Reexamining the Empirical Evidence for an Environmental Kuznets Curve

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Abstract
This paper uses an updated and revised panel data set on ambient air pollution in cities world-wide to examine the robustness of the evidence for the existence of an inverted-U-shaped relationship between national income and pollution. We test the sensitivity of the pollution-income relationship to functional forms, to additional covariates, and to changes in the nations, cities, and years sampled. We find that the results are highly sensitive to these changes, and conclude that there is little empirical support for an inverted-U-shaped relationship between several important air pollutants and national income in these data.

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I. Introduction

Several recent and often-cited papers on the relationship between pollution and economic growth find that many forms of air and water pollution "initially worsen but then improve as incomes rise" (World Bank, 1992). Grossman and Krueger (1995), in particular, report that for most pollutants, this turning point in environmental quality typically occurs at incomes below $8000 per capita. Because of its similarity to the pattern of income inequality documented by Kuznets (1955), this inverse-U-shaped pollution-income pattern is sometimes called an "environmental Kuznets curve."

In response to these empirical findings, a number of researchers have sought further evidence for inverse-U-shaped pollution-income relationships.[1] Others have proposed theoretical explanations for the relationship between pollution and economic growth.[2] There are two key questions being asked. The first is whether or not an inverted-U-shaped pollution-income path can be consistent with Pareto optimality. This is the subject of much of the theoretical literature. The second question is whether there is sufficient empirical evidence to conclude that environmental quality does improve eventually with economic growth, for at least some subset of pollutants. This latter question is the focus of this paper. While the existing literature appears to demonstrate numerous circumstances in which pollution follows an inverse-U, eventually declining with income, we argue that the evidence is less robust than it appears.

Far from being an academic curiosity, this debate is of considerable importance to national and international environmental policy. Based on the existing research, some policy analysts have concluded that developing countries will *automatically* become cleaner as their economies grow.[3] Others have argued that it is natural for the poorest countries to become more polluted as they develop. These types of conclusions depend on the apparently growing conventional wisdom that pollution follows a deterministic inverse-U-shaped environmental Kuznets curve.

In this paper we re-examine the empirical evidence documenting inverse-U-shaped pollution-income relationships using the air pollution data studied by the World Bank (1992) and by Grossman and Krueger (1995), with the benefits of a retrospective data cleaning and ten additional years of data**.** We analyze three common air pollutants: sulfur dioxide (SO_2), smoke, and total suspended particulates (TSP).[4] These are the three pollutants for which the most complete data are available. All three are widely considered to cause serious health and environmental problems. Two of the three, SO_2 and smoke, exhibit the most dramatic inverse-U-shaped patterns in the World Bank's report (1992) and in Grossman and Krueger (1995). We also test the sensitivity of the pollution-income relationship to the functional forms and econometric specifications used, to the inclusion of additional covariates besides income, and to the nations, cities, and years sampled.

Our conclusion is that the evidence for an inverted-U is much less robust than previously thought. We find that the locations of the turning points, as well as their very existence, are sensitive both to slight variations in the data and to reasonable permutations of the econometric specification. Merely cleaning up the data, or including newly available observations, makes the inverse-U shape disappear. Furthermore, econometric specifications that extend the lag structure of GDP per capita as a dependent variable, include additional country-specific covariates, or include country-level fixed effects, generate predicted pollution-income relationships with very different shapes.

II. Data

Data on ambient pollution levels have been collected by the Global Environmental Monitoring System (GEMS), sponsored by the World Health Organization (WHO) and the United Nations.[5] The EPA maintains these data in its Aerometric Information Retrieval System (AIRS). For each pollution monitoring station, the data set we obtained contains the annual mean and maximum for each pollutant monitored, along with descriptive variables about the neighborhood and city in which the monitor is located.

Table 1 lists some descriptive statistics for both the original data used by Grossman and Krueger (1995), which they have graciously made available, and for the data available from AIRS as of December 1998. The new data contain substantially more usable observations than were originally available. For sulfur dioxide, the number of observations increases from 1352 to 2381, with 25 new cities, and three new countries. These data add 4 new years of observations, from 1989 to 1992, and 6 additional years of older observations, from 1971 to 1976. In addition, missing observations for existing cities have been filled in by the World Health Organization.

The new AIRS data also include revisions of some of the original observations. To determine the extent of these revisions, we matched the observations from the original data with those in the new data, and then compared the pollution concentration numbers.[6] Observations that appear to come from the same site and year often have very different reported pollution concentrations. In addition, 92 of 1021 observations in the TSP data used by Grossman and Kreuger are obvious duplicate entries, as are 76 of the 488 in the smoke data. These duplications are not present in the new AIRS data set. Table 2 gives summary statistics showing the extent of the revisions. For the 485 SO_2 observations that we are most certain we have correctly matched to the original data set, the correlation between mean sulfur dioxide levels in the new and old data is only 0.75. For TSP and smoke this correlation is 0.996 and 0.77 respectively.

In the analyses that follow, we examine the data on ambient concentrations of SO_2, TSP, and smoke together with a set of variables describing national income, political structure, investment, trade, and population density, as well as control variables that account for where the monitoring station was located. For national income we use real per capita gross domestic product, in 1985 dollars, from the Penn World Tables as described in Summers and Heston (1991). This is the same income measure used by most previous studies. Our measure of democratization is an index described in Jaggers and Gurr (1995). This index, which ranges from 0 to 10 with 10 being most democratic, is available for every year and country in the AIRS data. We measure trade intensity using the ratio of imports plus exports to GDP, and we measure investment as a fraction of GDP, both from the Penn World Tables.

III. The effects of changes in the data

To demonstrate the effects of the revisions to the existing data, we need to begin with a benchmark econometric specification. Because Grossman and Krueger's (1995) paper is among the most carefully done and widely cited works, we start with their specification. They estimate

$$Y_{it} = G_{it} b_1 + G_{it}^2 b_2 + G_{it}^3 b_3 + L_{it} b_4 + L_{it}^2 b_5 + L_{it}^3 b_6 + \mathbf{X}_{\mathbf{it}}^{'} \mathbf{ß}_{\mathbf{7}} + m_i + n_{it},$$

where G_{it} is per capita gross domestic product at time t for the country in which monitoring site i is located, L_{it} is a three-year average of lagged per capita GDP, and $\boldsymbol{X_{it}}$ are country and site-specific descriptors. This model was estimated using random effects, so $:_i$ is assumed to be a site specific effect that is uncorrelated with the right-hand-side variables, and $<_{it}$ is a normally distributed error term.

Table 3 estimates this equation for SO_2. Column 1 replicates the Grossman and Krueger results exactly, using their data. The dependent variable in column 1 is the median annual sulfur dioxide reading from each monitor. Because the version of the data we obtained from the EPA reports mean values rather than medians, in column 2 we report results from an identical specification substituting means for medians, again using the original data. This difference in the dependent variable seems unimportant: the pattern of coefficient signs, sizes, and statistical significance remains largely unchanged.

Figure 1 plots the predicted pollution-income paths with all regressors other than income set at their means.[7] Line 1 in Figure 1 plots the results of column 1 of Table 3. Line 2 uses mean values from column 2, rather than the medians from column 1. The second line is virtually identical to the first, though it is somewhat higher due to the fact that the pollution data are skewed, with means higher than medians. Both plots peak at about $4000 per capita. Because the most recent public release of AIRS data contains only mean pollution readings, in the rest of the analysis we use means, relying on the comparison of columns 1 and 2 to show that the difference is insubstantial.

Column 3 of Table 3 uses the same sample of cities and years as columns 1 and 2, 1977 to 1988, but incorporates the corrections and additions in the latest release of the AIRS data, eliminating duplications in the original. Since the earlier release contained missing descriptive statistics, the regressions in columns 1 and 2 contain an indicator variable for the cases when covariates were unavailable. The most recent data from the World Health Organization contain no such gaps, and so we drop the corresponding indicator variable. Similarly, we dropped a variable documenting the type of pollution monitor, available in the original data but not in the new version.[8] As can be seen from Table 3, even using the same observations and econometric specification, the changes in the data yield large changes in the regression results and the shape of the predicted pollution-income relationship. Line 3 of Figure 1 depicts these differences. Rather than increasing and then peaking at $4,000, line 3 declines initially, then starts to increase at about $7,000, at nearly the same point where the second regression line was actually decreasing at its highest rate. The line then starts to decrease again at about $14,000, about where the second regression line starts to increase.

Column 4 in Table 3 uses the most recent AIRS data, and all available observations from 1971 to 1992. The individual GDP coefficients are generally highly significantly different from zero, which is not true of all of the preceding regressions, perhaps due to the increase in sample size. Again, the estimated pollution-income equations change significantly from those fit using the original data, though the changes from column 3 are minor. Line 4 of Figure 1 plots the predicted values from column 4. The difference in the shape of the curve is insubstantial.

For the other air pollutants we studied, TSP and smoke, there were fewer changes to the data and therefore the regression results are less sensitive to those changes. Appendix Table 1 presents the effects of changes in the data on the estimates of TSP and smoke as a function of GDP. In both the original and new data TSP decreases monotonically with GDP, although the slopes at $10,000 and $12,000 are smaller in the new data. For smoke, in both the original and new data the pollution concentrations exhibit an inverted-U, with a peak at about $6000.

Finally, the last line of Table 3 presents chi-squared statistics from a Hausman test of whether the random-effects error terms are uncorrelated across the monitoring stations. In three of the four samples, this hypothesis can be rejected, suggesting that fixed monitoring-station effects are more appropriate. Therefore, in the next section we use the most recent version of the AIRS data with a fixed effects model to explore the effects of changing the econometric specification of the pollution-income relationship.

IV. The effects of changes in the specification

Because the reduced form relationships typically estimated in this literature are not driven by any particular economic model, there is little theoretical guidance for the correct specification. Consequently, we believe the best approach is to see if conclusions are robust across a variety of specifications. Table 4 summarizes the results of regressions for SO_2 using fixed monitoring-station effects with different covariates and functional forms. All these regressions use the most complete version of the data available to us, the same as that used in column 4 of Table 3. Column 1 of Table 4 is a fixed-effects version of the regression in column 4 of Table 3, excluding those regressors that do not vary over time.[9] The results are comparable, suggesting that although a Hausman test may reject the random-effects specification, in practice the predicted pollution-income paths from the two models are comparable.

In column 2 we lengthen the lag structure of the income variable. Lagged values of GDP per capita, averaged over the previous three years, were included in the original specifications as a measure of permanent income. In other words, pollution is positively correlated with temporary changes in GDP, as increases and decreases in economic activity generate more or less pollution. Of more interest are the effects of long-run secular changes in income, which may increase or decrease pollution levels, depending on the sources of economic growth and on the nature of any induced policy responses. If, for example, policymakers in wealthier countries enact more stringent pollution regulations, then the effect of permanent income on GDP may be negative. To separate these temporary and permanent effects more distinctly, in column 2 we use the average GDP per capita for the past 10 years, rather than the 3-year lag in the original specification. These longer lags eliminate more of the temporary fluctuations from the measure of permanent income. They also provide more time for secular changes in GDP to become incorporated in social values, for those social values to be used to determine government policy, and then for those policy changes to be implemented. Comparing columns 1 and 2 of Table 4, these longer lags do not dramatically alter the regression results.

Column 3 of Table 4 adds a number of covariates to the specification. First, it adds the square of the time trend to measure nonlinearities in the time path of pollution. If environmental degradation or improvement has accelerated over time for reasons unrelated to GDP growth, and if the econometric models include only a linear time trend, the acceleration may be inaccurately attributed to GDP changes.

Column 3 also includes a measure of national trade intensity, an index of democratic government, relative GDP (national GDP divided by the average of all countries' GDPs), and the percentage of GDP going to investment. All are statistically significant, with the exception of relative GDP. Including all of these additional covariates alters the magnitude of the coefficients on the GDP polynomials, though not their general pattern.

In column 4 of Table 4, we include only trade intensity and the democracy index as additional covariates. In column 5 we substitute annual year indicators for the year quadratic, allowing even more flexibility in the aggregate time pattern of pollution. Finally, in columns 6 and 7 of Table 4, we estimate models in which the dependent variable is the log of the mean annual pollution reading at each monitoring station, rather than the level. None of these changes substantially alters the pattern of GDP coefficients; however, they do alter the predicted pollution-income paths.

In Figure 2 we plot several of the regressions in Table 4. To focus solely on the GDP coefficients, we have normalized all of the other coefficients so that the starting point of the pollution-income path (when GDP = 0) is at 100. Columns (1) and (4) of Table 4 yield U-shaped paths, with troughs at about $10,000. By contrast, the logarithmic specification, in column (7), yields an S-shaped curve with a peak at $3000 and a trough at about $13,000.

Although there is no *a priori* reason to prefer any one of the specifications in Table 4 to the others, the specifications generally show a U-shaped, rather than inverted U-shaped relationship between income and sulfur dioxide pollution. This finding is troubling, for two reasons. First, if we assume that when GDP is zero, pollution must also be zero, then we know that the true pollution-income relationship cannot be U-shaped. Second, even though the pattern of coefficients is similar across specifications in Table 4, the slopes at any particular income and the location of the turning points vary considerably. As a consequence, we feel that we can say very little about any underlying relationship between GDP and ambient levels of SO_2.

This conclusion, that we can discern little about pollution-income patterns, also holds for smoke and TSP. Appendix Table 2 contains various specifications with the smoke and TSP measurements from new AIRS data, similar to those for SO_2 in Tables 3 and 4. For smoke and TSP the predicted pollution-income paths have inverted-U-shapes, though the location and magnitudes of the peaks vary widely with the specification.

Another means of demonstrating the uncertainty about the GDP-pollution relationship is to draw confidence bands around the entire predicted path, rather than around individual coefficients. Since the underlying variables, GDP, its polynomial, and lagged values, are correlated, these bands will be wider than might be inferred from the coefficients' standard errors. When we constructed these bands, we found that they were wide enough to incorporate a variety of GDP-pollution paths over the relevant range of GDP. Monotonically rising or falling pollution-income paths, U-shaped or inverted-U-shaped paths, or more complicated relationships all can easily fit within the 95 percent confidence bands, further demonstrating the extent of the uncertainty about the relationship between economic grown and pollution.[10]

V. Outliers, collinearity, functional forms, data clustering, and other pollutants.

What accounts for the fragility of these results? We have considered several potential sources. First, to examine the effect of outliers, we used the Hadi procedure (Hadi, 1994) to drop the 5 percent of the observations constituting the largest outliers.[11] We then re-estimated column 4 of Table 4. The coefficients can be seen in column (1) of Table 5. A plot of the results (line (1) of Figure 3) is indistinguishable from plots of the full data set.

A second potential source for the fragility of the results is collinearity. As might be expected there is a high degree of correlation both between current and lagged income, and between these measures and their squared and cubic terms. Despite this, the sample size is large enough that many of the coefficients of these variables are estimated with reasonable precision. However, with cubic polynomials, even small coefficient differences can produce large differences in the shape of the estimated functions. Therefore the cubic functional form may be problematic when the independent variables are highly correlated. We addressed this issue by fitting spline functions.[12] Splines allow for nonlinearities in the shape of the pollution path without including correlated polynomial terms. Comparing the cubic and spline results for each dataset and for a representative specification, we found that at intermediate levels of income, between 5 and 15 thousand dollars GDP per capita (where most of the data lie), the shapes of the predicted pollution paths using splines are not that dissimilar from those using cubics. Outside of that range, however, the paths differ dramatically.

Another potential issue is the fact that by using data at the level of individual pollution monitoring stations, we are automatically giving more weight to countries with more numerous monitors, such as the U.S. We first addressed this clustering by estimating the basic specification weighted by the number of observations in each country, where the weights are 1/n, with n being the number of observations per country. Column (2) of Table 5 repeats column (4) of Table 4, with the observations weighted by the inverse of the number of observations in each nation. The coefficients do not change significantly. Though the peak turning point changes, its value is far outside the relevant data. We have also tried a specification using the *average* values for each country, so that each country has only one observation per year. Column (3) of Table 5 contains those results. Again, the predicted function has a trough, rather than a peak, in the middle of the data, and a peak far outside the relevant data. These two specifications are plotted as lines (2) and (3) of Figure 3.

Yet another source of fragility in the results may stem from fundamental differences between developing and developed countries. For example some countries may have actually passed a turning point and begun to clean up, while others may still be becoming increasingly polluted. We find that excluding Canada and the U.S., which together account for almost one-third of the SO_2 observations, that pollution decreases steadily with GDP per capita. Conversely, focusing only on the North American observations, pollution increases steadily with income. Finally, in column (4), when we limit the data to observations with greater than 8 thousand dollars GDP per capita, predicted pollution increases steadily with income, with no obvious peak.[13] This result is plotted as line (4) of Figure 3. It differs starkly from lines plotted using the entire sample, suggesting just how sensitive these results can be to the sample of countries.

These results suggest that alternative shapes of the pollution-income paths at intermediate incomes are not spurious results of multi-collinearity, the cubic functional form, or clustering of the data alone. However, the varying predictions at income levels outside this middle range, particularly at high incomes, may well be driven by the cubic function and by coefficient estimates that are imprecise due to multi-collinearity. In sum, the results here suggest that neither outliers in the data nor collinearity *per se* have caused the fragility of the early results depicting environmental Kuznets curves. Rather, the largest variations in the predicted pollution-income path have been the result of revisions and additions to the underlying data.

Finally, we have run these same sets of regressions for airborne lead, nitrogen oxide, and other sizes of particulates. These sample sizes are much smaller, and the results are generally less statistically significant. Predicted paths for soil index particulates, light scatter particulates, and small particulates (less than 10 micrometers) do not display anything resembling inverse-U's. Lead appears to peak around $14,300, and nitrogen oxide peaks around $5400. Like the results from SO2, these results differ substantially from previously published results, and are themselves susceptible to small changes in the data.[14]

VI. Conclusion

The literature to date has carefully noted that these reduced-form empirical analyses are only loosely motivated by theory, and are therefore somewhat arbitrary. That is appropriate, however, because the point of the literature has been descriptive, leaving it up to others to provide theoretical explanations and policy implications. Our point with this paper is merely that the empirical evidence to date is far less robust than has been claimed. We demonstrate that point by altering previous specifications in modest ways (adding different countries, including fixed rather than random effects, adding years, and adding new control variables). The empirical specifications presented here are not any less arbitrary than those made by previous researchers, and the fact that our alternative specifications yield such drastically different patterns demonstrates the fragility of those earlier results.

The key insight of this literature so far has been that pollution does not necessarily increase deterministically with economic growth. While this point may be obvious to economists, Grossman and Krueger were the first to document that fact empirically. Since then, however, the literature has focused on estimating a deterministic inverse-U-shaped pollution-income pattern. In fact, if it is true that pollution does not inevitably increase with economic growth but rather declines at some point, then the pollution-income path *must* be inverse-U-shaped. (What goes down must, after all, have first gone up.)

Proving this latter point, that pollution can decline with growth, is relatively simple. All one needs to do is show that some pollutants have declined in some countries even as their economies grew. List and Kunce (2000), and Greenstone (2001) have recently done just that for air quality in the U.S. The trouble arises when we try to estimate the entire path of pollution as a function of countries' GDP. For three important air pollutants, SO_2, smoke, and TSP, we find that the estimated relationship between pollution and GDP is sensitive to both sample selection and empirical specification. For these pollutants, there is little if any empirical support for the existence of an inverted-U-shaped "environmental Kuznets curve." However, we believe this statement deserves at least two qualifications.

First, there are theoretical arguments, such as those cited in our introduction, which suggest that an inverted-U-shaped relationship may not only be possible, but in fact may be quite plausible. Do these results refute that theory? It may be that most of the world's nations have not yet reached income levels sufficient to generate the turning points predicted by those theories. Alternatively, the existing data on a few pollutants, drawn from a few monitoring stations in a small nonrepresentative sample of cities over a relatively short period of time, may simply be insufficient to detect the true relationship between pollution and economic growth, should that be an inverted U.

Yet another possibility is that the data, while not necessarily insufficient in quantity, are too noisy to detect the inverted U. Monitoring stations measurements may be inaccurate. Furthermore, pollution around a given monitoring station is almost certainly related to local economic activity and population density, neither of which we measure.

The second point worth highlighting here is that while this paper shows that air quality does not necessarily *improve* with economic growth, we have found no evidence in these data that environmental quality necessarily *declines* with growth either. Our conclusion is simply that, for these pollutants, the available empirical evidence cannot be used to support either the proposition that economic growth helps the environment, or the proposition that it harms the environment.

The next important empirical step for this line of research to take will be to categorize those pollutants and countries for which pollution has already begun to decline, simultaneously with economic growth. Rather than trying to fit a universal, reduced-form, pollution-income relationship, it would be useful to know what common features are shared by pollutants and countries where emissions are decreasing and income is increasing. Such detail will better allow the various theoretical explanations to be tested and will enable analysts to draw more convincing policy implications.

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[1] See, for example, Holtz-Eakin and Selden (1995), Selden and Song (1994), Hilton and Levinson (1998), Shafik (1994).

[2] See, for example, Selden and Song (1995), Stokey (1998), Jaeger (1998), Jones and Manuelli (1995), Andreoni and Levinson (2001), Chaudhuri and Pfaff (1997). In addition, recent special issues of two journals, *Environment and Development Economics* in November 1997 and *Ecological Economics* in May 1998 have been devoted to papers on the environmental Kuznets curve.

[3] See, for example, Beckerman (1992) or Bartlett (1994). Bartlett writes that "existing environmental regulation, by reducing economic growth, may actually be reducing environmental quality."

[4] We also tested models on lead, NOx, and other sizes of suspended particulate matter. Sample sizes were small, and the independent variables had generally insignificant coefficients.

[5] GEMS was initiated in the early 1970s to coordinate the worldwide collection of comparable measures of ambient air and water quality. See Bennet et al. (1985) and UNEP and WHO (1983), (1984), (1992) and (1994) for reports on the history and results of the GEMS air monitoring project.

[6] These matches were not always easy to make. We began by matching observations by pollutant, city, and year. In most cases there were several monitoring sites per city, so observations were then paired by comparing the number of measurements and mean values reported. For some cities the number of observations was consistently the same, for others it was consistently different, and for still others it was a mix.

[7] In drawing this and related figures, we followed Grossman and Krueger (1995) and set lagged

GDP equal to current GDP.

[8] This variable did not have statistically significant coefficients in any of the original specifications.

[9] Column 1 also replaces the time-invariant city-level measure of population density with an annual national-level measure. For these fixed effect models, this amounts to a measure of population, since area does not vary with time.

[10] We have not reproduced the confidence bands here. They may be seen in Harbaugh *et al.* (2000).

[11] For the original data, these outliers were generally high-income, low-pollution cities in the US and Canada. For the new AIRS data, the influential outliers were generally low-income cities in China and Africa with either very low or very high pollution. A complete list is available from the authors.

[12] These spline results are available separately from the authors.

[13] This may seem counter-intuitive. SO2 concentrations in Canada and the US have declined over time at ever decreasing rates, and the regressions in Table 5 only include a linear time trend. So the curvature over time is absorbed by the GDP polynomial. After de-trending the data with the time function, pollution appears to increase as a function of GDP.

[14] These other results are all available separately from the authors.

Table 1
Comparison of summary statistics.

	Grossman and Krueger (1995)					AIRS				
SO_2	**Obs.**	**Mean**	**S.D.**	**Min.**	**Max.**	**Obs.**	**Mean**	**S.D.**	**Min.**	**Max.**
Median SO_2 Conc.	1352	33.2	33.3	0	291	Not available				
Mean SO_2 Conc.	1261	49.0	40.9	2.36	354	2401	49.4	50.9	0.782	1160
GDP per Capita	1352	7.51	4.83	0.619	17.3	2381	9.43	5.73	0.765	18.1
3-yr-avg. lag GDP	1352	7.18	4.62	0.626	16.2	2389	9.10	5.56	0.779	18.0
10-yr-avg. lag GDP						2389	8.48	5.25	0.753	16.8
Year	1352	1982	3.28	1977	1988	2401	1983	5.17	1971	1992
Population Density	1352	3.35	4.56	0.00210	24.7	2401	2.75	3.99	0.00210	24.7
Industrial	1352	0.291	0.455	0	1	2401	0.0875	0.283	0	1
Residential	1352	0.360	0.480	0	1	2401	0.820	0.384	0	1
Center City	1352	0.550	0.498	0	1	2401	0.862	0.345	0	1
Coastal	1352	0.555	0.497	0	1	2401	0.565	0.496	0	1
% GDP Invested						2381	23.1	5.49	4.20	41.5
Trade Intensity						2381	42.5	32.9	8.84	262
Democracy Index						2322	7.23	4.16	0	10
Relative GDP						2381	1.121	0.910	-0.85	2.10
# sites	239					285				
# cities	77					102				
# countries	42					45				

TSP	**Obs.**	**Mean**	**S.D.**	**Min.**	**Max.**	**Obs.**	**Mean**	**S.D.**	**Min.**	**Max.**
Median TSP Conc.	1021	147	127	0	715	Not available				
Mean TSP Conc.	1021	163	140	10.7	796	1092	177	146	9.80	796
GDP per Capita	1021	8.11	5.99	0.619	17.3	1085	6.95	5.65	0.765	17.5
3-yr-avg. lag GDP	1021	7.71	5.72	0.626	16.2	1092	6.65	5.39	0.779	17.3
10-yr-avg. lag GDP						1092	6.11	4.95	0.753	15.9
Year	1021	1982	3.29	1977	1988	1092	1984	4.88	1972	1992
Population Density	1021	3.07	4.16	0.00210	24.7	1092	3.84	4.59	0.00150	24.7
Industrial	1021	0.303	0.460	0	1	1092	0.0375	0.190	0	1
Residential	1021	0.347	0.476	0	1	1092	0.920	0.271	0	1
Center City	1021	0.467	0.499	0	1	1092	0.943	0.232	0	1
Coastal	1021	0.529	0.499	0	1	1092	0.509	0.500	0	1
Desert	1021	0.0411	0.199	0	1	1092	0.00916	0.0953	0	1
% GDP Invested						1085	22.9	6.15	3.70	39.3
Trade Intensity						1085	45.8	39.2	8.84	286
Democracy Index						1063	5.66	4.55	0	10
Relative GDP						1085	0.653	1.05	-1.08	2.03
# sites	161					149				
# cities	62					53				
# countries	29					30				

Smoke	**Obs.**	**Mean**	**S.D.**	**Min.**	**Max.**	**Obs.**	**Mean**	**S.D.**	**Min.**	**Max.**
Median Smoke Conc.	488	42.2	42.6	0	312	Not available				
Mean Smoke Conc.	487	53.4	48.6	1.30	325	710	56.7	50.7	1.300	307
GDP per Capita	488	6.81	3.00	1.34	12.2	687	6.78	3.22	1.293	13.5
3-yr-avg. lag GDP	488	6.61	2.88	1.25	11.4	687	6.60	3.05	1.187	12.4
10-yr-avg. lag GDP						687	6.22	2.84	1.117	11.6
Year	488	1982	3.33	1977	1988	710	1982	4.89	1972	1992
Population Density	488	3.64	5.30	0.00210	24.7	710	3.87	5.10	0.00210	24.7
Industrial	488	0.275	0.447	0	1	710	0	0	0	0
Residential	488	0.311	0.464	0	1	710	1	0	1	1
Center City	488	0.568	0.496	0	1	710	1	0	1	1
Coastal	488	0.607	0.489	0	1	710	0.513	0.500	0	1
Desert	488	0.107	0.309	0	1	710	0.0465	0.211	0	1
% GDP Invested						687	21.4	6.16	4.30	41.5
Trade Intensity						687	56.0	37.9	8.96	210
Democracy Index						646	6.13	4.36	0	10
Relative GDP						687	0.975	0.540	-0.350	1.75
# sites	87					96				
# cities	30					32				
# countries	19					21				

Table 2

Comparison of mean pollutant levels from AIRS with Grossman and Krueger (1995) data.

	SO_2	TSP	Smoke
No. of paired city-years	485	300	192
Correlation within pairs	0.745	0.996	0.766
Mean of AIRS means	47.4	164	53.3
Mean of G&K means	47.2	164	56.2

Table 3

Effects of changes in the data on sulfur dioxide regressions.

Random effects models.

	Replicates Grossman and Krueger (1995) [with median SO2]	Replicates Grossman and Krueger (1995) [with mean SO2]	New AIRS data: Only G&K's cities & years [with mean SO2]	New AIRS data: All years & cities [with mean SO2]
	(1)	(2)	(3)	(4)
GDP	-7.37	-5.72	-29.9**	-29.3**
	(9.15)	(9.71)	(10.2)	(7.41)
$(GDP)^2$	1.03	1.41	3.45**	4.06**
	(1.11)	(1.20)	(1.21)	(0.769)
$(GDP)^3$	-0.0337	-0.0543	-0.104*	-0.127**
	(0.0384)	(0.0415)	(0.0407)	(0.0232)
Lagged GDP	20.9*	14.7	10.6	14.1
	(9.75)	(10.5)	(11.0)	(7.32)
$(Lagged\ GDP)^2$	-3.22*	-2.92*	-1.40	-2.85**
	(1.26)	(1.38)	(1.40)	(0.780)
$(Lagged\ GDP)^3$	0.117*	0.109*	0.0382	0.0991**
	(0.0461)	(0.0507)	(0.0502)	-0.0239
Year	-1.40**	-1.50**	-0.475*	-1.51**
	(0.218)	(0.239)	(0.240)	(0.159)
Population Density	1.14	0.495	-0.647	-0.717
	(1.23)	(0.551)	(1.26)	(1.05)
Industrial	-0.485	-0.383	-34.6	-2.72
	(5.26)	(6.96)	(46.6)	(24.9)
Residential	-11.1*	-6.69	-30.2	-5.39
	(4.85)	(6.38)	(33.3)	(17.7)
Center City	3.06	11.4*	28.3	26.5
	(4.31)	(5.71)	(29.2)	(15.5)
Coastal	-12.7**	-15.6**	-22.8	-24.7*
	(3.78)	(5.12)	(11.8)	(8.94)
# obs.	1352	1261	1403	2381
# groups	239	233	227	282
R^2 (within)	0.0995	0.0953	0.0316	0.099
Turning Points				
Peak	$4,000	$3,718	$13,741	$20,081
	(355)	(649)	(1,419)	(2,592)
Trough	$13,534	$14,767	$7,145	$9,142
	(599)	(1,297)	(915)	(877)
Slopes				
at $10,000	-5.30**	-4.90**	2.10	0.721
	(0.609)	(0.969)	(1.334)	(0.825)
at $12,000	-3.07**	-3.75**	1.66	1.92*
	(0.91)	(1.072)	(1.44)	(0.826)
Hausman Chi^2	81.7**	223**	11.7	21.5*

Note: Standard errors in parentheses. An overall constant term was also included in all regressions. Grossman and Krueger (1995) include dummy variables for the type of monitoring device and for missing land-use and location information. These are not available in the AIRS data.

* $p < 0.05$
** $p < 0.01$

Table 4

Effects of changes in the sulfur dioxide regression specifications.

Fixed effects models.

	Short set of explanatory variables, 3-year lags	Longer lag structure but no additional regressors	All explanatory variables	Base model explanatory variables	Year dummies	Log dependent, year dummies	Log dependent
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
GDP	-33.3**	-42.3**	-19.5	-34.7**	-39.2**	-0.410**	-0.302*
	(7.57	(6.50)	(10.3)	(6.79)	(7.18)	(0.139)	(0.129)
$(\mathrm{GDP})^2$	4.33**	4.67**	2.13*	3.78**	4.17**	0.0382*	0.0278*
	(0.781)	(0.698)	(0.848)	(0.717)	(0.781)	(0.0151)	(0.0136)
$(\mathrm{GDP})^3$	-0.133**	-0.133**	-0.0610**	-0.108**	-0.126**	-0.00110*	-0.000697
	(0.0235)	(0.0215)	(0.0238)	(0.0217)	(0.0242)	(0.000468)	(0.000411)
Lagged GDP	7.86	16.3*	13.8*	20.3**	27.8**	0.488**	0.399**
	(7.46)	(6.96)	(6.73)	(6.71)	(6.86)	(0.133)	(0.127)
$(\mathrm{Lagged\ GDP})^2$	-2.35**	-2.86**	-1.55	-3.22**	-3.52**	-0.0523**	-0.0470**
	(0.787)	(0.778)	(0.797)	(0.761)	(0.822)	(0.0160)	(0.0144)
$(\mathrm{Lagged\ GDP})^3$	0.0868**	0.0968**	0.0525	0.115**	0.129**	0.00177**	0.00150**
	(0.0241)	(0.026)	(0.0272)	(0.0255)	(0.0287)	(0.000556)	(0.000482)
Year	-1.49**	-1.20**	-568**	-2.28**			-0.0541**
	(0.174)	(0.215)	(106)	(0.266)			(0.00503)
$(\mathrm{Year})^2$			0.143**				
			(0.0266)				
National Population Density	14.2**	8.92	524**	520**	586**	9.80**	9.23**
	(4.68)	(4.80)	(46.2)	(46.1)	(45.7)	(0.887)	(0.872)
Trade Intensity			-0.582**	-0.600**	-0.450**	-0.00931**	-0.0110**
			(0.0868)	(0.0876)	(0.0915)	(0.00177)	(0.00166)
Democracy Index			-3.63**	-3.24**	-3.09**	-0.0400**	-0.0390**
			(0.509)	(0.499)	(0.494)	(0.00958)	(0.00945)
Relative GDP			-26.7				
			(20.2)				
Investment			0.661**				
			(0.21)				
# obs.	2381	2381	2314	2314	2314	2314	2314
# groups	282	282	267	267	267	267	267
R^2 (within)	0.1044	0.1035	0.2236	0.2072	0.2664	0.2413	0.2197
Turning Points							
Peak	$18,800	$22,500	$39,700	-$64,700	-$151,000	$3,770	$3,120
	(1,460)	(4,970)	(49,300)	(152,000)	(764,000)	(3,860)	(2,388)
Trough	$9,790	$10,600	$5,650	$10,900	$8,300	$10,300	$12,800
	(798)	(835)	(5,070)	(683)	(845)	(1,654)	(948)
Slopes							
at $10,000	0.251*	-0.828	3.30	-1.33	2.47*	-0.00346	-0.0458*
	(0.987)	(1.08)	(2.69)	(1.06)	(1.12)	(0.0220)	(0.0200)
at $12,000	2.07*	1.59	4.49	1.78	5.47**	0.0285	0.0161
	(0.931)	(1.11)	(2.37)	(1.11)	(1.19)	(0.023)	(0.0210)
Hausman Chi^2	25.1**	22.7**	132**	155**	125**	635**	93.9**

Note: Standard errors in parentheses.

* $p < 0.05$

** $p < 0.01$

Table 5
Effects of outliers, functional form, clustering, etc. on the sulfur dioxide results.
Fixed effects models.

	Drop outliers (5%)	Weight by inverse of number of monitors	Average reading per country-year	Only countries with GDP > $8000
	(1)	**(2)**	**(3)**	**(4)**
GDP	-46.9**	-39.1**	-43.7**	116**
	(6.73)	(7.05)	(16.2)	(30.1)
$(GDP)^2$	4.93**	3.93**	4.05*	-6.67**
	(0.706)	(0.798)	(1.82)	(2.21)
$(GDP)^3$	-0.140**	-0.109**	-0.107	0.129*
	(0.0213)	(0.0263)	(0.0596)	(0.0530)
Lagged GDP	23.3**	27.8**	23.0	-60.5**
	(6.48)	(6.97)	(15.6)	(20.0)
$(Lagged\ GDP)^2$	-3.55**	-4.18**	-2.81	3.07
	(0.735)	(0.857)	(1.91)	(1.65)
$(Lagged\ GDP)^3$	0.127**	0.147**	0.0885	-0.0260
	(0.0246)	(0.0316)	(0.0699)	(0.0439)
Year	-2.75**	-2.27**	-1.68**	-5.34**
	(0.269)	(0.228)	(0.496)	(0.502)
National Population Density	512**	511**	269**	936**
	(44.2)	(46.3)	(91.3)	(76.9)
Trade Intensity	-0.535**	-0.481**	-0.378*	-0.598**
	(0.0852)	(0.0773)	(0.177)	(0.0983)
Democracy Index	-2.74**	-3.49**	-4.78**	(dropped)
	(0.489)	(0.452)	(1.02)	
Fixed effects	monitors	monitors	countries	monitors
# obs.	2198	2314	461	1358
# groups	262	267	41	148
R^2 (within)	0.240	0.1919	0.2157	0.3750
Turning Points				
Peak	$65,500	-$8,059	$34,634	none
	(60,700)	(6,580)	(52,038)	
Trough	$9840	$12,317	$10,890	none
	(526)	(598)	(1,951)	
Slopes				
at $10,000	0.322	-4.78**	-1.20	14.2**
	(1.077)	(1.12)	(2.42)	(2.82)
at $12,000	4.24**	-0.727	1.38	13.4**
	(1.155)	(1.33)	(2.84)	(2.19)
Hausman Chi^2	136**	n.a.	21.6*	244**

Note: Standard errors in parentheses. An overall constant term was also included in all regressions.

* $p < 0.05$

** $p < 0.01$

Figure 1: Plot of Table 3 regressions
Different data sets for sulfur dioxide

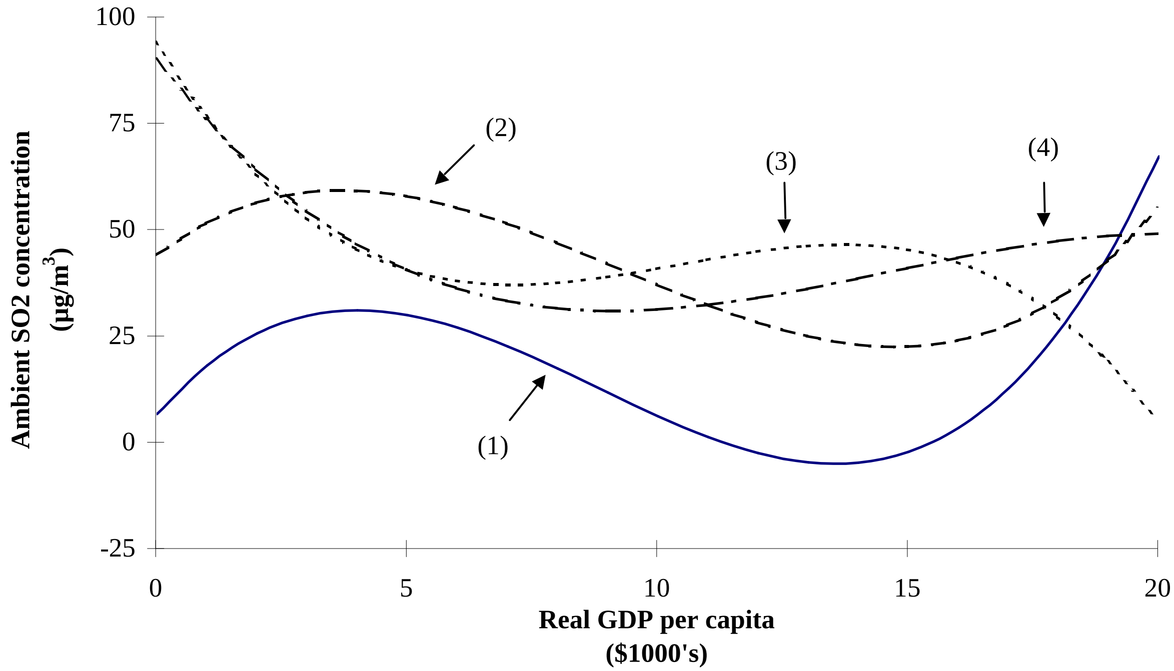


Figure 2: Plot of Table 4 regressions
Different fixed effects specifications for sulfur dioxide

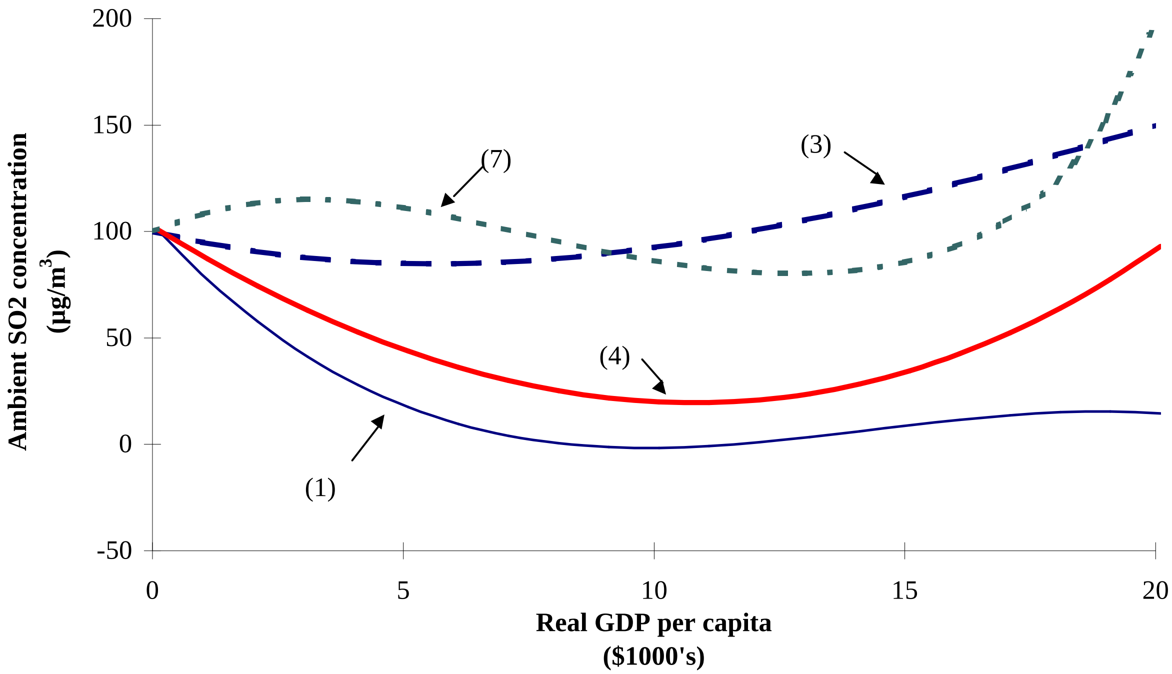
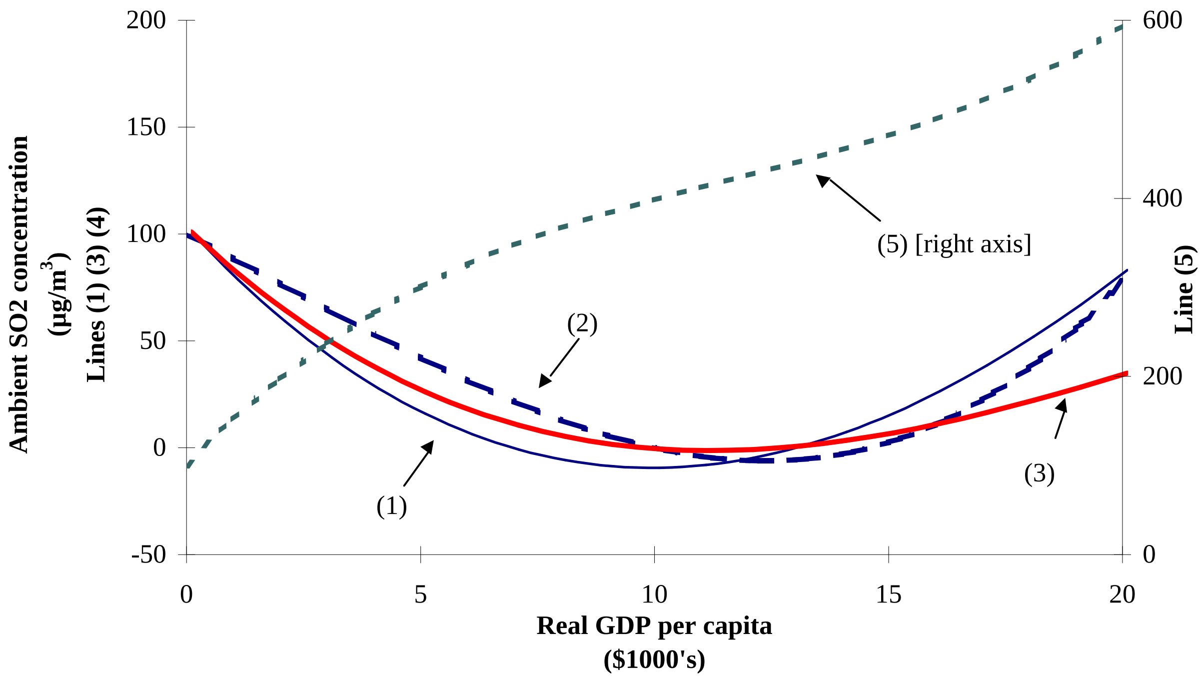


Figure 3: Plot of Table 5 regressions
Outliers, collinearity, functional form, clustering, etc.



Appendix Table 1

Effects of changes in the data on TSP and smoke regressions.

Random effects models.

	Median TSP concentration, Grossman and Kreuger's (1995) results. (1)	Median TSP concentration, Grossman and Kreuger's (1995) model with AIRS data. (2)	Median smoke concentration, Grossman and Kreuger's (1995) results. (3)	Median smoke concentration, Grossman and Kreuger's (1995) model with AIRS data. (4)
GDP	17.4	22.3	24.5	18.4
	(21.5)	(21.1)	(20.9)	(21.1)
$(GDP)^2$	-0.922	-2.02	-7.64*	-2.22
	(2.65)	(2.34)	(3.58)	(3.17)
$(GDP)^3$	0.0136	0.0595	0.443**	0.102
	(0.0902)	(0.0737)	(0.171)	(0.139)
Lagged GDP	-60.7**	-43.6*	12.6	62.0**
	(23.3)	(20.9)	(22.0)	(23.2)
$(\text{Lagged GDP})^2$	4.35	3.45	3.44	-9.07*
	(3.12)	(2.40)	(3.96)	(3.67)
$(\text{Lagged GDP})^3$	-0.115	-0.0951	-0.313	0.373*
	(0.112)	(0.0783)	(0.199)	(0.170)
Year	0.744	-1.84**	-1.23**	-2.29**
	(0.631)	(0.462)	(0.358)	(0.254)
Population Density	-0.699	4.04*	2.39**	1.60
	(1.40)	(1.83)	(0.853	(0.952)
Industrial	23.8	-26.4	-11.6	(dropped)
	(17.4)	(61.1)	(10.7)	
Residential	7.35	-98.0*	-13.9	4450**
	(16.4)	(38.9)	(9.36)	(502)
Center City	26.2	-149**	4.05	(dropped)
	(14.5)	(42.2)	(8.86)	
Coastal	-21.1	-40.6*	-33.7**	-34.2**
	(12.1)	(17.2)	(8.35)	(9.16)
Desert	162**	252**	7.08	52.8*
	(26.1)	(58.1)	(11.2)	(25.2)
# obs.	1021	1085	488	687
# groups		148		92
R^2 (within)	0.0004	0.0195	0.188	0.190
Turning Points				
Peak	none	none	$6,194	$5,399
			(539)	(236)
Trough	none	none	$15,455	$10,447
			(6600)	(452)
Slopes				
at $10,000	-5.16	-3.27	-8.05	-2.93
	(5.16)	(2.45)	(12.74)	(2.64)
at $12,000	-4.81*	-2.24	-7.78	14.6*
	(2.08)	(2.12)	(8.65)	(6.48)
Hausman Chi^2	122**	151**	4.81	24.6**

Notes: Standard errors in parentheses. Grossman and Krueger (1995) also include dummy variables for monitor type and missing site information, none of which were significant.

* $p < 0.05$

** $p < 0.01$

Appendix Table 2
Effects of changes in the specification on TSP and smoke regressions.
Fixed effects models.

	Mean TSP, base model explanatory variables (1)	Log of mean TSP, base model explanatory variables (2)	Mean TSP, only observations with GDP>$8,000 (3)	Mean smoke, base model explanatory variables (4)	Log of mean smoke, base model explanatory variables (5)	Mean smoke, only observations with GDP>$8,000 (6)
GDP	60.6**	0.165	-155*	55.6**	0.975**	-197
	(20.1)	(0.103)	(76.5)	(19.8)	(0.327)	(229)
$(GDP)^2$	-3.58	-0.00402	11.8*	-7.13*	-0.149**	16.4
	(2.30)	(0.0118)	(5.30)	(2.89)	(0.0479)	(21.8)
$(GDP)^3$	0.0759	0.0000549	-0.282*	0.271*	0.00638**	-0.448
	(0.0730)	(0.000375)	(0.121)	(0.125)	(0.00207)	(0.686)
Lagged GDP	-35.9	-0.157	43.5	-8.33	-0.846*	223
	(20.6)	(0.105)	(76.7)	(21.59)	(0.357)	(246)
$(Lagged\ GDP)^2$	2.62	0.00663	-4.22	0.959	0.138*	-24.5
	(2.59)	(0.0133)	(6.01)	(3.45)	(0.0573)	(26.3)
$(Lagged\ GDP)^3$	-0.0750	-0.000357	0.0982	-0.0593	-0.00709*	0.859
	(0.0934)	(0.000479)	(0.154)	(0.170)	(0.00282)	(0.951)
Year	-1.62	-0.00642	1.13	0.639	0.00442	0.906
	(0.836)	(0.00429)	(1.06)	(0.742)	(0.0123)	(1.38)
Population Density	-206	-0.153	-536**	-1080**	-10.5	-2244
	(139)	(0.715)	(172)	(325)	(5.39)	(1273)
Trade Intensity	0.478	0.00138	-0.0489	0.0986	0.000886	0.404*
	(0.267)	(0.00137)	(0.162)	(0.146)	(0.00241)	(0.156)
Democracy Index	-8.72**	-0.0394**	dropped	-2.94**	-0.0337**	dropped
	(2.21)	(0.0113)		(0.642)	(0.0106)	
# obs.	1056	1056	400	646	646	245
# groups	144	144	49	89	89	37
R^2 (within)	0.114	0.190	0.335	0.216	0.136	0.231
Turning Points						
Peak	$13,057	$7,013	none	$5,258	$4,227	$1,845
	(2384)	(3147)		(586)	(1599)	(10,698)
Trough	$764,867	-$1,247	none	$14,146	-$14,284	$11,325
	(53,176,425)	(12,685)		(3543)	(64,509)	(2922)
Slopes						
at $10,000	5.71	-0.0304	-15.7*	-12.5*	-0.299**	-13.3
	(4.11)	(0.0211)	(6.70)	(5.71)	(0.095)	(11.9)
at $12,000	1.97	-0.0598**	-9.64	-9.20	-0.435*	8.45
	(3.99)	(0.0205)	(5.03)	(10.9)	(0.181)	(26.1)
Hausman Chi^2	61.6*	35.4**	28.03**	37.8**	32.7**	25.44**

Notes: Standard errors in parentheses. Grossman and Krueger (1995) also include dummy variables for monitor type and missing site information, none of which were significant.

* $p < 0.05$

** $p < 0.01$