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ANALYSIS

The demand for environmental quality and the environmental Kuznets Curve hypothesis

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Abstract

Household demand for better environmental quality is the key factor in the long-term global applicability of the Environmental Kuznets Curve (EKC) hypothesis. We argue that, for given consumer preferences, the threshold income level at which the EKC turns downwards or the equilibrium income elasticity changes sign from positive to negative depends on the ability to spatially separate production and consumption. We test our hypothesis by estimating the equilibrium income elasticities of five pollutants, using 1990 data for the United States. We find that the change in sign occurs at lower income levels for pollutants for which spatial separation is relatively easy as compared to pollutants for which spatial separation is difficult. Our results suggest that even high-income households in the United States have not yet reached the income level at which their demand for better environmental quality is high enough to cause the income–pollution relationship to turn downwards for all the pollutants that we analyzed.

Keywords: Environmental Kuznets Curve; Income-pollution relationship; Production and consumption

1. Introduction

The Environmental Kuznets Curve (EKC) hypothesis predicts an inverted-U-shaped relationship between income and pollution: pollution rises with income as long as income is relatively low and declines once income has exceeded a threshold level. Economists have proposed several reasons for a relationship between income and pollution,[1] which can be classified into three categories: increasing economic scale, structural change (changes in the output mix of the economy), and increasing demand for environmental quality as household income

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[1] See Grossman and Krueger (1992, 1995), Selden and Song (1994), Suri and Chapman (1998), Torras and Boyes (1998), and Barrett and Graddy (2000).

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increases. While the first category provides an explanation for a positive income–pollution relationship, the other two categories can explain positive as well as negative relationships.[2]

Most analysts have investigated the EKC hypothesis with multicountry panel data sets, using GDP as measure of country income. Because changes in GDP reflect the effects of changes in economic structure as well as changes in income, such multicountry analyses provide information about the relationship between economic growth and pollution but not about the individual magnitudes of the structural and the income effect, and they make it difficult to separate the impact of technological factors from the influence of consumer preferences. Yet such separation is necessary to identify the main factors that drive the relationship, which in turn is fundamental for the development of effective environmental policies.

In this paper, we analyze the impact of the demand for environmental quality on the income–pollution relationship by focusing on the nature of the pollutant, in particular, by focusing on whether it is possible for consumers to spatially separate themselves from the source of pollution. We argue that the possibility to spatially separate production and consumption plays a decisive role in the consumer's decision to reduce his or her exposure to pollution as income increases, and that the income–pollution relationship turns negative at lower income levels for goods which spatial separation is possible.

Similar arguments have been made before. For example, Shafik and Bandhopadhyay (1992) argue that, because of the greater local benefits of abatement, local pollutants tend to decline with income when countries reach the middle income level, while global pollutants continue to increase. Suri and Chapman (1998) show that, when trade in energy-intensive goods is taken into account, per capita energy consumption continues to increase with GDP. However, these analyses use aggregated models and multicountry panel data that combine the effects of structural change, technology, and changes in the demand for environmental quality. In contrast, we use cross-sectional census-tract-level data for the United States to isolate the effects of differences in consumer income from changes in the other factors. We show that, given consumer preferences and technology, the location of the turning point—the income levels at which the reduced form income–pollution relationship turns from positive to negative—does not depend on whether a pollutant has deleterious local or global effects but on the cost of reducing exposure to pollution—specifically, on the ability to spatially separate the production and consumption of pollution-generating activities.

The most straightforward way of testing our hypothesis is to compare the locations of the turning points for different pollutants. However, the turning-point estimator in standard reduced form EKC models tends to follow a nonsymmetric distribution, which makes it difficult to evaluate and compare different turning-point estimates. Fortunately, the turning point coincides with the income level at which the equilibrium income elasticity of pollution—the percentage change in equilibrium pollution due to a change in income—changes sign from positive to negative. The estimator of the equilibrium income elasticity of pollution has an asymptotically normal distribution under standard model assumptions, which greatly simplifies model assessment.

We therefore test our hypothesis by estimating the equilibrium income elasticities of five measures of air pollution: sulfur dioxide (SO_2), particulate matter (PM_{10}), carbon monoxide (CO), ground level ozone (O_3), and nitrogen oxides (NO_x). The primary sources of emissions of SO_2 and PM_{10} are copper smelters and coal-burning facilities such as electric utilities for which spatial separation of production and consumption is relatively straightforward. For these two pollutants, we obtain income elasticities that are declining and negative over most of the income range. Motor vehicles are the primary source of emissions for CO, O_3, and NO_x, and the spatial separation of the production and consumption of transportation is fairly expensive. Our analysis suggests positive and increasing income elasticities of pollution, although the

[2] Barbier (1997, p. 370) and Carson et al. (1997, p.434) suggest that additional explanations, such as technological change, increases in civil and political liberties, and changes in environmental and trade policies, are simply the means through which changes in the demand for environmental quality are realized into changes in pollution levels.

relationship is statistically significant only for NO_x.

Our analysis provides an intuitive explanation for why the income–pollution relationship of even local and "hot-spot" pollutants such as O_3 and CO need not become negative at relatively low income levels. Although the marginal benefits from abatement are likely to be high for these pollutants, the difficulty in spatially separating the production and consumption of the pollution-generating activities causes the opportunity cost of reducing such pollution to be high as well. We find support for the trade and embodied pollution argument set forth in Suri and Chapman (1998): when it is possible to "export" pollution to other regions or emigrate from polluted areas by spatially separating production and consumption, increases in consumer income are likely to be associated with a decline in exposure to pollution. This explains why currently available data and empirical analyses thereof have provided support for the EKC hypothesis for some (local and regional) pollutants but not for others.

2. The nature of the equilibrium income elasticity of pollution

The amount of pollution that consumers are willing to tolerate depends on the marginal rate of substitution between consumption and pollution (the slope of the indifference curve), and the marginal rate of transformation between consumption and pollution (the slope of the consumption possibilities frontier or the opportunity cost of reducing pollution). The equilibrium income–pollution path depends on the relative change in the slopes of the indifference curve and the consumption possibilities frontier as the consumer's income increases. Using the standard static model of a single infinitely lived consumer, Lieb (2002) has shown that the equilibrium income–pollution path turns downwards when the marginal rate of substitution between consumption and pollution declines faster than the marginal rate of transformation between consumption and pollution as income (resources) increases. This implies that, for given consumer preferences, the location of the turning point varies directly with the opportunity cost of reducing pollution—the lower the opportunity cost, the lower the income level at which the turning point occurs.

The cost of reducing exposure to pollution depends on two factors: (1) the availability of technology to reduce pollution per unit of output (the pollution intensity of consumption) and (2) the consumer's ability to reduce his or her exposure to pollution by means other than reducing the pollution intensity of consumption. If it is relatively inexpensive to reduce the pollution intensity of consumption, then the income–pollution path turns downward (the equilibrium income elasticity changes from positive to negative) at a relatively low income level. An example is the relatively simple and inexpensive switch from leaded to unleaded gasoline that has almost entirely eliminated lead pollution.

If it is either impossible or too costly to reduce the pollution intensity of consumption, then the cost of reducing exposure to pollution depends on the consumer's ability to spatially separate production and consumption by either exporting the associated pollution to other areas or by relocating. If spatial separation is possible, then the opportunity cost of lowering pollution is likely to be relatively low, and the turning point is likely to occur at a relatively low income level. In this case, an increase in household income is associated with lower exposure to pollution at relatively low income levels. In other words, the equilibrium income elasticity of such pollutants is likely to become negative quickly.

In cases in which spatial separation of production and consumption is not possible, the only way to reduce pollution is to reduce consumption and/or to change the production process. Because the opportunity cost of lowering exposure to pollution is relatively high, the turning point is likely to occur at a relatively high income level. As long as income is low, an increase in income is associated with higher consumption as well as higher pollution, and the equilibrium income elasticity of pollution is positive. An example is the pollution caused by the use of gasoline-powered motor vehicles. The demand for cars (measured in vehicle miles traveled) has a positive and relatively high-income elasticity, with estimates varying from about 0.5 to over 1, and spatial separation of the production and consumption of transportation is rather difficult.[3] Immediate pollution reduction (e.g., the use of mass transit) is often prohibitively expensive in areas with low-population density, and the export of pollution (e.g., through the move to electric vehicles for which spatial separation of energy generation and energy use is possible) is fairly expensive. Even in one of the richest economies, the United States, the use of gasoline-powered vehicles is rising despite the pollution that they generate. In contrast, the production of many other pollution-intensive goods, for example, ore refining, has moved to countries with lower per capita incomes, and imports of these goods are used to supplement domestic production by the United States.

In the following section, we test our hypothesis that the income level at which the equilibrium income elasticity of pollution changes from positive to negative depends on the ability to spatially separate production and consumption. We use data for five different pollutants. For two of these, SO_2 and PM_{10}, the primary sources of emissions are electric utilities and copper smelters, which are processes for which it is straightforward to spatially separate production and consumption. The major sources of emissions of the remaining three pollutants, CO, O_3, and NO_x, are motor vehicles, for which such spatial separation is much more difficult. We expect that the equilibrium income elasticity of pollution will change from positive to negative at lower income levels for SO_2 and PM_{10} compared to CO, O_3, and NO_x.

To increase the possibility of finding the income level at which the equilibrium income elasticity of pollution becomes negative, we use socioeconomic data for the United States, a country with one of the highest incomes in the world. Ambient concentrations data allow us to capture exposure to pollution better than emissions data that reflect pollution that is generated locally but might mostly affect other areas. We use cross-section data to eliminate the impact of changes in preferences and technology over time. Because preferences are likely to vary spatially, we use data on the census-tract-level, the smallest geographical unit for which detailed socioeconomic data are available.

[3] See Agras and Chapman (1999) for a summary of elasticity estimates.

It is useful to distinguish our use of the term equilibrium income elasticity from the structural income elasticity. The structural relationship between income and pollution reflects consumer preferences and describes the change in consumer demand for environmental quality in response to a change in consumer income, assuming that the relative price of consumption and pollution remains unchanged. The structural income elasticity of pollution therefore measures the percentage increase in consumer demand for environmental quality due to an increase in consumer income, ceteris paribus. The income–pollution relationship associated with the EKC hypothesis, however, refers to the equilibrium relationship between income and pollution that reflects the impact of increasing consumer income as well as the impact of changes in the relative price of consumption and pollution. The equilibrium income elasticity of pollution is the percentage change in equilibrium pollution that results from an increase in income and any associated change in relative prices. When the income–pollution path turns downward, the equilibrium income elasticity is negative.[4]

3. The empirical model and data

We assume that the reduced form relationship between the ambient concentrations of pollutant j in census tract i, A_{ji} and its covariates can be expressed as

$$\ln(A_{ji}) = \beta_{1j}\ln(\mathrm{inc}_i) + \beta_{2j}(\ln(\mathrm{inc}_i))^2 + \boldsymbol{X}_{ji}^T\boldsymbol{\gamma}_j + \varepsilon_{ji}, \tag{1}$$

where inc_i is the median household income in region i, $\boldsymbol{X}_{ji}$ is a vector of other covariates, γ_j is the

[4] Lieb (2002, pp. 438; who generalizes McConnell (1997)) has shown that a negative (positive) structural income elasticity of pollution (environmental quality) is a necessary but not a sufficient condition for a negative equilibrium income elasticity of pollution. The difference between the two concepts of the income elasticity of pollution does not seem to be well understood. For example, Bimonte (2002) aims to test the hypothesis that the demand for environmental quality is income-elastic, but he estimates the equilibrium relationship between income and pollution. We thank an anonymous referee for bringing the distinction between these two concepts of the income elasticity of pollution to our attention.

corresponding vector of slope coefficients for pollutant j, and ε_{ji} is a random error term.

We estimate separate models for five criteria pollutants under the United States Clean Air Act.[5] We obtained data on the annual ambient concentrations in 1990 and on the number of observations taken at each monitor from the Environmental Protection Agency's (EPA) AIRS database.[6] This database also provides the geographic coordinates (latitude and longitude) for each monitor, which we used to identify the census tracts in which the monitors were located.

Most empirical studies on the EKC focus on the aggregate relationship between pollution and income. They use national-level panel data and include only income (typically GDP per capita) and variables that are unlikely to be correlated with income so as to capture the direct and indirect effects of income on pollution, but we are interested in the effect of spatial separability between consumption and production on the pollution–income relationship, given preferences, and technology. To isolate the influence of this factor, we include variables that are likely to be correlated with income and that describe the effect of changes in income on pollution at any given location.

The literature on the distribution of air pollution in the United States suggests that pollution in any given area is influenced by race, education, the structural composition of the workforce, housing tenure, and population density, and we include these variables in our analysis.[7] Census-tract-level data on all these variables are available from the 1990 Census.

There is evidence that populations with a greater propensity for collective action tend to be less exposed to pollution.[8] We follow Brooks and Sethi (1997) and measure the propensity for collective action by the ratio of the number of registered voters in the 1992 Presidential elections to the estimated voting age population.[9] Data on the number of registered voters in the 1992 Presidential Elections and the estimated voting age population are available only at the county level.[10]

We control for the impact of economic structure on environmental quality by including the percentage of working age population employed in manufacturing in each census tract.[11] To measure the level of economic activity, we include the distance of the EPA monitors from the closest highway in the analyses of CO, NO_x, and O_3. This distance serves as a proxy for economic activity because on-road vehicles are a primary source of emissions for these three gases. The primary sources of SO_2 and PM_{10} are

[5] Carson et al. (1997) estimate models for the same pollutants using 1990 state level data on per capita emissions and per capita income. In all cases, they find a negative relationship between emissions and income.

[6] Some sites have multiple monitors for the same gas, and we determined the average ambient concentrations at these sites as the weighted average of the concentrations at all monitors at a site, with the number of observations from each monitor as the weights. In some cases, the number of observations at a monitor did not meet the National Ambient Air Quality Standards data completeness requirements. The EPA excluded these observations from the data set that it made available to us (David Mintz, personal communication, November 3, 2000).

[7] See Brooks and Sethi (1997) and the references cited there. We provide the definitions of the variables used in our analysis in the Appendix.

[8] See Brooks and Sethi (1997) and Arora and Cason (1999).

[9] Our source for the voting data (Election Data Services) does not report data voter's turnout data for many jurisdictions and so we could not use the ratio of voter turnout to voter registration to capture collective action. Data for Wisconsin and Alaska are also not reported. We predicted the log of the voter registration rate in these two states with an auxiliary regression, using county-level data for the entire United States. North Dakota does not require voter registration, and we used the ratio of voter turnout to voting age population.

[10] Using county level election data in our analysis is equivalent to assuming that voting behavior is uniformly distributed within a county. Because this assumption may be incorrect, we attempted to estimate the census tract level voter registration using county level data for the entire United States. Under this approach we estimated a model for voter registration using county data, and calculated census tract level voter registration by using the census tract values for all the covariates and the estimated coefficients. This attempt led to a high degree of multicollinearity because many of our other right-hand side variables are closely correlated with voter registration, and the results that we report are based on the county level data.

[11] Manufacturing is an aggregate category, and pollution intensity may vary across the different industries within the manufacturing sector. Unfortunately, detailed data on employment in different manufacturing industries are not available at the census-tract level. We thank an anonymous referee for drawing our attention to this possible aggregation bias.

Table 1
Statistical summary—means and standard deviations (1990)

Regression model variable	CO	O_3	NO_x	SO_2	PM_{10}
Median household income ($)	25,385 (13,119)	30,807 (12,606)	29,877 (13,378)	26,751 (11,051)	25,630 (11,758)
Population density (persons/km^2)	5696 (9546)	2599 (5804)	5217 (11,040)	3219 (8187)	3176 (7009)
% population minorities	27.1 (25.6)	17.8 (22.1)	25.3 (27.0)	18.1 (25.4)	18.5 (23.2)
% labor force unemployed	8.9 (6.7)	7.0 (5.7)	8.3 (6.7)	8.6 (6.4)	8.6 (6.4)
% labor force employed in manufacturing	11.1 (5.9)	14.6 (6.4)	12.9 (6.1)	14.9 (6.4)	13.5 (6.6)
% population with high school degree	17.2 (6.1)	19.4 (6.4)	17.5 (6.4)	21.0 (6.6)	20.0 (6.4)
% voting age population registered to vote[a]	72.6 (10.2)	72.9 (10.6)	72.0 (10.2)	75.0 (10.7)	75.9 (11.8)
% houses renter occupied	57.5 (26.1)	37.0 (22.5)	45.9 (23.1)	39.0 (23.8)	44.4 (23.2)
% monitors in urban areas	90.77 (28.98)	59.51 (49.11)	73.44 (44.23)	59.27 (49.17)	58.83 (49.23)
Distance from closest highway (m)	528.51 (2016.46)	1374.57 (2741.76)	804.31 (1712.16)	–	–
Proportion of sites located in a county with AR electric utility	–	–	–	67.19 (46.99)	–
Number of AR electric utilities in EPA region in which site is located	–	–	–	–	64.57 (78.82)
CO (ppm)	5.49 (2.6)	–	–	–	–
O_3 (ppm)	–	0.110 (0.03)	–	–	–
NO_x (ppm)	–	–	0.019 (0.01)	–	–
SO_2 (ppm)	–	–	–	0.007 (0.005)	–
PM_{10} (μg/m^3)	–	–	–	–	68.73 (38.64)
Total number of observations	509	820	305	707	1331
Number of census tracts	495	791	284	620	1176
Number of states[b]	48	51	39	48	51

"ppm" refers to parts per million by volume. "μg/m^3" refers to micrograms per cubic meter. "AR electric utilities" refers to electric utilities that are monitored under the EPA's Acid Rain Program.
Standard deviations are shown in parentheses.
[a] Refers to the 1992 Presidential elections. Values shown in the table do not include the predicted data for Wisconsin and Alaska.
[b] Includes the District of Columbia.

coal-burning facilities such as electric utilities and copper smelters. We include a dummy variable in the SO_2 model that indicates the presence of one or more electric utilities in the county that is being monitored under the EPA's Acid Rain Program. The PM_{10} model includes the number of such utilities located in that EPA region.

Suri and Chapman (1998) argue that models of the relationship between pollution and income ought to account for the fact that pollution levels in one area are related to the volume of goods that are imported and/or exported from there. If trade between census tracts is correlated with income, then ignoring the effects of such microlevel trade will affect the reliability of the estimates of the income coefficients. Because data on the flow of goods between census tracts are unavailable, we must accept the possibility that our estimates of the income coefficients suffer from an omitted variable bias. To account for omitted factors whose impacts are constant across regions, we include dummy variables to represent the 10 EPA regions.[12]

Table 1 shows summary statistics of our key right-hand-side variables. The five data sets include different census tracts because the EPA does not monitor all pollutants at each location, and we report the summary statistics separately for each data set. The 95% confidence intervals around the mean value of each variable overlap for all pollutants, which suggests that there are no statistically significant differences between the socioeconomic characteristics across data sets.

[12] The coefficients on these variables were generally statistically significantly at the 5% level. In each analysis, we also include 2–3 dummy variables to account for "influential observations." These are data points with unusually large Studentized residuals, DFFITS, DFBETAS, and/or unusual observations on the partial regression plots. We estimated the models without dummy variables for these observations, and the results are qualitatively similar.

4. Results

The number of observations varies substantially from site to site and also across pollutants at a given site. To accommodate differences in the variances across sites, we estimated Eq. (1) with weighted least squares using the number of observations at each site as weights.[13] Table 2 contains the results of our analyses.[14]

The signs of almost all estimated coefficients of the nonincome socioeconomic variables are consistent with those reported in the literature on the distribution of air pollution. For example, more densely populated communities tend to have higher levels of pollution, and communities with a greater propensity for collective action, as measured by the voter registration rate, tend to have lower pollution levels. The exception is the analysis of CO, where we obtain a positive and significant coefficient for the propensity of collective action.[15] In all models, the socioeconomic variables are jointly significant.

For CO and NO_x, the coefficient estimates on the distance of the EPA monitor from the closest road are negative and significant. This is intuitive given that census tracts located further away from a major highway are likely to have lower vehicular pollution. For SO_2 and PM_{10}, our estimates suggest that the presence and number, respectively, of electric utilities that are being monitored under the Acid Rain Program is associated with a statistically significantly higher level of pollution. The fact that we obtain the expected signs in most cases suggests that our models are unlikely to be badly misspecified.

The coefficients of the income terms are individually and jointly significant only for NO_x and PM_{10}.[16] For PM_{10}, the coefficient estimates imply the inverted U shape that the EKC hypothesis predicts. For NO_x, the coefficient estimates imply the opposite relationship—concentrations first decrease and then increase with median household income.

To test our hypothesis that the income–pollution relationship becomes negative at lower income levels in those cases where spatial separability between consumption and production is possible, we need to compare the estimates of the turning points obtained above. The estimator of the turning point for pollutant j, $\hat{\tau}_j$, is determined by the ratio of the estimators of income coefficients, $\hat{\beta}_{1j}$ and $\hat{\beta}_{2j}$, as

$$\hat{\tau}_j = -\frac{\hat{\beta}_{1j}}{2\hat{\beta}_{2j}}.$$

Plassmann and Khanna (2002) have demonstrated that $\hat{\tau}_j$ is likely to have a skewed distribution if $\hat{\beta}_{1j}$ and $\hat{\beta}_{2j}$ are (asymptotically) normally distributed, which makes it difficult to assess the precision of the turning-point estimates with standard techniques. However, the income level of the turning point coincides with the income level at which the equilibrium income elasticity of pollution changes signs. The estimator of the equilibrium income elasticity of pollutant j in region i, $\hat{\eta}_{ji}$, can be constructed from $\hat{\beta}_{1j}$ and $\hat{\beta}_{2j}$ as

$$\frac{\partial \ln(A_{ji})}{\partial \ln(\mathrm{inc}_i)} = \frac{\partial A_{ji}}{\partial \mathrm{inc}_i}\frac{\mathrm{inc}_i}{A_{ji}} = \hat{\eta}_{ji} = \hat{\beta}_{1j} + 2\hat{\beta}_{2j}\ln(\mathrm{inc}_i). \quad (2)$$

If the estimators $\hat{\beta}_{1j}$ and $\hat{\beta}_{2j}$ are (asymptotically) normally distributed, then $\hat{\eta}_{ji}$ is (asymptotically) normally distributed as well. It is therefore possible to calculate an (asymptotic) 95% confidence interval around the point estimate of $\hat{\eta}_{ji}$ by adding and subtracting 1.96

[13] The Breusch–Pagan test rejected the null hypothesis that errors are uncorrelated with the number of observations at each site in all cases except NO_x. However, White's test rejects the null hypothesis that the errors are homoscedastic. For NO_x, we therefore report the OLS estimates with the heteroscedasticity consistent standard errors as well.

[14] Use of least squares requires the assumption that the right-hand-side variables are uncorrelated with the error term. We tested this assumption with respect to income using two instrumental variables—the proportion of population that is older than 65 years and the proportion of female-headed households. The tests do not reject the null hypothesis that income is exogenous in any of the five models.

[15] The signs and statistical significance of the estimated coefficients on this variable remain unchanged if we use the estimated census tract level voter registration in place of the county-level data.

[16] The coefficients on the income terms for SO_2 are not individually statistically significant, but the null hypothesis that they are simultaneously equal to zero is rejected at the 5% level. For CO and O_3, the null hypothesis that the coefficients of the income terms are simultaneously equal to zero is not rejected at the 10% level. For each of the five pollutants, we also estimated a model with a cubic income term, and we obtained qualitatively similar results in all cases.

Table 2
Regression results

	CO	O_3	NO_x		SO_2	PM_{10}
	(WLS)	(WLS)	(OLS)	(WLS)	(WLS)	(WLS)
Median household income	−1.247	−0.551	−4.081**	−3.992**	1.795	3.083**
	(0.988)	(0.592)	(1.111)	(1.255)	(1.362)	(0.713)
Median household income squared	0.059	0.028	0.206**	0.201**	−0.099	−0.165**
	(0.050)	(0.029)	(0.055)	(0.062)	(0.068)	(0.036)
Population density	0.150**	0.016**	0.094**	0.094**	0.060**	0.019**
	(0.016)	(0.006)	(0.020)	(0.016)	(0.014)	(0.007)
% minority population	0.036*	0.024**	0.072**	0.071**	−0.059**	−0.012
	(0.021)	(0.010)	(0.021)	(0.022)	(0.023)	(0.013)
% labor force unemployed	−0.052	−0.008	−0.065	−0.069	0.050	0.085**
	(0.038)	(0.019)	(0.054)	(0.049)	(0.047)	(0.024)
% labor force in manufacturing	0.050	0.033*	0.121**	0.117**	0.0007	0.067**
	(0.035)	(0.019)	(0.045)	(0.044)	(0.050)	(0.026)
% population with high school degree	−0.032	−0.008	0.052	0.044	0.044	−0.161**
	(0.045)	(0.026)	(0.057)	(0.056)	(0.065)	(0.032)
% voting age population registered to vote	0.223*	−0.165**	−0.669**	−0.682**	0.102	−0.200**
	(0.128)	(0.067)	(0.140)	(0.148)	(0.169)	(0.095)
% houses renter occupied	0.062	−0.013	0.059	0.051	−0.078	−0.095**
	(0.044)	(0.020)	(0.054)	(0.050)	(0.049)	(0.030)
Distance of monitor from closest road	−0.027**	0.002	−0.057**	−0.057**		
	(0.012)	(0.006)	(0.014)	(0.013)		
Acid Rain Program electric utility					0.098**	0.0005**
					(0.044)	(0.0002)
Dummy variable for urban areas	0.293*	0.003	0.278**	0.281**	−0.012	0.113**
	(0.080)	(0.024)	(0.078)	(0.070)	(0.061)	(0.032)
R^2	0.4977	0.3371	0.7991	0.8006	0.5358	0.2551
Number of observations	509	820	305	305	707	1331

All variables are expressed in natural logs, except the dummy variables and the Acid Rain Program electric utility variable. All models include dummy variables for the EPA regions and for influential observations.
We report White's heteroscedasticity consistent standard errors in the case of the OLS estimates for NO_x.
Standard errors are shown in parentheses.
* Indicates statistical significance at the 10% level.
** Indicates statistical significance at the 5% level.

times the estimated standard error of $\hat{\eta}_{ji}$. This standard error is the positive square root of the estimate of

$$\mathrm{Var}\left(\hat{\eta}_{ji}\right) = \mathrm{Var}\left(\hat{\beta}_{1j}\right) + 4(\ln(\mathrm{inc}_i))^2\mathrm{Var}\left(\hat{\beta}_{2j}\right) + 4\ln(\mathrm{inc}_i)\mathrm{Cov}\left(\hat{\beta}_{1j}\hat{\beta}_{2j}\right). \quad (3)$$

Note that $\hat{\eta}_{ji}$ and Var($\hat{\eta}_{ji}$) vary with income but do not depend on the other right-hand-side variables.

Fig. 1 shows the estimated equilibrium income elasticities of pollution for the five pollutants, together with the 95% confidence intervals, over the income range \$0 to \$100,000 (we have chosen different scales for the vertical axes to make the panels easier to read).

The EKC hypothesis predicts that the equilibrium income elasticity decreases monotonically with income and that it eventually changes sign from positive to negative. We have argued that the change in sign should occur at relatively low income levels for pollutants whose production and consumption can be spatially separated. We find such a change in sign only for SO_2 and PM_{10}, the two pollutants for which spatial separation is comparatively straightforward. The equilibrium income elasticity of PM_{10} is positive at very low levels of income and negative at higher income levels, and the equilibrium income elasticity of SO_2 is negative over most of the income range of our sample. The income levels at which the income elasticities switch signs are \$8,653 for SO_2 and \$11,412 for PM_{10}. Both are sufficiently far to the left of the median income levels of the two data sets (\$25,336 for SO_2 and \$24,375 for PM_{10}) to suggest

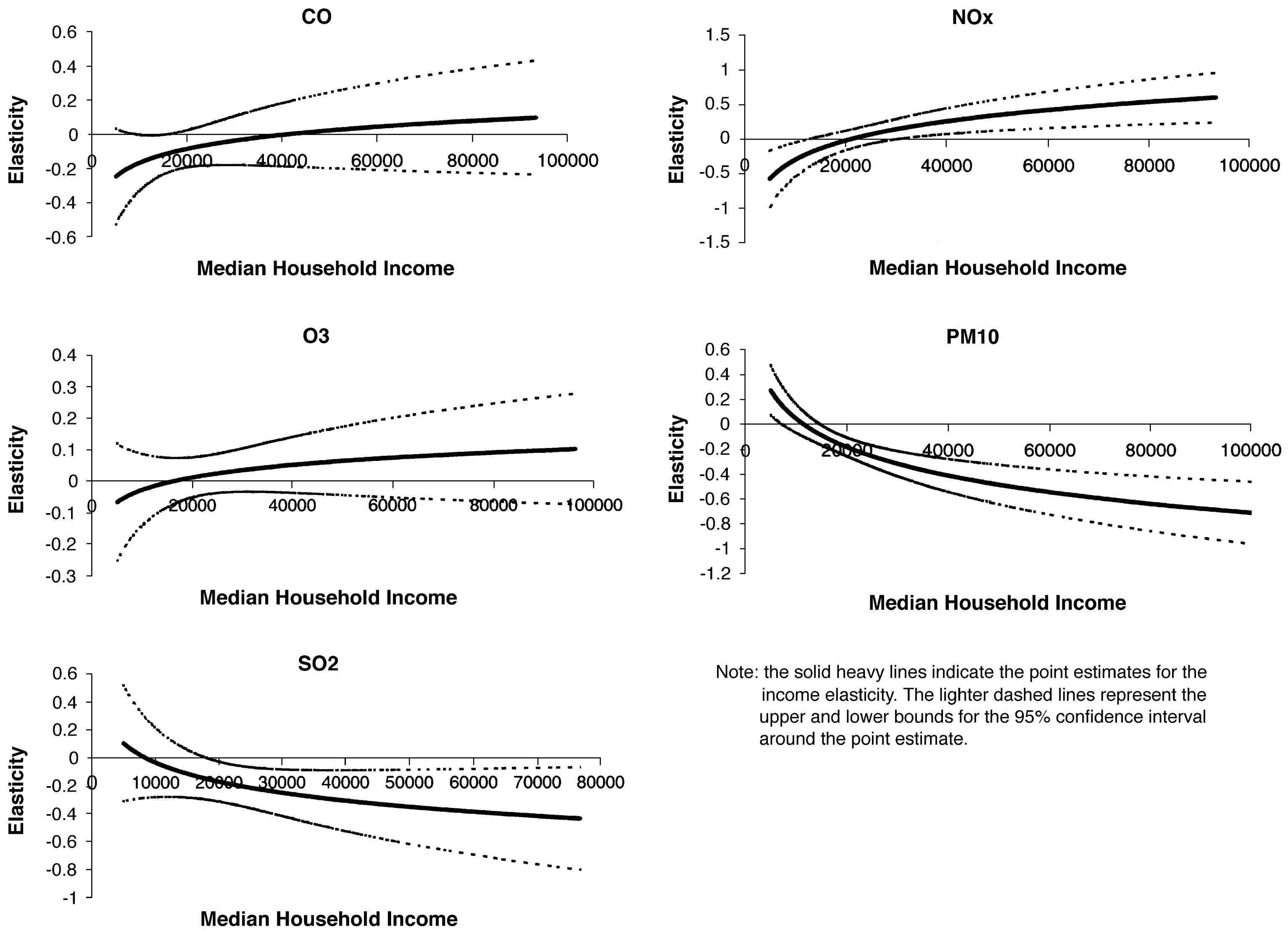

Fig. 1. Estimated income elasticity of pollution.

that we are estimating (mainly) the downward branch of the two EKC relationships. We conclude that there is strong support for the hypothesis that the income elasticities for these two pollutants switch signs at relatively low levels of income.

For the three pollutants for which spatial separation is much costlier, the coefficients of income are negative, and the coefficients of income-squared are positive.[17] The estimates imply increasing equilibrium income elasticities of pollution in all three cases. The 95% confidence intervals for CO and O_3 indicate that the estimated equilibrium elasticities are never significantly different from zero (except for a small interval between \$9,250 and \$15,500 in the case of CO), which is not surprising because the income coefficients of CO and O_3 are neither individually nor jointly significant. Although these coefficient estimates imply that there is no statistically significant association between income and the ambient concentrations of these two gases, this does not necessarily constitute evidence against the EKC hypothesis. If our hypothesis regarding the equilibrium income elasticity of pollution is correct, then the income level at which these elasticities change sign from positive to negative may exceed the upper end of our sample income range in the case of these two gases.[18]

For NO_x, the equilibrium income elasticity is significantly negative at income levels below \$12,500 and significantly positive at income levels above \$30,000. While it is somewhat surprising that we find a significantly negative elasticity at the low end of the income range, this is likely to be an artifact of our extrapolated confidence interval. The average median household income level in our NO_x data set is \$29,877, and the data set includes only 21 census tracts with median household incomes below \$12,500 but 140 census tracts with median household incomes above \$30,000. Because we only have few observations of incomes below \$12,500 at which the extrapolated 95% confidence interval does not include zero, it is likely that we underestimated the standard error of our estimates at this range and that the true 95% confidence interval does include zero. We conclude that NO_x has a positive equilibrium income elasticity over the range of our income data, which implies that it will become negative (if it does) only at a very high income level.

5. Conclusions

The ongoing debate about the shape of the EKC has focused mostly on the question of whether there is empirical evidence for an inverted-U-shaped relationship between income and pollution. On an intuitive level, we find it difficult to argue that the hypothesis can be incorrect. In the past, pollution levels have increased as economies developed and income levels rose so there is much empirical evidence for the upward sloping part of the relationship. Because pollution has negative effects on human health, it is unlikely that it will continue to rise or stay high forever as real incomes continue to increase. The relevant question is an empirical one: up to which income levels will different types of pollution continue to increase?

The EKC hypothesis refers to an equilibrium relationship between income and pollution that is based on the interaction between consumer preferences and the cost of reducing exposure to pollution. We argue that the equilibrium income elasticity of pollution is not uniform across pollutants and that, given consumer preferences and technology, it depends on the ability to spatially separate the production and consumption of goods and services. Where such spatial separation is possible, the opportunity cost of pollution abatement is likely to be low, and the equilibrium income elasticity of pollution changes sign from positive to negative (the EKC turns downwards) at relatively low income levels. Where such spatial separation is not possible, the equilibrium income elasticity of pollution remains positive until relatively high income levels.

If current incomes have not yet reached these high levels, then an empirical analysis of existing data will not yield an inverted-U-shaped relationship between income and pollution, even if the true relationship has such a shape over a wider income range. Such an

[17] If the dummy variables for the “influential observations” are excluded, then the coefficients on income and income-squared are statistically significant against the one-tailed alternative hypotheses that they are negative and positive, respectively. However, they remain individually and jointly statistically insignificant against the two-tailed alternative.

[18] The only alternative is a relatively easy end-of-pipe type of technological change that lowers the abatement cost of these gases and causes the income elasticity to become negative at a lower than otherwise expected income level.

analysis will estimate only the left leg of the relationship and might suggest a convex, a linear, or a concave relationship, depending on how far beyond the available data the turning point is located.

While our results for CO, O_3, and NO_x do not provide evidence against the EKC hypothesis, they support the conclusions of Ekins (1997), Selden and Song (1994), and Stern et al. (1996) that further growth in income is likely to lead to a worsening in certain measures of world pollution rather than an improvement. These authors base their conclusion on the expectation that the rapid increase in emissions from currently developing countries will more than offset the potential decline in developed country emissions. Our results suggest that, even for developed countries such as the United States, there is no guarantee that ambient concentrations of all pollutants will decline with future economic growth, and the ambient concentrations of some pollutants may even increase.

The upshot of our results is that, for the near future, environmental policies such as energy taxes and higher fuel economy standards will be important tools for reducing emissions of CO, O_3, and NO_x. While such measures tend to be politically unpopular, consumers are unlikely to voluntarily reduce such pollution given current preference structures. For the long term, our results reinforce the need for developing relatively low-cost pollution abatement technologies and for increasing public awareness of the harmful effects of pollution. With greater awareness, consumer preferences may change in favor of lower pollution, and there will be greater support for pollution abatement measures.

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Appendix A. Definition of constructed variables

Population density	Total population/tract area
% population minorities	Non-White population/total population
% labor force unemployed	Persons unemployed/labor force
Labor force	Persons 16 years or older
% labor force employed in manufacturing	Persons employed in durable and nondurable manufacturing/labor force
% population with high school degree	High school graduates/total population
% voting age population registered to vote	Persons registered to vote/voting age population
% houses renter occupied	Renter occupied housing units/occupied housing units

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