (0.39)
RE	Dummy variable - 1 indicates the study used a random effects model, 0 otherwise.	—	0.25 (0.43)
CROSSECT	Dummy variable - 1 indicates the study used cross-sectional data only, 0 otherwise.	—	0.40 (0.49)
SOCIO	Dummy variable - 1 indicates the study controlled for socio-demographic differences, 0 otherwise.	—	0.12 (0.33)
ECONACT	Dummy variable - 1 indicates the study controlled for the economic activity of geographic areas, 0 otherwise.	—	0.25 (0.44)
	Pollutant Categories		
TOXIC	Dummy variable - 1 indicates the pollutant is toxic emissions, 0 otherwise.	—	0.08 (0.28)
URBANAIR	Dummy variable - 1 indicates the pollutant is smoke or dark matter, 0 otherwise.	Positive	0.05 (0.22)
DEFOREST	Dummy variable - 1 indicates the pollutant is deforestation, afforestation, or park areas, 0 otherwise.	No effect or positive	0.06 (0.25)
PARTIC	Dummy variable - 1 indicates the pollutant is suspended or heavy particulates, 0 otherwise.	No effect	0.11 (0.31)
URBANQ	Dummy variable - 1 indicates the pollutant is urban sanitation, safe [drinking] water, or fecal coliform, 0 otherwise.	Positive	0.07 (0.26)
H_2OPOLL	Dummy variable - 1 indicates the pollutant is BOD, COD, dissolved oxygen, or nitrates, 0 otherwise.	Positive	0.05 (0.22)
HMETALS	Dummy variable - 1 indicates the pollutant is heavy metals, 0 otherwise.	Positive	0.05 (0.22)
SO_2	Dummy variable - 1 indicates the pollutant is sulfur dioxide, 0 otherwise.	Positive	0.17 (0.37)
COMBUST	Dummy variable - 1 indicates the pollutant is carbon monoxide or nitrogen oxides, 0 otherwise.	Positive	0.12 (0.33)
HW	Dummy variable - 1 indicates the pollutant is hazardous waste, 0 otherwise.	Positive	0.03 (0.18)
CO_2	Dummy variable - 1 indicates the pollutant is carbon dioxide, 0 otherwise.	Positive	0.19 (0.40)

[a]The number of observations is 155.

tors. URBANQ attempts to capture those indicators that directly affect living standards and consumption capabilities. They are a direct link between local environmental quality and consumption. Other categories contain a single pollutant, such as SO_2 and CO_2.

For the dependent variable, if an ITP is not explicitly calculated in a study, it is calculated by partially differentiating the estimated equation with respect to income (ignoring all higher order income terms than the quadratic); setting the equation to zero, and solving. If no ITP exists, the in-

Table 2. Pollutant Descriptive Statistics

Pollutant Measure	N[a]	Mean on Actual ITPs[b]	Improves with Increases in Income[c]	Worsens with Increases in Income[d]
TOXIC	13	1,900	2	1
URBANAIR	8	4,445	1	0
DEFOREST	10	2,865	1	0
PARTIC	17	1,650	9	2
URBANQ	11	4,535	2	2
H_2OPOLL	8	7,330	1	1
HMETALS	8	10,830	0	0
SO_2	26	5,015	2	8
COMBUST	19	19,341	2	2
HW	5	21,165	0	0
CO_2	30	28,565[e]	0	5

[a]Does not include observations classified as no relationship, nor observations for studies without empirical statistics.
[b]Per capita ITPs in 1992 U.S. dollars.
[c]As income increases, environmental problem improves.
[d]As income increases, environmental problem worsens. Includes N-shaped and U-shaped relationships.
[e]Includes two observations with ITPs of $102 million and $9.96 million.

come-environment relationship is described as either worsening or improving, depending on the sign on the linear income term. The information on ITPs, either available or calculated, for various pollutants is summarized in table 2.[3]

Modeling Considerations

The basic model used to explain variations in ITPs includes both a set of dummy variables for pollutant categories, and a set of methodological variables. The general form of the model is:

$$\text{(4)} \qquad \ln ITP_i = P_i\gamma + S_i\beta + e_i,$$

where ITP_i is the per capita ITP for observation (that is, study) i, P is a vector of pollutant categories, S is a vector of variables measuring differences in study methods, γ and β are the vectors of corresponding parameters to be estimated, and e is a mean-zero error term.

Since per capita ITPs are calculated from parameter estimates from other econometric studies whose estimated standard errors are available, estimated variances can also be calculated. These variances can be used for efficient estimation. That is, (4) is a heteroscedastic model with "known" variances for each e_i, $i = 1,..., N$. Hence, a possible approach is generalized least squares (GLS) estimation. From (1), the ITP estimates are given by ITP $= -\beta_1/2\beta_2$, where the sampling distribution of β_1 and β_2 are assumed to be approximately normal. Using the delta method approximation (Greene 1997), the variances of the estimates of β_1 and β_2 are used to calculate the variances for the ITPs, assuming zero covariances between β_1 and β_2. It is possible that if this covariance information were available, the calculated covariances on the ITPs (and hence the weights in the GLS estimation) would be different. Since there were large differences in the ITPs and their computed variances, the natural log specification is used in (4), and the inverse of the natural log of the ITP variance is used to weight the observations for estimation.

In selecting an estimation approach, an important issue was whether to include all observations (i.e., those that demonstrate an EKC, and those that show monotonically increasing and decreasing relationships). Based on the general form of the model given in (4), a series of linear models by GLS were estimated as well as weighted tobit models. For the GLS, the usable sample consisted of 101 observations, which included observations with an estimated ITP or with monotonically decreasing income-environment relationships. In order to capture observations with a positive income-environment relationship, observations with extremely high estimated ITPs were not truncated from the data. For example, two of the 101 observations had estimated ITPs of $9.6 million and $102 million. ITPs for observations where pollutants monotonically decreased with income were set at $500 or $\ln ITP = 6.21$. (Results were qualitatively similar when the ITP for monotonically decreasing relationships was set at either $1000 or $3700.) This income level was chosen based on a review of the lowest national per capita income levels for industrializing, OPEC, and other developing and developed nations.

As an alternative to the GLS, a weighted tobit approach can be used to include all usable observations (and thus increases the sample size to 121). Specifically, a tobit model with upper censoring is used (Greene 1997). The upper censored model allows observations outside the date range (i.e., those demonstrating positive income-environment relationships) to be included in estimation. Let $\ln ITP_i = y_i$, then:

$$\text{(5)} \quad y_i = P_i\gamma + S_i\beta + e_i \qquad \text{if } P_i\gamma + S_i\beta + e_i < T,$$

$$\text{(6)} \quad y_i = T \qquad \text{if } P_i\gamma + S_i\beta + e_i \geq T,$$

where T is the censoring limit, $i = 1, 2,.., N$, and

[3] A full reference list for data sources and an appendix with detailed information about all studies included are available from the lead author upon request.

N is the number of observations. The dependent variable is censored at $\ln ITP \geq 13.12$ (i.e., $T \geq$ \$500,000) for those observations where the environmental problem monotonically increases with income, otherwise $y_i = \ln ITP_i$, using $\ln ITP = 6.21$ for monotonically decreasing relationships.[4] The log-likelihood for the censored regression model is:

(7)

$$\ln L = \sum_{y_i < T} -\frac{1}{2}\left[\ln(2\pi) + \ln \sigma^2 + \frac{(y_i - P_i\gamma - S_i\beta)^2}{\sigma^2}\right] + \sum_{y_i \geq T} \ln\left[1 - \Phi\left(\frac{P_i\gamma + S_i\beta}{\sigma}\right)\right]$$

The tobit technique estimates a regression line using all possible observations, both those censored at a limit and those within the limit. It is a mixture of a continuous distribution for the nonlimit observations and a discrete distribution for the limit values. Since the model uses all observations, it is preferred to techniques that only use observations not censored by a limiting value (McDonald and Moffitt 1980).[5]

Empirical Results

Estimation results of the tobit and GLS models are presented in table 3. Models I and II are specifications of the tobit; Models III and IV are specifications of the GLS. For comparison, Models I and III include all methodological variables and pollutant categories, while Models II and IV include only those explanatory variables representing the pollutant categories. Overall, the regressions have adequate measures-of-fit. For the tobit models, Maddala's R^2 for Model I is 0.55 and 0.44 for Model II. In the GLS, the R^2 for Model III is 0.69 and 0.50 for Model IV. Thus, methodological variables explain much of the variation in ITPs.

In both the tobit and the GLS, methodological variables significantly affect the magnitude of ITPs. Of note, the estimated coefficient on DEVELOP in both estimations (I and III) is negative and significant at the 1% level. If a study uses developed nations only, then these studies tend to find lower ITPs. This suggests that ITP results are not necessarily representative across different nations, but sensitive to the nations included in a study.

The estimated coefficient on EMISSION is positive and significant at the 5% level in the tobit (Model I), and the 1% level in the GLS (Model III). As hypothesized by Kaufman et al. (1998) and Seldon and Song (1994), pollutants measured as emissions rather than ambient concentrations will have higher ITPs. Unlike emissions, since ambient concentrations are defined by a geographical area, they may be more visible, and thus receive attention at lower income levels.

In addition, the estimated coefficient on TRADE is positive and significant at the 1% level in the tobit (Model I) and the 5% level in the GLS (Model III). Suri and Chapman (1998) find much higher ITPs when they include trade effects, which are generally only proxied by the quadratic income term used in reduced form equations. The meta-analysis results confirm that including trade effects as an explanatory variable will yield higher ITPs.

Two hypothesis tests were performed to determine the joint significance of methodological differences (S) on ITPs. For both the tobit and GLS specifications, a joint significance test was conducted on all coefficients in the vector S (I vs. II and III vs. IV). The χ^2 value for a likelihood ratio test (restricted versus unrestricted) in the tobit case was 31.30, and thus the null that $\beta = 0$ was rejected. Similarly, the F-statistic testing nine linear restrictions in the GLS was 7.12, and again the null was rejected. Thus, Models I and III are the focus of the following discussion.

The estimated coefficients on the pollutant dummies gauge the effects of different pollutants on ITPs. For both Models I and III, the estimated coefficient on CO_2 is positive and significant at the 1% level. In addition, the estimated coefficient on COMBUST is positive and significant at the 5% level in Model I and at the 1% level in Model III. For the other pollutant categories there is greater variability across models and specifications. From the full GLS specification (Model III), not only are the coefficients on COMBUST and CO_2 positive and significant, but so are the estimated coefficients on DEFOREST, URBANAIR, SO_2, and HW. It is predicted that these environmental indicators will have relatively higher ITPs than toxic emissions (TOXIC), particulate matter (PARTIC), urban quality (URBANQ), and water pollution (H_2OPOLL).

The results from the full weighted censored tobit

[4] Since it is unclear at what income level censoring begins for observations outside the data range, a sensitivity analysis was performed on the upper threshold by testing thresholds below and above \$500,000. The predicted ITP on CO_2 increases by approximately \$100,000 when a threshold of \$900,000 is used, otherwise model results were qualitatively similar. The full set of results is available upon request.

[5] A discrete choice multinomial logit model was also attempted to explain the probability of the existence of an ITP. The three choice categories were: (i) an ITP exists; (ii) no ITP and monotonically increasing relationship; and (iii) no ITP and monotonically decreasing relationship. The model did not converge due to insufficient variation.

Table 3. Modeling Results

	Weighted Censored Tobit[a]		GLS Estimates[b]	
Variable	Model I	Model II	Model III	Model IV
Constant	5.72***[c]	8.10***	3.16**	7.62***
	(3.62)[d]	(10.13)	(2.17)	(9.41)
DEVELOP	−2.07***		−3.58***	
	(−3.02)		(−5.29)	
SAMPLE	0.23*		0.54***	
	(1.74)		(4.36)	
EMISSION	1.39**		2.13***	
	(2.20)		(3.79)	
POP	−0.36		−0.28	
	(−0.82)		(−0.68)	
TRADE	1.36***		0.94**	
	(2.83)		(2.06)	
RE	−0.09		0.27	
	(−0.19)		(0.61)	
CROSSECT	0.63		0.97	
	(1.00)		(1.56)	
SOCIO	0.19		0.03	
	(0.22)		(0.03)	
ECONACT	0.74		−1.10**	
	(1.32)		(−2.04)	
URBANAIR	0.48	0.23	2.82**	0.70
	(0.34)	(0.18)	(2.17)	(0.57)
DEFOREST	0.50	−0.21	2.50**	0.27
	(0.39)	(−0.20)	(2.13)	(0.25)
PARTIC	0.71	0.38	1.19	0.41
	(0.66)	(0.41)	(1.19)	(0.45)
URBANQ	0.72	−0.28	1.23	−0.02
	(0.56)	(−0.27)	(1.03)	(−0.19)
H_2OPOLL	0.78	0.27	0.73	0.33
	(0.57)	(0.22)	(0.58)	(0.27)
HMETALS	1.71	1.03	2.26	1.50
	(1.04)	(0.67)	(1.53)	(1.00)
SO_2	1.85*	1.33	2.15**	1.03
	(1.70)	(1.51)	(2.09)	(1.15)
COMBUST	2.35**	3.57***	2.55***	3.99***
	(2.32)	(4.14)	(2.64)	(4.59)
HW	2.72**	1.79	3.19***	2.26*
	(2.02)	(1.33)	(2.64)	(1.70)
CO_2	4.23***	4.09***	4.14***	4.44***
	(4.07)	(4.40)	(4.13)	(4.60)
σ	1.59***	1.80***		
	(13.96)	(13.95)		
N	121	121	101	101
R^2	—	—	0.69	0.50
Maddala R^2	0.55	0.44	—	—

[a]Dependent variable is ln *ITP* censored with an upper threshold of $500,000.
[b]Dependent variable is ln *ITP*.
[c]***, **, *denotes significance at the 1%, 5%, and 10% levels, respectively.
[d]T-statistics given in parentheses.

specification (Model I) are of primary interest since all usable observations are included in estimation. In addition to the positive and significant coefficients on COMBUST and CO_2, the estimated coefficients on SO_2 and HW are positive and significant at the 10% and 5% levels, respectively. The ITPs for these four environmental indicators will be greater than the ITPs for toxic emissions (TOXIC), urban air quality (URBANAIR), deforestation (DEFOREST), particulate matter (PARTIC), urban quality (URBANQ), water pollution (H_2OPOLL), and heavy metals (HMETALS). On a general level, these results resemble the means for pollutants calculated from the summary of prior ITP results. In table 2, HW, COMBUST, and CO_2 have the highest mean ITPs while eight of 26 SO_2 observations have positive income-environment relationships.

Table 4. Predicted Per Capita ITPs by Type of Pollutant[a]

Variable	Model I - Censored Tobit[b]	Model III - GLS
TOXIC	$3,020	$1,645
URBANAIR	$4,860	$27,605
DEFOREST	$4,940	$20,130
PARTIC	$6,075	$5,435
URBANQ	$6,180	$5,622
H_2OPOLL	$6,515	$3,405
HMETALS	$16,390	$15,755
SO_2	$18,925	$14,110
COMBUST	$30,840	$20,980
HW	$44,610	$40,160
CO_2	$199,345	$103,840

[a]Figures rounded to the nearest $5.
[b]Using McDonald and Moffitt's (1980) Decomposition of E[y|x], the scale factor for marginal effects is 0.9901.

The meta-analysis ITP estimates presented in table 4 are obtained by pooling different ITP estimates from various studies, controlling for methodological factors, and then predicting the new underlying ITPs from the coefficients on pollutant dummies. Since Model I from the tobit specification uses all possible observations, it is the preferred model and the basis of the following discussion. The predicted per capita ITPs are calculated by scaling the coefficients by a factor for marginal effects and evaluating methodological variables at their means. The predicted ITPs range from $3020 for TOXIC to $199,345 for CO_2. By including monotonically increasing relationships in the tobit model, the resulting ITP predictions for all pollutants, with exception to URBANAIR AND DEFOREST, are higher than the ITP predictions obtained from the GLS model.

Income-environment relationships vary depending on the characteristics of pollutants. Many pollutants or environmental problems have different dispersion effects. For example, CO_2 is a stock pollutant, which easily crosses international or regional boundaries, while other air pollutants, such as particulate matter, may remain within a regional air shed. Even though the ITP for CO_2 of $199,345 is well outside the range of national per capita incomes today, the result is not unexpected since CO_2 is a public bad whose abatement and reduction in the atmosphere require coordinated actions.[6] That is, attempts by a single jurisdiction to control CO_2 would not generate any local benefits as the pollutant is saturated into the atmosphere by neighboring regions. As a greenhouse gas and a source of potential global climate change (see review in Goodstein 1999), regulation of CO_2 may require international cooperation. In addition, environmental problems that pose severe health or environmental risks, or highly visible environmental problems (e.g., urban sanitation) would be expected to have lower ITPs compared to colorless or odorless air or water pollutant problems. For example, the predicted ITPs for TOXIC, H_2OPOLL, (both pose health risks) and URBANQ, PARTIC, and URBANAIR (all visible problems) are lower than the predicted ITPs for colorless and odorless pollution problems, such as SO_2 and COMBUST.

The predicted ITPs on COMBUST and HW are higher than their sample means. Closer examination reveals that Carson et al. (1997), which analyzed the income-environment relationship for the United States only, is the sole study to find a negative income-environment relationship for CO and NO_X. After controlling for methodological choices, for example by using a dummy variable for developed countries, the predicted ITP for COMBUST is actually much higher.

Similarly, both studies that evaluate HW use data from the United States. The predicted ITP on HW is actually much higher after controlling for methodological variables. Furthermore, the high ITP for HW is expected. HW sites are different from most air or water pollutants in that they are not easily shiftable to other areas. For example, upon examining the relationship between per capita income and HW, Berrens et al. (1997) find a relatively high ITP. Subsequent work by Gawande et al. (forthcoming) finds that the EKC is partially explained by wealthier households moving away from a build-up of sites rather than any abatement process. This (dis)amenity driven net-out migration occurs at relatively high per capita incomes.

Conclusions

Emerging evidence on the EKC relationship will likely continue to be the focus of considerable attention, and thus underscores the task of summarizing current evidence. This empirical analysis makes two contributions. First, the meta-analysis is used to statistically summarize the existing empirical values from the EKC literature by controlling for methodological factors. Second, the meta-analysis results are used to predict new ITPs for eleven different pollutants. These predictions are in some sense more reliable than those obtained from

[6] As suggested by an anonymous reviewer, a different explanation for the high ITP for CO_2 is because the damages from CO_2 will occur in the future when incomes are much higher, and thus the impetus for current action is diminished.

a single study since they draw on information from all the available EKC studies.

The meta-analysis results indicate that those EKC studies that estimated the empirical income-environment relationship for developed countries tend to find lower ITPs. This suggests that ITP results are not necessarily representative across nations. Furthermore, the meta-analysis results confirm an accepted conjecture that emission estimates clearly exceed their ambient concentration counterparts, and therefore one should not conclude that emission and ambient concentrations of a particular pollutant will result in comparable ITPs. Finally, those studies that include trade effects as an explanatory variable, rather than income alone capturing these effects, tend to find higher ITPs; this confirms the recent arguments of Suri and Chapman (1998).

In summary, the meta-analysis demonstrates that methodological choices can significantly influence results (i.e., the magnitude of an ITP). As a general cautionary note to the applied researcher, this result is repeatedly found in other meta-analyses in environmental economics. More specifically, this finding will help to inform the interpretation of current results and development of future EKC studies. Empirical EKC evidence has accumulated very rapidly and apparently innocuous choices may be influencing estimation, and resulting inferences. Thus, interpreting available EKC evidence should always be done with caution (i.e., estimated ITPs may not have the precision needed for detailed policy inferences).

While the EKC relationship has now been widely identified in many cases, where it does exist the identified ITP may be quite large relative to mean per capita incomes for most of the world's population. Our meta-analysis results help identify the pollution categories where predicted ITPs are extremely high; these categories include combustion by-products, hazardous waste, and CO_2. The implication, in the near term at least, is that many pollutants, especially CO_2, will continue to increase in total levels.

References

Arrow, K., B. Bolin, R. Costanza, P. Dasgupta, C. Folke, C.S. Holling, B.O. Jansson, S. Levin, K.G. Mäler, C. Perrings, and D. Pimentel. 1995. "Economic Growth, Carrying Capacity, and the Environment." *Science* 268:520–21.

Beckerman, W. 1992. "Economic Growth and the Environment: Whose Growth? Whose Environment?" *World Development* 20 (4):481–96.

Barbier, E. 1997. "Introduction to the Environmental Kuznets Curve Special Issue." *Environment and Development Economics* 2 (4):369–81.

Berrens, R., A. Bohara, K. Gawande, and P. Wang. 1997. "Testing the Inverted-U Hypothesis for U.S. Hazardous Waste: An Application of the Generalized Gamma Model." *Economic Letters* 55(3):435–40.

Bohara, A., K. Gawande, R. Berrens, and P. Wang. 1999. "Environmental Kuznets Curve(s) for U.S. Hazardous Waste Sites: Theory and Evidence." Manuscript, Department of Economics, University of New Mexico.

Carson, R., Y. Jeon, and D. McCubbin. 1997. "The Relationship Between Air Pollution Emissions and Income: US Data." *Environment and Development Economics* 2 (4): 465–84.

Ekins, P. 1997. "The Kuznets Curve for the Environment and Economic Growth: Examining the Evidence." *Environment and Planning A* 29 (5):805–30.

Gawande, K., A. Bohara, R. Berrens, and P. Wang. Forthcoming. "Internal Migration and the Environmental Kuznets Curve for U.S. Hazardous Waste Sites." *Ecological Economics* (forthcoming).

Goodstein, E. 1999. *Economics and the Environment.* New Jersey: Prentice Hall.

Greene, W. 1997. *Econometric Analysis.* New Jersey: Prentice Hall.

Grossman, G., and A. Krueger. 1996. "The Inverted-U: What Does It Mean?" *Environment and Development Economics* 1 (2):119–22.

Grossman, G., and A. Krueger. 1995. "Economic Growth and the Environment." *The Quarterly Journal of Economics* 110 (2):353–77.

Grossman, G. and A. Krueger. 1993. "Environmental Impacts of a North American Free Trade Agreement." In *The U.S.-Mexico Free Trade Agreement,* ed. P. Garber. Cambridge, MA: MIT Press.

Holtz-Eakin, D. and T. Selden. 1995. "Stoking the Fires? CO_2 Emissions and Economic Growth." *Journal of Public Economics* 57 (1):85–101.

Hunt, M. 1997. *How Science Takes Stock: The Story of Meta-Analysis.* New York, NY: The Russell Sage Foundation.

Kaufmann, R., B. Davidsdottir, S. Garnham, and P. Pauly. 1998. "The Determinants of Atmospheric SO_2 Concentrations: Reconsidering the Environmental Kuznets Curve." *Ecological Economics* 25 (2):209–20.

Kuznets, S. 1955. "Economic Growth and Income Inequality." *American Economic Review* 45:1–28.

Loomis, J., and D. White. 1996. "Economic Benefits of Rare and Endangered Species: Summary and Meta-Analysis." *Ecological Economics* 18 (3):197–206.

Lucas, R., D. Wheeler, and H. Hettige. 1992. "Economic Development, Environmental Regulation and the International Migration of Toxic Industrial Pollution: 1960–88." In *International Trade and the Environment,* P. Low, ed. World Bank Discussion Paper No. 159. Washington DC: World Bank.

McDonald, J. and R. Moffitt. 1980. "The Uses of Tobit Analysis." *Review of Economics and Statistics* 62:318–21.

Panayotou, T. 1997. "Demystifying the Environmental Kuznets Curve: Turning a Black Box into a Policy Tool." *Environment and Development Economics* 2 (4):465–84.

Rock, M. 1996. "Pollution Intensity of GDP and Trade Policy:

Can the World Bank Be Wrong?" *World Development* 24 (3):471–79.

Selden, T., A. Forrest, and J. Lockhart. 1999. "Analyzing the Reductions in U.S. Air Pollution Emissions: 1970 to 1990." *Land Economics* 75 (1):1–21.

Selden, T., and D. Song. 1994. "Environmental Quality and Development: Is There a Kuznets Curve for Air Pollution Emission?" *Journal of Environmental Economics and Management* 27 (2):147–62.

Smith, V.K., and L. Osborne. 1996. "Do Contingent Valuation Estimates Pass a 'Scope' Test? A Meta-Analysis." *Journal of Environmental Economics and Management* 31 (3): 278–301.

Smith, V.K., and J.C. Huang. 1995. "Can Markets Value Air Quality? A Meta-Analysis of Hedonic Property Value Models." *Journal of Political Economy* 103 (1):209–27.

Smith, V.K., and Y. Kaoru. 1990. "Signals or Noise? Explaining the Variation in Recreation Benefit Estimates." *American Journal of Agricultural Economics* 72 (2):419–33.

Stern, D., M.S. Common, and E. Barbier. 1996. "Economic Growth and Environmental Degradation: The Environmental Kuznets Curve and Sustainable Development." *World Development* 24 (7):1151–1160.

Suri, V., and D. Chapman. 1998. "Economic Growth, Trade and Energy: Implications for the Environmental Kuznets Curve." *Ecological Economics* 25 (2):195–208.

van den Bergh, J., and K. Button. 1997. "Meta-Analysis of Environmental Issues in Regional, Urban and Transport Economics." *Urban Studies* 34 (5–6):927–44.

Walsh, R., D. Johnson, and J. McKean. 1992. "Benefit Transfer of Outdoor Recreation Demand Studies, 1968–1988." *Water Resources Research* 28 (3):707–13.