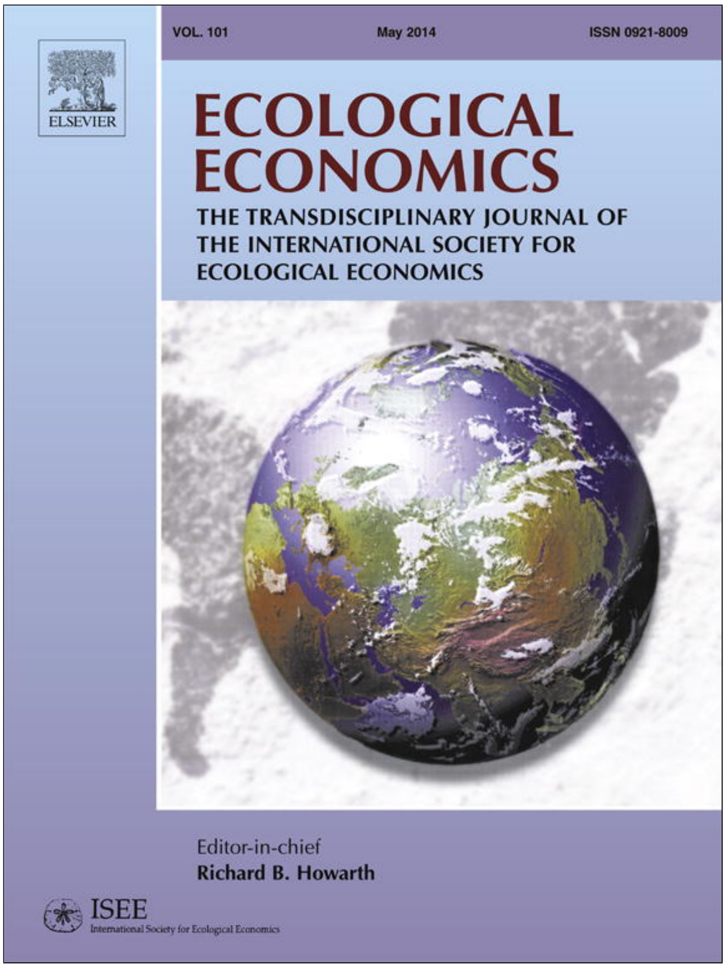
VOL. 101
May 2014
ISSN 0921-8009
ELSEVIER
ECOLOGICAL ECONOMICS
THE TRANSDISCIPLINARY JOURNAL OF THE INTERNATIONAL SOCIETY FOR ECOLOGICAL ECONOMICS
Editor-in-chief
Richard B. Howarth
ISEE
International Society for Ecological Economics

Ecological Economics 101 (2014) 81–89

Contents lists available at ScienceDirect

Ecological Economics

journal homepage: www.elsevier.com/locate/ecolecon

Methodological and Ideological Options

Visibility has more to say about the pollution–income link

Bin Du [a], Zhigang Li [b,*], Jia Yuan [c]

[a] Department of Economics, Rutgers University, New Jersey Hall, 705 Hamilton Street, New Brunswick, NJ 08901, USA
[b] School of Economics and Finance, The University of Hong Kong, Hong Kong
[c] Faculty of Business Administration, The University of Macau, Macau

ARTICLE INFO

Article history:
Received 1 October 2010
Received in revised form 8 January 2014
Accepted 16 February 2014
Available online 31 March 2014

JEL Classification:
O13
Q21
Q25

Keywords:
Air visibility
Environment Kuznets curve
Economic growth

ABSTRACT

We show that visibility data contain crucial information for learning the air pollution–income linkage. First, visibility reflects air pollutants (e.g. fine particulates) that are typically omitted by publicly reported indicators of air pollution, typically SO_2 and TSP. Second, data on visibility cover almost the entire world, whereas the typical pollution indicators cover a smaller and non-representative sample. We show that both features matter, in a significant way, by employing visibility as a proxy of air quality to re-estimate its relationship with income. Using the findings of Grossman and Krueger (1995) and Harbaugh et al. (2002) as benchmarks, we find that the test of the Environmental Kuznets Curve hypothesis is highly sensitive to the coverage of countries. More importantly, we find that this visibility–income linkage is only partially driven by publicly monitored pollutants, but is dominated by the "unobserved" ones. Addressing both issues, we find the inverse-U shape relationship supported for most of the economies.

1. Introduction

Economic growth may affect the natural environment. This linkage has an important implication for sustainable growth and health, and has been estimated by a large number of studies. The influential work of Grossman and Krueger (1995) (GK), for example, uses panel data across countries to estimate that the relationship between sulfur dioxide and per capita income follows an inverse-U shape (as implied by the Environmental Kuznets Curve hypothesis). This relationship, however, received mixed evidence from more recent studies. Harbaugh et al. (2002) (HLW), in particular, find that the EKC SO_2-income path disappears when the augmented GK data are used.[1]

The current study provides new evidence on the EKC hypothesis, but testing it is not our emphasis. Instead, our objective is to address two potentially fatal, yet largely omitted, limitations of the existing studies. Both of them concern the sample of commonly used pollution data. One is on the geographical coverage. The early influential studies mainly focus on developed countries and hence the sample is unrepresentative (Carson, 2010). Even in the later studies, for example, the data used in HLW (2002), cover less than 45 countries, which over-sample Asia and Europe. It is important to note that even if a true EKC path exists between pollution and income, the estimate of the path based on a non-representative sample may be severely biased if the functional form is mis-specified (see Fig. 1 for an illustration with hypothetical data).[2]

Another limitation of the existing data is that they may miss important pollutants in the air. For example, in most countries, the particles with diameters greater than 10 μm are monitored and reported, but finer particles are not (Roumasset et al., 2008). Hence, by focusing on the observed air pollutants, the literature might have omitted a significant component of the pollution–income dynamics. More importantly, this selective monitoring may give polluters an incentive to substitute their production of unmonitored particles for the observed ones so as to avoid penalty. This substitution effect could further distort the estimates based on observed pollutants. So the data quality issue has become one problem in testing the existence of EKC (Carson, 2010).

To address these two issues, at least partially, we utilize visibility, a measure of air quality that has been rarely used in the literature, to re-visit the EKC hypothesis. Air visibility reflects the outcome of both observed and unobserved air pollutants (especially particles with diameters less than 10 μm). Moreover, data available on air visibility

* Corresponding author. Tel.: +852 97223859; fax: +852 25481152.
E-mail address: zli.economics@gmai.com (Z. Li).

[1] Copeland and Taylor (2004) discuss extensively the reasons for which the reduced-form tests of the EKC hypothesis may be uninformative.

[2] In Fig. 1, the true pollution–income path (the solid line) is consistent with the EKC hypothesis. We approximate this path by a triple-polynomial function of income. The dashed line represents the fitted value after the regression using full sample. It shows an inverse-U shape that reasonably approximates the true path. When we restrict the sample such that the income is greater than 20, the fitted value (the dotted line) shows little support for the EKC pattern.

http://dx.doi.org/10.1016/j.ecolecon.2014.02.022
0921-8009/

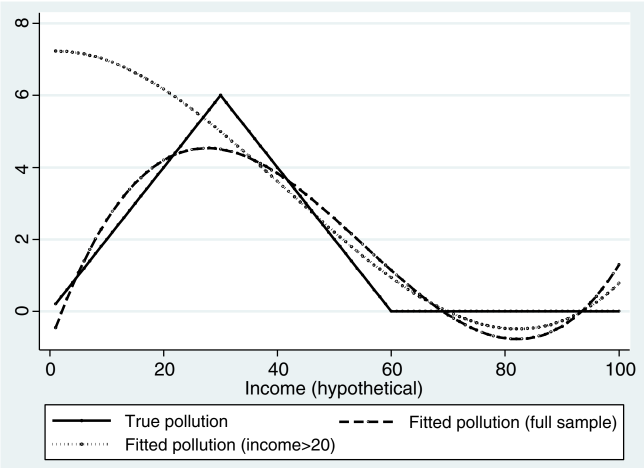

Fig. 1. An illustration of the bias due to the non-representative sub-sample.

cover over 18,000 sites from 184 countries since 1950, which is much more extensive than the existing data on air pollutants.[3]

In general, we find that the omitted countries and pollutants can bias the estimates significantly. Specifically, using the full sample of the visibility data, we find robust evidence supporting the EKC hypothesis for most of the economies, following the methodology of HLW (2002). The turning point is generally within a narrow range (between $3000 and $6000 per capita) for different specifications. Once we restrict the sample coverage to the countries that also report on sulfur dioxide (SO_2) and total suspended particulates (TSP), the foregoing EKC relationship disappears. In addition, when the concentrations of SO_2 and TSP are added to the visibility regressions, we find that they only partially explain the visibility–income path. The other pollutants, those that are unobserved, appear to be the key underlying factor of the EKC relationship.

The following section demonstrates how air visibility may be used to test the EKC hypothesis. It is followed by a section describing the data. Section four reports the estimated relationship between air visibility and income. The last section concludes.

2. Methodology

This section shows how air visibility may be used as a proxy for air quality to estimate the pollution–income linkage and to recover the effect of omitted air pollutants.

2.1. Visibility as a Measure of Air Pollution

In the literature, researchers have adopted various air pollutant indicators to study the Environmental Kuznets Curve. Typical indicators include Sulfur dioxide (SO_2),[4] nitrogen oxide (NOx), suspended particle matter (SPM), dark matter (fine smoke), carbon oxide (CO), carbon dioxide (CO_2), vehicle hydrocarbon emissions, etc. Readers can refer to Panayotou (2000) and Dinda (2004) for details. In this paper, we propose to exploit a rarely used database on air visibility to measure air pollution. This approach allows us to provide additional complementary evidence to the EKC literature by addressing some remaining controversies.

Air visibility refers to “the greatest distance at which an observer can just see a black object viewed against the horizon sky” (Malm, 1999). It is determined by the density of particles (e.g. black carbon) and gases (mainly NO_2) in the atmosphere. The sources of these aerosol matters can be manmade or natural. They reduce visibility by scattering and absorbing light.[5]

Compared with typical pollutant indicators used in the literature, the air visibility data has the following major advantages. First, as air visibility is less technical to measure and is a basic measure of air quality, it is systematically recorded in most of the places in the world for a long time span (1950–now). Hence, sample selection, which is a potential issue with studies of the existing literature, may be avoided using the visibility data. Second, for technical reasons, such as the lack of cost-effective measuring devices, important pollutants may be omitted by the data of typical air pollutants. For example, PM2.5, which refers to the particulate matter with 2.5 μm or smaller in size, has important health impact.[6] However, data on PM2.5 is lacking in many developing countries. Nevertheless, because PM2.5 is the primary cause for the scattering of visible light and the cause of the degradation of visibility (Sloane et al., 1991), air visibility may help to address this issue.

Despite the advantages, air visibility has seen limited use in the literature, possibly for the following reasons. First, visibility is affected by both man-made pollutants and natural conditions. To address this issue, we shall control for as many weather factors that can affect visibility in our regressions as possible. Generally, we do not find that adding the weather factors have material effects on our estimates. Second, measurement technologies of visibility have changed over time and might be prone to the endogenous technology adoption issue. In our analysis, we will conduct robustness checks by conducting regressions by different time period, so as to check the robustness of our estimates over time. Third, air visibility does not completely capture all harmful pollutants. Hence, our estimates do not provide the compete answer to the pollution–growth linkage. Nevertheless, we can advance the literature in this direction with the insufficiently used data on air visibility.

Following the meteorological literature (e.g., Malm et al., 1994; Wang, 2003; Watson, 2002), the inverse of visibility may be modeled as a linear function of the density of particles and gases: [7]

$$1/Visibility_{it} = \sum_{j=1}^{n} w_{ij} A_{ijt}. \tag{1}$$

Here A_{ijt} is the concentration of pollutant j for site i in year t. The parameter w_{ij} reflects the light property (scattering and absorbing) of this pollutant. According to the existing studies, particles (e.g. dust, smoke, elemental carbon, and naturally occurring hydrometeors) dominate gases (especially NO_2) in reducing visibility in the world (see Eidels-Dubovoi, 2002, for discussion).[8] Note that w_{ij} could vary by site. For example, visibility would be lower in more humid regions given the same pollutant concentration.

[3] This data set has been used in Husar et al. (2000) to study the spatial distribution of air quality across the world, but they have not linked visibility to economic growth.

[4] Stern (2005) employs a database of SO_2, which documents and imputes the global sulfur emissions at the country level during 1850–2003.

[5] Aerosol refers to particles and the gas together. Some of the aerosols occur naturally, originating from volcanoes, dust storms, forest and grassland fires, living vegetation, and sea spray. Human activities, such as the burning of fossil fuels in vehicles, power plants and various industrial processes also generate significant amounts of aerosols. Averaged over the globe, anthropogenic aerosols – those made by human activities – currently account for about 10% of the total amount of aerosols in our atmosphere (Hardin and Kahn, 1999).

[6] Cohen et al., 2005 estimates that “… fine particulate air pollution (PM(2.5)), causes about 3% of mortality from cardiopulmonary disease, about 5% of mortality from cancer of the trachea, bronchus, and lung, and about 1% of mortality from acute respiratory infections in children under 5 years, worldwide.” (doi:10.1080/15287390590936166).

[7] For example, the IMPROVE project (Interagency Monitoring of Protected Visual Environments) models the inverse of visibility as a linear function of sulfate, nitrate, organics, light-absorbing carbon, soil, and coarse mass (Malm et al., 1994).

[8] Particulate, alternatively referred to as particulate matter (PM) or fine particles, are tiny particles of solid or liquid suspended in a gas. Hydrometeors are large droplets or crystals of water (>5 μm) and they occur as rain, fog, clouds, and snow.

2.2. The Visibility–Income Linkage

Following GK (1995) and HLW (2002), we model the emission of pollutant j at site i in year t, A_{ijt}, as follows:

$$A_{ijt} = G_{it}\beta_{1j} + G_{it}^2\beta_{2j} + G_{it}^3\beta_{3j} + L_{it}\beta_{4j} + L_{it}^2\beta_{5j} + L_{it}^3\beta_{6j} + X'_{it}\beta_{7j} + \mu_{ij} + v_{jit}. \quad (2)$$

Here G_{it} is the per capita GDP of the country where site i locates. L_{it} is the three-year average of lagged GDP per capita. X_{it} include country- and site- specific characteristics that may vary over time and affect the emission of air pollutants. The factors constant over time are summarized by the variable μ_{ij} (unique for each site–pollutant combination). Combining models (1) with (2), we have

$$1/Vsibility_{it} = G_{it}\theta_{1i} + G_{it}^2\theta_{2i} + G_{it}^3\theta_{3i} + L_{it}\theta_{4i} + L_{it}^2\theta_{5i} + L_{it}^3\theta_{6i} + X'_{it}\theta_{7i} + \mu_i + v_{it} \quad (3)$$

where

$$\theta_{ki} = \sum_{j=1}^{I} w_{ij}\beta_{kj}. \quad (4)$$

Here I is the number of the types of air pollutants. The visibility–growth linkage is thus a weighted sum of the linkages between income and different air pollutants.

2.3. The "Omitted" Pollution–Income Linkage

Various pollutants may affect visibility, but only some are monitored. For example, fine particles (less than 10 μm in diameter) are the products of combustion of fossil fuels. They are much more damaging in terms of health complications than bigger particles. However, the fine particles are not included in TSP, which is for bigger particles (up to 40 μm in diameter) (Roumasset et al., 2008).

Nevertheless, the missed link between income and unobserved air pollutants may be partially uncovered via visibility. To illustrate, let I^o index those pollutants observed and I^u for the unobserved, then model (2) can be re-written as:

$$1/Vsibility_{it} = \sum_{j\in I^o} w_{ij}A_{ij} + G_{it}\widetilde{\theta}_{1i} + G_{it}^2\widetilde{\theta}_{2i} + G_{it}^3\widetilde{\theta}_{3i} + L_{it}\widetilde{\theta}_{4i} + L_{it}^2\widetilde{\theta}_{5i} + L_{it}^3\widetilde{\theta}_{6i} + X'_{it}\widetilde{\theta}_{7i} + \mu_i + v_{it} \quad (5)$$

where

$$\widetilde{\theta}_{ki} = \sum_{j\in I^u} w_{ij}\beta_{kj}. \quad (6)$$

As we have controlled for observed pollutants, the parameters $\widetilde{\theta}_{ki}$ thus indicate the linkage between income and unobserved pollutants.

2.4. Estimation and Identification Issues

With panel data, models (3) and (5) may be estimated with random effect or fixed effect estimators, as in GK (1995) and HLW (2002).[9] To facilitate the comparison of their findings with ours, we shall consider both estimators. Moreover, we shall follow HLW (2002) to consider various specifications and robustness checks.

Note that the parameters θ_{ki} and $\widetilde{\theta}_{ki}$ could vary by region, but we are only estimating their averages over different pollutants and sites, $E(\theta_{ki})$ and $E(\widetilde{\theta}_{ki})$. According to Wooldridge (2004), the estimates of these averages are consistent for the fixed effect model under weak conditions. In contrast, the random-effect estimator may be inconsistent unless θ_{ki} and $\widetilde{\theta}_{ki}$ are uncorrelated with the regressors. This assumption requires that the local economic growth is unrelated with local amenities (e.g. geography or environment), which may not hold in general. The estimates of the random-effect model may need to be treated more cautiously.

Another identification issue concerns the measurement of visibility. Most of the visibility readings in our sample were made by human observers (using visual targets at known distance such as large buildings and hills), which generally underestimates the actual visual range (see Husar et al., 2000, for discussion). Our model estimates may thus be biased by these measurement errors if their variations over time are correlated with the independent variables. This is possible, for example, if more rapid economic growth accelerates the adoption of technology that can measure visibility more precisely. This endogeneity issue cannot be addressed directly in this study as we have no information on the actual measurement method used. Nevertheless, we may compare the estimates for different sub-periods: since the new measurement technology was introduced in more recent years, comparing the estimates for earlier and later sub-periods may help us check the sensitivity of our estimates.[10]

3. Data

Below we introduce the data used in this study.

3.1. Climate Data

Visibility records used in this study result from the data exchanged under the World Meteorological Organization (WMO) World Weather Watch Program according to WMO Resolution 40 (Cg-XII) (WMO, 1996). The data used are distributed by the National Climatic Data Center. As shown in Table 1, this data set covers over 18,000 sites in 184 countries from 1950 to 2004. Countries with missing observations are mainly in Africa. For comparison, the data in GK (1995) cover 239 sites from 42 countries, and 285 sites from 45 countries are covered in HLW (2002) (the sample varies by pollutants).

Besides air visibility, the data set also contains temperature, pressure, dew point, wind speed, total precipitation, snow depth, and the indicators of fog, rain, snow, hail, thunder, and tornado. The daily mean values of these weather measures (based on at least four valid hourly readings per day) are reported. The observational procedures are specified in the guidelines issued by the World Meteorological Organization (WMO, 1996). Part of the data (1994–1998) has been used in Husar et al. (2000) to study the spatial distribution of air quality around the world.

For the purpose of this study, we first aggregate the data from daily to annual frequency by taking either the annual average or median for each site.[11] This aggregation reduces the sample size to around 330,000 site–year observations. Summary statistics of major variables are reported in Table 1. Mean air visibility is around 20 miles within the sample.

In order to filter out observations affected by extreme weather conditions (e.g. high concentration of naturally occurring hydrometeors,

[9] The random effect estimator assumes that the site-specific fixed effects μ_i are uncorrelated with the independent variables and that v_{it} is normally distributed. These assumptions are not needed in the fixed effect approach, in which site-specific dummy variables are included in the regression.

[10] For example, Automated Surface Observing System is one of the two primary systems deployed at airports across the U.S. (http://www.nws.noaa.gov/asos/obs.htm). This system includes visibility sensors (based on xenon light), which generate measures of visibility that are used as part of the visibility data set (for the airport in the U.S. with this system). The preparation of the ASOS in the U.S. began in 1991 and was completed in 2004 (according to Wikipedia.com).

[11] In calculating the annul mean or median of visibility, the daily observations with extreme air visibility (below 1 mile and above 100 miles) are excluded.

Table 1
Summary statistics and the comparison with GK (1995) and HLW (2002).

	Grossman and Krueger (1995)			Harbaugh et al. (2002)			This study				
	Obs.			Obs.							
Variable	SO2	TSP	Smoke	SO2	TSP	Smoke	Obs	Mean	Std. dev.	Min	Max
Pollution concentration (μg/m^3)	1261	1021	487	2401	1092	710					
Mean visibility (miles)							329,160	19.805	23.489	1	99.9
Mean inverse visibility							329,160	0.118	0.071	0.010	1
Temperature (Fahrenheit)							329,160	53.165	16.655	−9.9	99.3
Precipitation (inches)							329,160	0.070	0.138	0	17.17
Snow depth (inches)							329,160	0.586	2.237	0	110.2
Fog or not							329,160	0.096	0.138	0	1
Rain or not							329,160	0.247	0.178	0	1
Snow or not							329,160	0.097	0.134	0	1
Hail or not							329,160	0.004	0.015	0	1
Thunder or not							329,160	0.050	0.072	0	1
Tornado or not							329,160	0.000	0.003	0	1
GDP per capita (thousand USD)	1352	1021	488	2381	1085	687	265,960	10.940	10.090	0.059	54.285
Three-year avg. lag GDP (Thousand USD)	1352	1021	488	2389	1092	687	259,520	10.084	9.417	0.062	49.723
Ten-year avg. lag GDP (Thousand USD)	1352	1021	488	2389	1092	687	232,561	9.097	8.377	0.073	41.558
Population density (Thousand per sq.km.)	1352	1021	488	2401	1092	710	318,918	0.070	0.185	0.001	17.772
% GDP invested				2381	1085	687	265,960	21.118	7.369	0.15	66.62
Trade intensity				2381	1085	687	266,132	44.421	33.411	2.14	623.46
Democracy				2322	1063	646	291,998	5.695	4.555	0	10
Year	1352	1021	488	2401	1092	710	329,160	1983.821	13.637	1950	2004
# of cities	239	161	87	285	149	96	18,111				
# of countries	42	29	19	45	30	21	184				

Note: The Grossman and Krueger (1995) sample covers the 1977–1988 period, and the Harbaugh et al. (2002) sample covers the 1971–1992 period.

such as rain, snow, and fog) and measurement errors, we introduce an algorithm adapted from that of Husar et al. (2000). This would further reduce the sample size by about a half. Details of the filter are available in Appendix A.

3.2. Other Variables

From Penn World Table (PWT 6.2, including 188 countries, 1950–2004, 2000 as base year), we obtain country-level information on real GDP per capita (standardized by Purchasing Power Parity), population, the investment share of real GDP, and trade intensity (the sum of import and export divided by real GDP). These data have been used by a number of studies in the literature, including GK (1995) and HLW (2002). The democracy index is obtained from the website of "Kristian Skrede Gleditsch, Polity Data Archive". The range of this index is from 0 to 10; the larger the index, the more democratic the economy is. In addition, the area (to calculate the population density) and other natural conditions of each country (e.g. whether the country is landlocked or not) are obtained from the French Research Center in International Economics (CEPII).

In addition, HLW have graciously made the AIRS data used in their work in 2002 available for the current study. This data set provides high quality measures of SO_2 and TSP, which are critical variables in our regressions to infer the relevance of unobserved air pollutants. Their data also include several additional variables indicating whether the sites are close to industrial, residential, or center cities.

3.3. Preliminary Pattern of Visibility–Income Relationship

Fig. 2 plots the national average of inverse visibility against GDP per capita for the whole sample (non-filtered). The "lowess smoother" in STATA is used to summarize their relationship.[12] Interestingly, inverse visibility first increase (implying more severe air pollution) in income but then slowly decline (for economies with income level less than $30,000 per capita). The turning point is around $6000 per capita.

[12] The Lowess smoother conducts locally weighted regressions of inverse visibility on income and then piece together the predicted inverse visibility given each income level.

4. Evidence on Visibility–Income Paths

The objective of our research is to examine whether the typical findings in the literature is robust to our data, which has a wider coverage of countries in the world and may be a more comprehensive measure of air pollution. We shall first report regression results comparable to those in GK (1995) and HLW (2002). Evidence on unobserved air pollutants is then provided.

4.1. Baseline Estimates

The estimates of model (3) with alternative visibility measures and specifications are reported in Table 2. The dependent variable is the annual median of inverse visibility for column (1), and is the annual average for column (2). In the first two regressions, we do not include site-specific fixed effects. Both sets of estimates imply a similar inverse-U relationship between inverse-visibility and income for economies with GDP per capita less than $27,000. The peak implied is

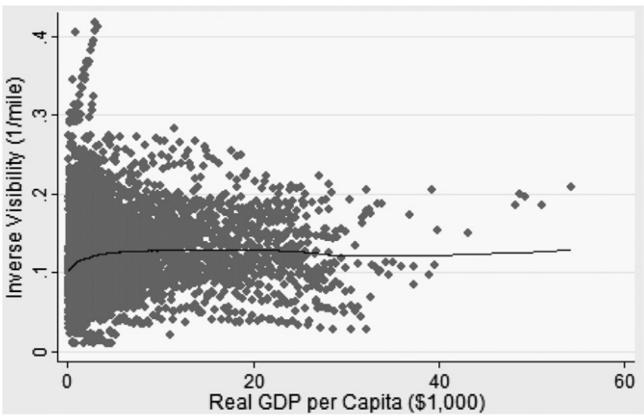

Fig. 2. Inverse visibility versus real GDP per capita (1950–2004).

Table 2
Baseline estimates.

	(1) Median; RE Full sample	(2) Mean; RE Full sample	(3) Mean; FE Full sample	(4) Mean; FE Restricted sample
GDP	0.458	2.141	3.086	47.039
	(0.382)	(0.404)[a]	(0.406)[a]	(20.670)[b]
$(GDP)^2$	−0.061	−0.148	−0.189	−5.378
	(0.018)[a]	(0.019)[a]	(0.019)[a]	(2.424)[b]
$(GDP)^3$	0.001	0.003	0.003	0.163
	(0.000)[a]	(0.000)[a]	(0.000)[a]	(0.077)[b]
Lag GDP	0.452	−0.801	−1.021	−63.183
	(0.414)	(0.437)[c]	(0.440)[b]	(21.071)[a]
$(\text{Lag GDP})^2$	−0.103	−0.033	−0.019	7.992
	(0.021)[a]	(0.022)	(0.022)	(2.589)[a]
$(\text{Lag GDP})^3$	0.002	0.001	0.001	−0.269
	(0.000)[a]	(0.000)[a]	(0.000)[a]	(0.085)[a]
Year	0.775	0.740	0.687	0.001
	(0.013)[a]	(0.014)[a]	(0.014)[a]	(0.000)
Population Density	33.120	39.985	29.418	170.672
	(1.311)[a]	(1.392)[a]	(1.599)[a]	(49.785)[a]
Coastal	−11.783	−8.912		
	(1.048)[a]	(1.116)[a]		
Temperature	0.169	0.135	−0.181	2.741
	(0.013)[a]	(0.016)[a]	(0.018)[a]	(0.558)[a]
Precipitation	26.513	20.100	21.449	132.567
	(0.615)[a]	(0.585)[a]	(0.585)[a]	(19.320)[a]
Snow depth	0.017	−0.246	−0.228	−2.701
	(0.049)	(0.048)[a]	(0.048)[a]	(8.075)
Fog	19.790	61.420	58.556	−12.811
	(0.471)[a]	(0.867)[a]	(0.887)[a]	(28.742)
Rain	14.559	41.873	39.167	118.734
	(0.340)[a]	(0.726)[a]	(0.744)[a]	(17.992)[a]
Snow	28.522	48.270	46.707	30.944
	(1.009)[a]	(1.425)[a]	(1.469)[a]	(37.698)
Hail	13.614	−15.600	−12.035	−1,825.756
	(5.907)[b]	(5.242)[a]	(5.312)[b]	(501.267)[a]
Thunder	4.145	−11.405	−14.672	−138.100
	(1.302)[a]	(1.439)[a]	(1.459)[a]	(55.456)[b]
Tornado	−59.317	−13.465	−22.251	−1377.724
	(22.516)[a]	(18.986)	(19.375)	(959.213)
Observations	251,280	251,280	251,280	762
Number of group	16,589	16,589	16,589	112
R-squared	0.07	0.09	0.09	0.3109
Peak	3080.0705	4260.934	6055.80	12,267.19
	(275.08)	(248.57)	(196.37)	(1043.25)
Trough	27,332.662	27,831.81	27,788.11	4126.91
	(121.22)	(135.62)	(135.47)	(1433.74)
Hausman chi^2	2442.21	7028.82	8464.12	188.23

Note: (1) The dependent variable is the annual average of the inverse of visibility.
(2) All estimates have been scaled up 1000 times to facilitate presentation.
(4) In column 4, the sample includes the cities reporting SO2, TSP (based on the HLW data) and visibility (based on the WMO weather data) during the 1971–1992 period.
[a] Significance level of 1%.
[b] Significance level of 5%.
[c] Significance level of 10%.

below \$5000 per capita.[13] For economies with GDP per capita greater than \$27,000, the estimates suggest a positive relationship between income and pollution, which is inconsistent with the EKC hypothesis. This pattern is also found in GK (1995), which adopts the same function form.

We now turn to the fixed effect estimates of the baseline model, using mean inverse visibility as the dependent variable (column 3). Similar to what HLW (2002) find, the Hausman test clearly rejects the random effect in favor of the fixed effect model, but in terms of economic significance, the pollution–income paths implied by both the RE and FE estimates do not differ much: the turning point increases from \$4260 per capita in the RE regression to \$6056 in the FE regression.

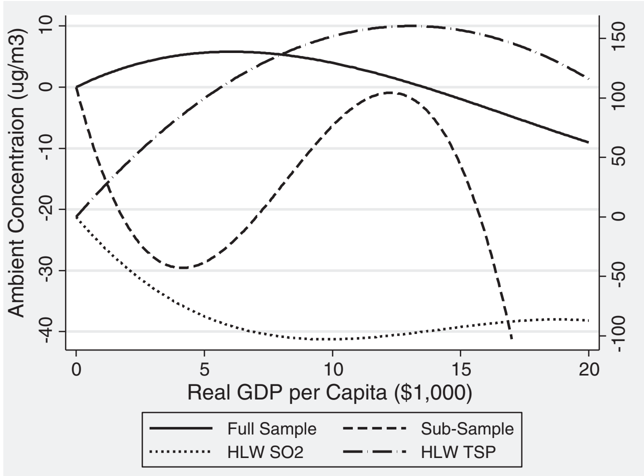

Fig. 3. Comparison of pollution–income paths.

The estimation results, however, appear to be highly sensitive to the sample of countries included. The coefficients of lagged GDP per capita changes dramatically when we exclude countries not considered by HLW (column 4 of Table 2).[14] As a result, the implied pollution–income path changes drastically. The pollution–income relationship now demonstrates an inverse N-shape, with the peak around \$12,267 and trough around \$4127.

To facilitate the comparison across studies, we follow HLW (2002) to plot the pollution–income paths in Fig. 3 (all based on fixed-effects estimates). The inverse-visibility–income path generally follows an inverse-U shape (for economies with income less than \$27,000) when the full sample is considered. With the restricted sample (column 4 of Table 2), the pattern is dramatically different.[15] For comparison, we also plot the SO_2–income and TSP–income paths implied by HLW (2002). They provide stark contrasts: the SO_2 path is against the EKC hypothesis, while the TSP path is supportive.

Turning to the estimates of other coefficients, we find that increasing population intensity by 1000 people per square kilometer would reduce visibility by over 3%. This is consistent with the findings in HLW (2002) although the magnitudes of their estimates are smaller. Interestingly, while both GK (1995) and HLW (2002) find negative time trends of SO_2 and TSP emissions, we find that visibility has been declining over time. This is possible if the emission of air pollutants other than SO_2 and TSP have been increasing over time.[16] Our model also includes a rich set of controls of climate conditions that might affect visibility. The estimates are generally consistent and the signs are as expected for the full and the restricted samples.

4.2. Robustness Checks

Applying visibility data to the same specification as in HLW (2002), we show some evidence for the inverse-U relationship between air quality and growth. However, we also find that this relationship is sensitive to the sample of countries considered. Below we shall further examine the robustness of the visibility–income paths discovered.

[13] Note that the inverse visibility is modeled as a triple-polynomial function of current and lagged GDP per capita. These estimates are all used in calculating the peak and trough of the implied visibility–income path following HLW. We thank HLW (2002) for providing the codes.

[14] Our sample is about 70% of the TSP sample in HLW because visibility information is missing for some of the cities they consider.

[15] Note that visibility becomes more responsive to the change in income in the restricted sample. This might be due to the less precise estimates for the reduced sample size.

[16] Our random effects estimates using the sample of HLW (not reported in the tables) show that coastal cities have less air pollution than inland cities, as is consistent with the findings of both GK (1995) and HLW (2002). The coefficients of the industrial, residential, and centre city indicators are insignificant, as is also the case in HLW (2002).

Table 3
Robustness checks.

	(1) FE, filtered sample	(2) FE, Longer lag	(3) All control variables	(4) Log dependent variable	(5) Weighted by inverse no. of stations	(6) Aggregated country–year
GDP	5.934	6.904	1.458	−12.947	6.817	6.030
	(0.440)[a]	(0.291)[a]	(0.343)[a]	(4.239)[a]	(0.281)[a]	(1.233)[a]
$(GDP)^2$	−0.348	−0.385	−0.178	−0.551	−0.268	−0.271
	(0.021)[a]	(0.016)[a]	(0.018)[a]	(0.220)[b]	(0.015)[a]	(0.067)[a]
$(GDP)^3$	0.005	0.006	0.004	0.021	0.003	0.003
	(0.000)[a]	(0.000)[a]	(0.000)[a]	(0.004)[a]	(0.000)[a]	(0.001)[a]
Lag GDP	−3.782	−6.659	−0.656	22.355	−5.257	−4.871
	(0.477)[a]	(0.356)[a]	(0.432)	(5.208)[a]	(0.364)[a]	(1.626)[a]
$(\text{Lag GDP})^2$	0.137	0.338	0.042	−1.768	0.041	0.036
	(0.025)[a]	(0.024)[a]	(0.028)	(0.336)[a]	(0.025)	(0.115)
$(\text{Lag GDP})^3$	−0.001	−0.005	−0.001	0.038	0.001	0.001
	(0.000)[a]	(0.000)[a]	(0.001)[c]	(0.007)[a]	(0.001)[b]	(0.002)
Year	0.569	0.824	1.710	6.629	1.244	1.337
	(0.016)[a]	(0.017)[a]	(0.042)[a]	(1.233)[a]	(0.015)[a]	(0.068)[a]
$(Year)^2$			−0.011			
			(0.001)[a]			
Population density	26.582	29.105	93.450	447.929	19.022	18.111
	(1.456)[a]	(2.032)[a]	(3.489)[a]	(38.109)[a]	(0.759)[a]	(3.423)[a]
Democracy			−0.276	2.152	−0.552	−0.445
			(0.052)[a]	(0.577)[a]	(0.038)[a]	(0.169)[a]
Tradeintensity			−0.228	−1.937	−0.107	−0.110
			(0.007)[a]	(0.075)[a]	(0.004)[a]	(0.019)[a]
Investment			0.353			
			(0.026)[a]			
Observations	123,427	225,993	210,969	210,969	209,453	3930
Number of group	10,514	15,426	14,913	14,913	13,397	147
R-squared	0.09	0.09	0.11	0.12	0.13	0.30
Peak	6265.70	2757.23	3269.29	2214.95	3857.18	2670.24
	(208.19)	(1280.86)	(520.29)	(373.49)	(254.70)	(1169.32)
Trough	27,240.19	45,886.52	30,442.75	24,056.13	31,878.21	33,529.68
	(172.31)	(10,191.73)	(11,347.45)	(299.09)	(1055.21)	(5014.05)

Note: (1) The dependent variable is the annual average of the inverse of visibility, except for column 4.
(2) All estimates have been scaled up 1000 times to facilitate presentation.
[a] Significance level of 1%.
[b] Significance level of 5%.
[c] Significance level of 10%.

4.2.1. Non-Parametric Specification for Weather Conditions

Besides air pollutants, air visibility may be affected by other weather conditions, especially humidity. In the baseline regressions, a linear specification of relevant weather indicators is included to control for their effects on visibility. Alternatively, we may use a non-parametric approach, in which we exclude those observations with unusual weather conditions that may affect visibility (e.g., high humidity). A filter of this kind is adapted from Husar et al. (2000) (see the Appendix A for detail). This filter reduces the original sample size by about a half, but the baseline estimates appear robust to this sample change. The fixed-effect estimates with the filtered sample and the implied visibility–income path (Table 3; column 1) are qualitatively the same as those based on the full sample.

4.2.2. Alternative Specifications

Below we test the robustness of the baseline estimates following various specifications considered by HLW (2002). We shall report the estimates using the full sample. All the estimates are based on the fixed effect model.

We first consider extending the three-year average of lagged income to the ten-year average (Table 3; column 2). As argued in HLW (2002), this extension may help further distinguish the permanent from the temporary effects of income on environment. The inverse-U shape pattern remains and the peak is reduced to $2757 per capita. In the discussion below the estimates with the three-year average income are considered.

The column (3) regression includes additional control variables: democracy index, trade intensity, investment share of GDP, and the square of year (to capture nonlinear time trend).[17] The estimates are generally significant. Both democracy and trade intensity reduce pollution. Investment share increases pollution. The time trend of pollution is concave. Except for the time trend, other estimates have the same signs as those in HLW (2002). Adding the control variables has little effect on the aforementioned inverse-U shape relationship between visibility and income per capita. The peak is around $3269 per capita. In HLW (2002), they show that excluding the investment share from the model significantly affects the estimated pollution–income path. We find this not to be the case using the visibility data.

In column (4), we replace the dependent variable in previous regressions by the logarithm of mean inverse-visibility. In column (5), each observation is weighted by the inverse of the number of observatories in each country. In column (6), the site-level observations are aggregated to the national level by taking averages. None of these changes have significant effect on the baseline estimates.

Some results are not reported in the tables but are worth mentioning. We have examined the effect of excluding outliers and replacing the time variable by year dummies. They do not have significant effects on our estimates either. We have also considered the sample of countries with income per capita greater than $8,000. The findings are similar to that in HLW (2002): air quality improves in income for this sub-sample. We think it is consistent with the inverse-U shape pollution–income path because the income of $8000 per capita already

[17] HLW (2002) has also controlled for relative GDP but its coefficient is insignificant. This variable is not included in our regression because it is not available in our data.

Table 4
Robustness check on the shape of the curve.

	(1) Mean; RE Full sample	(2) Mean; FE Full sample	(3) Mean; RE Full sample	(4) Mean; FE Full sample
GDP	1.619[a]	2.263[a]	0.545[a]	0.818[a]
	(0.0960)	(0.102)	(0.0347)	(0.0357)
$(GDP)^2$	−0.185[a]	−0.210[a]	−0.0129[a]	−0.0179[a]
	(0.00505)	(0.00527)	(0.000935)	(0.000955)
$(GDP)^3$	0.00362[a]	0.00395[a]		
	(0.0000848)	(0.0000878)		
Year	0.686[a]	0.646[a]		
	(0.0134)	(0.0143)		
Population density	40.11[a]	29.30[a]	61.94[a]	57.65[a]
	(1.363)	(1.561)	(1.355)	(1.541)
Coastal	−7.625[a]	−2.789[b]	0.726	6.921[a]
	(1.025)	(1.241)	(0.973)	(1.147)
Observations	259,752	259,752	259,752	259,752
R-squared	0.09	0.07	n.a.	0.009
Peak	5163.880	6638.178	21,124.031	22,849.162
Trough	27,788.11	28,763.811		

Notes: (1) The dependent variable is the annual average of the inverse of visibility.
(2) All estimates have been scaled up 1000 times to facilitate presentation.
[a] Significance level of 1%.
[b] Significance level of 10%.

exceeds the turning point, so the pollution–income gradient should be negative. These results are available from the authors.

Next, we check whether the estimates are sensitive to the inclusion of the lagged GDP terms. Excluding them have very little effect on the implied pollution–growth relationship (first two columns of Table 4). All the estimates show a robust inverted-U shape curve. The peak is located at from US$ 4000 to US$ 6600, and the trough is located at around US$ 28,000.

In the literature, there are also many other papers which adopt a quadratic function form. Panayotou (2000) has a good review on the literature regarding the function form of the regression function. To further check the sensitivity of our results, we conduct regressions using quadratic functions (last two columns of Table 4). When year time trend is not included, our estimates show a robust inverted-U shape curve with the peak locates from US$ 21,000 to US$ 25,000. Although these results are consistent with the findings in the literature, they differ significantly from our findings using cubic functions. When time trend is included, the inverted-U shape pattern disappears and becomes U-shape (estimates available from authors). As the cubic specification nests the quadratic specification, the large difference between their estimates implies that the quadratic specification is inappropriate. In this sense, the specification by GK (1995) and HLW (2002) are reasonable.

In sum, the estimates with alternative specifications generally support the EKC hypothesis. The turning points may vary by specification but are generally within the range of $3000 and $6000 per capita.

4.2.3. Alternative Sub-Samples

We first estimate the baseline models by decades. This exercise is important for two reasons. First, as discussed earlier, the adoption of visibility-measuring devices to replace the eye-measures may bias our estimates if this adoption is correlated with economic growth. A simple way to check the presence of this bias may be to compare the estimates for earlier and later periods (since the new measurement technology is a recent phenomenon). Second, since production technology may have changed dramatically over the past decades (especially due to the rapid progress of information technology), it may be desirable to relax the assumption that the pollution–income path is stable over time.

Table 5 reports the estimates of the fixed-effect model for each decade. The estimates based on the 1950–1970 sample (column 1 and 2) clearly diverge from the estimates using more recent data. The fact that estimates for the early periods 1950–1959 until 1970–1979 do not show the expected signs or significances may be an argument in favor of the EKC because most countries (lower income) are up to

Table 5
Estimates of model (3) by decade.

	(1)	(2)	(3)	(4)	(5)	(6)
Period	1950–1959	1960–1969	1970–1979	1980–1989	1990–1999	2000–2004
GDP	33.55	52.66[a]	−1.395	4.352[b]	−6.143[b]	6.951[b]
	(38.94)	(17.17)	(2.601)	(0.936)	(1.095)	(1.452)
(GDP)2	−39.99	−19.22[a]	−0.621[a]	−0.241[b]	0.385[b]	−0.362[b]
	(21.60)	(6.728)	(0.233)	(0.0440)	(0.0746)	(0.0643)
(GDP)3	9.784[c]	2.408[a]	0.0225[b]	0.00381[b]	−0.00724[b]	0.00483[b]
	(4.027)	(0.872)	(0.00564)	(0.000649)	(0.00158)	(0.000878)
Lag GDP	45.18	−26.50	5.150	−3.931[b]	9.711[b]	−10.82[b]
	(42.95)	(19.89)	(2.977)	(1.022)	(1.201)	(1.529)
(Lag GDP)2	−30.65	20.30[c]	0.0405	0.189[b]	−0.777[b]	0.366[b]
	(24.87)	(9.738)	(0.314)	(0.0497)	(0.0919)	(0.0723)
(Lag GDP)3	5.341	−3.382[c]	−0.00425	−0.00258[b]	0.0163[b]	−0.00470[b]
	(4.856)	(1.459)	(0.00828)	(0.000723)	(0.00215)	(0.00108)
Democracy index	0.00150[c]	0.000488[c]	0.000607[b]	−0.00058[b]	0.000773[b]	0.00101[c]
	(0.000652)	(0.000225)	(0.000152)	(0.000112)	(0.000123)	(0.000437)
Popdensity	606.8[b]	87.47	0.667	96.75[b]	33.75[a]	84.91[b]
	(119.6)	(61.20)	(26.19)	(22.70)	(13.01)	(19.89)
Tradeintensity	0.0781	0.0684	−0.0555	−0.0881[b]	−0.0204	−0.0350
	(0.131)	(0.0466)	(0.0320)	(0.0213)	(0.0115)	(0.0312)
Investment	0.0735	−0.0757	0.303[b]	0.265[b]	0.174[b]	0.0116
	(0.0898)	(0.0471)	(0.0613)	(0.0604)	(0.0414)	(0.0998)
Observations	10193	14404	40250	59926	72349	37896
Number of station	1703	1973	5362	5211	6322	4330
R-squared	0.119	0.039	0.141	0.058	0.105	0.288
Peak	727.172	3386.595	3981.049	4908.341	5689.513	−111,552.28
	(137.444)	(222.894)	(854.800)	(4401.524)	(377.009)	(295,607.9)
Trough	2385.989	−2644.797	17,185.604	23,169.816	23,015.642	89,368.645
	(104.896)	(2249.830)	(588.578)	(1784.707)	(550.801)	(76,178.717)

Note: All estimates have been scaled up 1000 times to facilitate presentation.
[a] Significant at 5%.
[b] Significant at 1%.
[c] Significant at 10%.

Table 6
Estimates of model (3) by season.

	(1) Full sample	(2) Season (1)	(3) Season (2)	(4) Season (3)	(5) Season (4)
GDP	−0.749	−2.554	0.300	1.156	−0.749
	(0.267)[a]	(0.534)[a]	(0.433)	(0.454)[b]	(0.509)
$(GDP)^2$	−0.009	0.069	−0.043	−0.078	−0.006
	(0.012)	(0.025)[a]	(0.020)[b]	(0.021)[a]	(0.024)
$(GDP)^3$	0.001	−0.000	0.001	0.002	0.001
	(0.000)[a]	(0.000)	(0.000)[a]	(0.000)[a]	(0.000)[b]
Lag GDP	1.937	3.343	1.133	0.129	1.681
	(0.290)[a]	(0.578)[a]	(0.470)[b]	(0.492)	(0.552)[a]
$(\text{Lag GDP})^2$	−0.168	−0.226	−0.125	−0.105	−0.162
	(0.015)[a]	(0.029)[a]	(0.024)[a]	(0.025)[a]	(0.028)[a]
$(\text{Lag GDP})^3$	0.003	0.004	0.002	0.002	0.003
	(0.000)[a]	(0.000)[a]	(0.000)[a]	(0.000)[a]	(0.000)[a]
Year	0.830	0.780	0.840	1.006	0.705
	(0.023)[a]	(0.047)[a]	(0.038)[a]	(0.039)[a]	(0.043)[a]
$(\text{Year})^2$	0.002	0.003	−0.000	−0.001	0.005
	(0.000)[a]	(0.001)[a]	(0.001)	(0.001)[b]	(0.001)[a]
Democracy index	−0.401	−0.592	−0.393	−0.456	−0.342
	(0.030)[a]	(0.059)[a]	(0.048)[a]	(0.050)[a]	(0.056)[a]
Popdensity	94.291	114.207	81.056	68.105	102.260
	(1.849)[a]	(3.750)[a]	(3.008)[a]	(3.082)[a]	(3.474)[a]
Tradeintensity	−0.237	−0.299	−0.214	−0.196	−0.261
	(0.004)[a]	(0.008)[a]	(0.006)[a]	(0.006)[a]	(0.007)[a]
Investment	0.335	0.234	0.221	0.287	0.449
	(0.013)[a]	(0.026)[a]	(0.021)[a]	(0.022)[a]	(0.024)[a]
Observations	875,389	217,100	218,256	219,917	220,116
No. of group	16,039	14,894	15,089	15,223	15,258
R-squared	0.15	0.10	0.09	0.10	0.10
Peak	3846.632	2750.906	5028.334	4027.527	3078.892
	(162.845)	(387.261)	(261.217)	(259.983)	(334.344)
Trough	27,458.404	28,036.131	27,303.738	27,832.173	28,360.916
	(86.153)	(190.479)	(159.474)	(148.254)	(178.613)

Note: All estimates have been scaled up 1000 times to facilitate presentation.
[a] Significant at 1%.
[b] Significant at 5%.

Table 7
Estimates of model (5): The relevance of omitted air pollutants.

	(1)	(2)	(3)	(4)
SO_2	−0.010			
	(0.055)			
TSP	0.026			
	(0.027)			
Smoke			−0.059	
			(0.092)	
GDP	46.392	47.039	−22.131	−23.702
	(20.715)[a]	(20.670)[a]	(47.527)	(47.412)
$(GDP)^2$	−5.370	−5.378	2.655	2.941
	(2.428)[a]	(2.424)[a]	(7.186)	(7.164)
$(GDP)^3$	0.163	0.163	−0.120	−0.134
	(0.077)[a]	(0.077)[a]	(0.325)	(0.324)
Lag GDP	−64.261	−63.183	106.000	102.265
	(21.123)[b]	(21.071)[b]	(45.333)[a]	(44.907)[a]
$(\text{Lag GDP})^2$	8.123	7.992	−16.627	−16.143
	(2.598)[b]	(2.589)[b]	(7.252)[a]	(7.204)[a]
$(\text{Lag GDP})^3$	−0.273	−0.269	0.762	0.742
	(0.085)[b]	(0.085)[b]	(0.341)[a]	(0.339)[a]
Year	0.001	0.001	−0.001	−0.001
	(0.000)	(0.000)	(0.001)[a]	(0.001)[a]
Population density	169.185	170.672	31.302	31.028
	(50.075)[b]	(49.785)[b]	(12.742)[a]	(12.721)[a]
Observations	762	762	346	346
Number of group	112	112	56	56
R-squared	0.3119	0.3109	0.1358	0.1345
Peak	12,219.46	12,267.19	4243.76	4184.22
	(1808,672.10)	(1043.25)	(4668.73)	(407.10)
Trough	4419.13	4126.91	10,252.59	10,296.75
	(236,422.77)	(1433.74)	(98,458.22)	(647.76)

Note: All estimates have been scaled up 1000 times to facilitate presentation.
[a] Significant at 5%.
[b] Significant at 1%.

1970 still located on the ascending part of the inverted U-shaped EKC (to the left of the peak) reflecting rather a regression line than an EKC curve.[18] Starting from 1970, the sampled economies are close to the full coverage. In the three decades between 1970 and 1999, the estimates confirm the N-shape pattern with peaks ranging from \$3981 to \$5689 and trough ranging from \$17,186 to \$23,016. As the adoption of visibility-measuring devices occurred mainly in the 1990s, the stable visibility–income relationship for the period 1990–1999 suggests that the measuring technology adoption does not have significant effects on the estimates. For the period from 2000 to 2004, empirical estimates differ significantly, possibly due to the reduction of stations sampled by one-third.

Another concern with our empirical estimates may be the omitted effects of seasonal variations. Seasonal weather conditions may affect visibility. Moreover, the productivity intensity and the subsequent pollutant emission could also vary by season. To shed some light on the possible seasonality of the pollution–income path, we aggregate the daily visibility data to season–year level averages. We then repeat the baseline estimation (fixed effect model) for each of the four seasons (Table 6). The estimates do suggest that the seasonality in weather conditions or production intensity could be relevant,[19] but the inverse-U shape relationship between inverse visibility and income is robust across seasons.

4.3. The Relevance of Omitted Air Pollutants

We now turn to estimating model (5) to infer how relevant the unobserved air pollutants may be to the pollution–income path. In particular, we add SO_2 and TSP to the baseline regression (Table 7; column 1). As has been discussed, this would significantly reduce the sample coverage, and the estimates may not be representative. Nevertheless, our focus here is on how much the observed pollutants can account for the visibility–income linkage, but not whether the linkage is consistent with the EKC hypothesis. For ease of comparison, in column (2) we report the estimates without SO_2 and TSP as control variables (but retain the same sample).

The main findings are as follows. First, the measures of SO_2 and TSP have some explanatory power for visibility. Their coefficients are insignificant, either individually or jointly when we use the fixed effect model.[20] As for random effect model, only the coefficient of TSP is significant. Second, the estimates of the visibility–income path are similar with or without SO_2 and TSP as regressors. In sum, these findings suggest that certain unobserved aerosols may be associated with economic growth and affect visibility at the same time. This is consistent with the foregoing example on unmonitored fine particles.

In columns (3) and (4) we also consider the effect of smoke, which is among the pollutants examined by HLW (2002). Smoke is not included in the earlier regressions because the sample with smoke is much smaller. The findings are similar: the effect of smoke on visibility is insignificant, regardless of random effect or fixed effect.

[18] We thank the referee for pointing this out.
[19] The turning point is the highest in the second quarter (\$5028 per capita) but decreases steadily, reaching the lowest level in the first quarter of the following year (\$2751 per capita).

[20] We have also tried controlling for SO2 and TSP separately. The results are similar: the coefficients of neither variables are significant. The EKC pattern is similar for FE and RE estimates, and we report RE estimates.

5. Conclusion

Existing studies have focused on several specific air pollutants (e.g. SO_2 and TSP) to test the Environmental Kuznets Curve hypothesis. The findings are ambiguous (HLW, 2002), possibly due to limited sample coverage and the omission of important pollutants in the air. In this study, we suggest that utilizing air visibility may address these two issues because the visibility data have much more representative sample coverage and contain information on un-monitored air pollutants.

Following the methodology of GK (1995) and HLW (2002), we find that the estimated visibility–income path supports the EKC hypothesis: air visibility first worsens in GDP per capita but then improves as the income level surpasses a certain threshold (generally less than US $5000 per capita). This finding is robust to various alternative specifications considered by HLW (2002) and to various sub-samples (excluding outliers, estimation by decades, and by seasons).

The key factor driving the deviation between our findings and the earlier ones seems to be the difference in sample coverage. The air visibility data cover over 120 countries of the world (since 1970). In contrast, the data by GK (1995) and HLW (2002) on common air pollutants cover less than 50 countries. When we restrict the visibility sample to the countries reporting SO_2 and TSP, the EKC pattern between visibility and income disappears.

In addition, we find that the visibility–income linkage may be mainly driven by "omitted" pollutants in the air: those pollutants that environmental agencies commonly fail to monitor. The two mostly commonly examined air pollutants, SO_2 and TSP, can account for only a small portion of the visibility–income linkage.

Acknowledgment

We gratefully acknowledge Kai-Yuen Tsui for suggesting the weather data. We also thank Hilary Sigman, Chung-Huang Huang and participants in the Economic Growth section of 4th World Congress of Environmental and Resource Economists for valuable comments and suggestions and Professor William T. Harbaugh for making available the data used in Harbaugh et al. (2002).

Appendix A

Following Husar et al. (2000), we consider the following two types of filters to reduce the effect of extreme weather conditions on visibility.

A.1. Single Data Point Filters

The following observations are eliminated from the sample.

1. The indicator for rain is one.
2. Precipitation is greater than 0.25 cm.
3. The difference between temperature and dew point is less than 2.2 °C (this temperature spread corresponds to about 90% relative humidity).
4. The indicator for fog is one, and the temperature-dew-point spread is less than 4 °C .
5. Temperature is less than −29.3 °C and wind speed is greater than 16 km/h.
6. Visibility is less than 1/3 of the visibility in the previous and next days.

A.2. Statistical Filters

1. All observations of a station that has less than 10 valid data points for any season of a year are eliminated for that year.
2. All observations of a station for which the ratio of the 50th and 25th percentile (in visibility) are less than 1.07 or if the ratio of the 25th to 10th percentile was less than 1.1 in a year are eliminated for that year.
3. All observations are eliminated for a year in which the ratio of annual maximum visibility and median visibility is less than 1.1.

Compared with the filters in Husar et al. (2000), our statistical filters only eliminate observations for the years with the specified conditions but not all observations for the station. This should retain more observations and yet avoid the effect of unusual observations.

In Husar et al. (2000) they further eliminate 29 stations that differed greatly from their surrounding stations. This is not followed in this study because the effect of the outliers would be controlled for by station-specific fixed effects in our regressions.

References

Carson, R.T., 2010. The environmental Kuznets curve: seeking empirical regularity and theoretical structure. Rev. Environ. Econ. Policy 4 (1), 3–23.
Cohen, A.J., Ross Anderson, H., Ostro, B., Pandey, K.D., Krzyzanowski, M., Künzli, N., Gutschmidt, K., Pope, A., Romieu, I., Samet, J.M., Smith, K., 2005. The global burden of disease due to outdoor air pollution. J. Toxicol. Environ. Health A Curr. Issues 68 (13–14). http://dx.doi.org/10.1080/15287390590936166.
Copeland, Brian R., Taylor, M.S., 2004. Trade, growth, and the environment. J. Econ. Lit. 42 (1), 7–71.
Dinda, S., 2004. Environmental Kuznets curve hypothesis: a survey. Ecol. Econ. 49, 431–455.
Eidels-Dubovoi, Silvia, 2002. Aerosol impacts on visible light extinction in the atmosphere of Mexico City. Sci. Total Environ. 287 (3), 213–220.
Grossman, G.M., Krueger, A.B., 1995. Economic growth and the environment. Q. J. Econ. 110 (2), 353–377.
Harbaugh, W.T., Levinson, A., Wilson, D.M., 2002. Reexamining the empirical evidence for an environmental Kuznets Curve. Rev. Econ. Stat. 84 (3), 541–551.
Hardin, M., Kahn, R., 1999. Aerosols and climate change. Earth Observatory (http://earthobservatory.nasa.gov/Features/Aerosols/what_are_aerosols_1999.pdf).
Husar, B.R., Husar, J.D., Martin, L., 2000. Distribution of continental surface aerosol extinction based on visual range data. Atmos. Environ. 34, 5067–5078.
Malm, W.C., 1999. Introduction to Visibility. Cooperative Institute for Research in the Atmosphere (http://www.epa.gov/air/visibility/introvis.pdf).
Malm, W.C., Sisler, J.F., Huffman, D., Eldred, R.A., Cahill, T.A., 1994. Spatial and seasonal trends in particle concentration and optical extinction in the United States. J. Geophys. Res. 99 (D1), 1347–1370.
Panayotou, T., 2000. Economic growth and the environment. CID Working Paper No. 56 (July, Environmental and Development Paper No. 4).
Roumasset, J., Burnett, K., Wang, H., 2008. Environmental resources and economic growth. In: Brandt, L., Rawski, T.G. (Eds.), China's Great Economic Transformation. Cambridge University Press, Cambridge, pp. 250–285.
Sloane, C.S., Watson, J., Chow, J., Pritchett, L., Willard Richards, L., 1991. Size-segregated fine particle measurements by chemical species and their impact on visibility impairment in Denver. Atmos. Environ. A Gen. Top. 25, 1013–1024.
Stern, D., 2005. Global sulfur emissions from 1850 to 2000. Chemosphere 58, 163–175.
Wang, T., 2003. Study of Visibility Reduction and Its Causes in Hong Kong. Research Centre for Environmental Technology and Management, the Hong Kong Polytechnic University, Hong Kong.
Watson, J.G., 2002. Critical review-visibility: science and regulation. J. Air Waste Manag. Assoc. 52, 626–713.
WMO, Resolution 40 (Cg-XII), 1996. Exchanging Meteorological Data: Guidelines on Relationships in Commercial Meteorological Activities: WMO Policy and Practice. World Meteorological Organization. WMO, Geneva92-63-10837-4 (WMO No. 837., http://www.ncdc.noaa.gov/cgibin/res40.pl?page"ghcn.html).
Wooldridge, M.J., 2004. Fixed-effects and related estimators for correlated random-coefficient and treatment-effect panel data models. Rev. Econ. Stat. 87 (2), 385–390.