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Abstract

The long-run average growth rates of per capita carbon dioxide emissions and GDP per capita are positively correlated, though the rate of emissions intensity reduction varies widely across countries. The conventional approach to investigating these relationships involves panel regression models of the levels of the variables, which are plagued by unit root and cointegration issues as well as the difficulty of identifying time effects. In this paper, we adopt a new representation of the data in terms of long-run growth rates, which allows us to test multiple hypotheses about the drivers of per capita emissions of pollutants in a single framework. It avoids the econometric issues associated with previous approaches and allows us to exploit the differences in growth performance across countries. We also apply our new approach to sulfur emissions. The results show that scale, environmental Kuznets, convergence, and, for sulfur, time effects are important in explaining emissions growth. Though the elasticity of emissions with respect to income declines with increased income, for carbon the effect of growth is monotonic. For sulfur, most of our specifications find an in sample turning point, but for our preferred specification the turning point is three times mean income. We also found that the Green Solow Model convergence effect is more important than GDP growth or the EKC effect in explaining sulfur emissions but that the latter is true for carbon emissions.

JEL Code: Q56, O44

Key Words: Economic growth, environmental Kuznets curve, decoupling

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Introduction

This paper is inspired by Figure 1, which shows that there is a strong positive correlation between the long-run average growth rate of total per capita carbon dioxide emissions and the long-run growth rate of GDP per capita. Fast growing economies see increases in CO_2 emissions while slow growing or declining economies tend to have declining emissions:

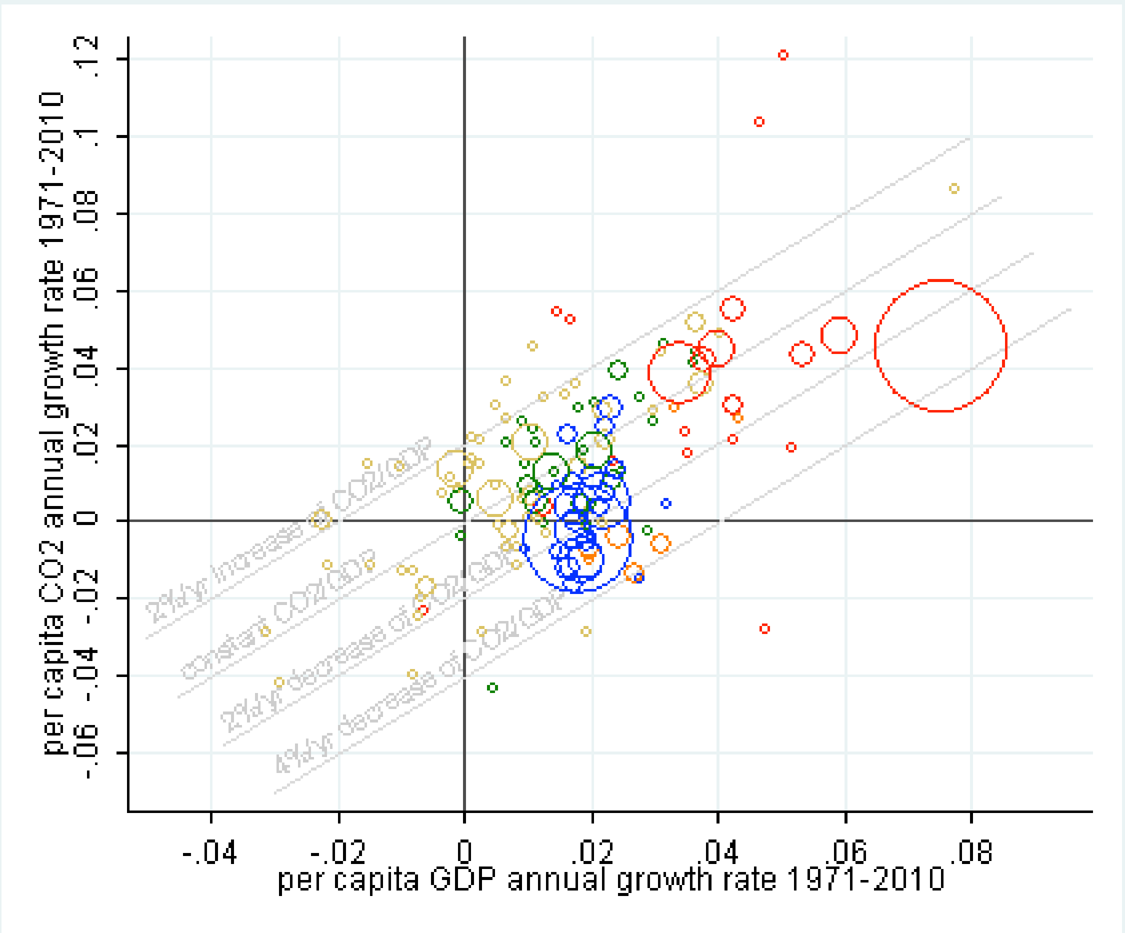

Figure 1: **Growth Rates of Per Capita Income and Per Capita Carbon Dioxide Emissions from Fossil Fuel Combustion and Cement Production**. The figure shows the relation between the average annual growth rates of per capita income and per capita emissions from 1971 to 2010. Points along the grey lines have either constant emissions intensity or emissions intensity increasing by 2% or declining at 2% or 4% per annum. The size of the circles is proportional to countries' emissions in 2010. The colors represent economic regions: Red – Non-OECD Asia; Blue – Countries that were OECD members in 1990, Yellow - Middle East & North Africa; Green - Latin America; and Orange – Eastern European countries. The upper right large red circle is China and the large blue circle is the USA. Sources: CDIAC and Penn World Table 8.0.

The principal axis in the data can be explained by the rate of economic growth. Variation around that linear relationship reflects different rates of change in emissions per dollar of GDP as shown by the parallel lines in the figure. Emissions intensity is declining in around half the countries and while there is variation in the rate of change of emissions intensity it is not sufficient to obscure the effect of the growth of the economy. Some fast growing economies such as China saw significant improvements in emissions intensity, which in the case of China declined more rapidly than in most developed countries. The number of slow growing non-OECD countries with declining emissions that we also see in Figure 1 suggests that a very simple environmental Kuznets curve (EKC) story – that economic growth in poor countries increases emissions while economic growth in rich countries reduces emissions - is not the whole explanation of the patterns we see in the figure.[1] Furthermore, some developed countries had declining emissions and some increasing.

In this paper, we represent the relationship between income growth and emissions growth in the way it is shown in Figure 1 by estimating the relationship between the long-run growth rates of emissions and income rather than using the popular EKC model. As we will show, this model has important econometric advantages over the conventional EKC representation and can be used to test various alternative theories about the development of emissions.

There has been an extensive debate on the drivers of pollution emissions and other environmental impacts. Until the 1980s, mainstream environmental thought held that environmental impact increased with the scale of economic activity, though either more or less environmentally friendly technology could be chosen. This approach is represented by the IPAT model proposed by Ehrlich and Holdren (1971). IPAT is an identity given by impact = population*affluence*technology. If affluence is taken to be income per capita, then the technology term is impact or emissions per dollar of income. Decomposition approaches to modeling emissions (e.g. Rafaj *et al*., in press) are ultimately derived from IPAT or the related Kaya Identity (Kaya, 1990).[2]

The 1980s saw the introduction of the sustainable development concept, which argued that, in fact, development was necessary in order to protect the environment (WCED, 1987). In line with the sustainable development idea, in the early 1990s Grossman and Krueger (1991, 1995) introduced the concept of the environmental Kuznets curve (EKC), which proposes that environmental impacts first increase and then decrease over the course of economic development. Proponents of the EKC argue that though economic growth at first increases

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[1] For recent critical reviews of the environmental Kuznets curve literature see Carson (2010), Pasten and Figueroa (2012), and Kaika and Zervas (2013a, 2013b).

[2] The STIRPAT approach of Dietz and Rosa (1997) and Rosa and Dietz (1998) is also derived from IPAT but allows the elasticities of population and affluence to deviate from unity and estimates technology as a residual.

environmental degradation, in the long run countries must become rich in order to clean up their environment (e.g. Beckerman, 1992). The EKC was popularized by the *1992 World Bank Development Report*, which relied on research by Shafik (1994). However, this research showed that carbon emissions did not seem to follow an inverted U-shaped curve, which was confirmed by Holtz-Eakin and Selden (1995), the classic paper on the carbon EKC (Stern *et al*., 2013). Stern and Common (2001) found that in a globally representative sample of countries, even for sulfur emissions, there was a monotonic relationship between emissions and income per capita when time effects were included in the regression model. Recent papers using more sophisticated econometrics find that the relationship between the levels of emissions and income per capita is monotonic when the effect of the passage of time is controlled for (Wagner, 2008; Vollebergh *et al*., 2009; Stern, 2010). Stern (2010) even finds that the emissions income elasticity is greater than unity for carbon dioxide.[3]

Stern (2004) argued that fast growing countries would find themselves moving up the environmental Kuznets curve faster than the curve shifted down due to the time effect, while slow growing countries would have declining emissions, as their movement along the income-emissions curve would be much slower. The fastest growing economies have been middle-income countries such as China and the Asian tiger economies that are catching up to the developed countries by adopting existing technologies and implementing them through capital accumulation.[4] Stern (2004) proposed that perhaps the high economic growth rate of these economies better explains their high level of emissions than their middle-income status does. This is a reformulation of the IPAT approach – the hypothesis is that increases in the scale of the economy always lead to more emissions, *ceteris paribus*, though improvements in technology can offset this effect.

A third approach to the evolution of emissions over time is to assume that (or test whether) they are converging to a common level. Several authors have tested for convergence in per capita emissions using sigma convergence or cointegration tests. Strazicich and List (2003)

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[3] This is probably exaggerated due to the lack of control variables in the regression. In particular, temperature, which is negatively correlated with income capita and positively correlated with energy use.

[4] Of course, to the extent that emissions-reducing technological change is correlated with general TFP growth, the emissions-income elasticity would be expected to be less than unity and countries reduce their emissions intensity in line with increasing their GDP per capita. Only reductions in emissions intensity that are unrelated to growth in income and are shared across all countries would result in downward shifts of the emissions-income curve.

and Aldy (2006) found convergence among the developed economies but Aldy found no convergence for the world as a whole. Westerlund and Basher (2008), however, found strong evidence of convergence for a panel of 28 developed and developing countries over a very long period. However, most recent research finds evidence of club convergence rather than global convergence (Herrerias, 2013). By contrast, Brock and Taylor (2010) use the beta convergence approach – that the lower emissions are initially, the faster they grow - and find statistically significant convergence across 165 countries between 1960 and 1998.

Brock and Taylor's (2010) theoretical Green Solow model is essentially the IPAT decomposition model with the addition of economic models to explain the A and T terms of the decomposition and population treated as an exogenous variable. They explain affluence or income per capita using the Solow growth model (Solow, 1956), in which poorer countries grow faster than rich countries. In Brock and Taylor's empirical analysis they assume a constant rate of technological progress in pollution "abatement" that is common across countries. [5] As a result, the growth rate of emissions is a function of initial emissions per capita and there is convergence in emissions per capita across countries over time. Depending on the specification chosen, this model explains from 14 to 42% of the variance in average national 1960-1998 emissions growth rates. We will test Brock and Taylor's assumption that growth has a one to one effect on emissions and attempt to explain why there are variations in the rate of decline of emissions intensity. Stefanski (2013) challenges Brock and Taylor's findings, arguing that instead the growth rate of GDP is much more constant than the rate of change of emissions intensity which tends to decrease over the course of economic development so that emissions intensity first rises and then falls.

The formulation of our new model in terms of long-term growth rates circumvents the unit root problem raised by Wagner (2008) and the identification of time effects issue raised by Vollebergh *et al*. (2009). Unit roots are differenced and we only estimate the global mean of the time effect. It also reduces the main problem associated with the between estimator (BE) proposed by Stern (2010) – that there may be omitted variables correlated with the levels of both emissions and income per capita resulting in biased estimates of the effect of income. In our new approach, the means of these variables are removed by differencing. Of course, it still is possible that omitted variables are correlated with the growth rates of both variables

[5] Abatement is written in inverted commas because emissions intensity might decline for reasons completely unconnected with active abatement activities.

and an attempt will be made to address this issue in future research. Our estimator is similar to Chirinko *et al*.'s (2011) Interval Difference Estimator, which aims to place more weight on long-run components of variability. This approach is also related to the "fresh specification" for the EKC of Bradford *et al*. (2005).[6]

Of course, our model cannot explain differences in the levels of emissions between countries that stem from effects other than the variables in our model. In any case, these are usually dealt with in the EKC literature by fixed effects and our model could be used to forecast the level of emissions with the addition of separately estimated fixed effects. Also, our model cannot address the emerging issue of the effect of the business cycle on emissions (Jotzo *et al*., 2012; York, 2012; Bowen and Stern, 2010; Li *et al*., 2014). Possible asymmetric effects of the decline or increase of GDP should be taken into account if our results were used for short-term forecasts of the growth rate of emissions.

The outline of the paper is as follows. First we lay out our research design. Then we describe the overall features of the data followed by the results, discussion, and conclusion and our plans for further research.

Hypotheses, Models, and Methods

Our basic model is:

$$\hat{E}_i = \alpha + \beta \hat{G}_i + \varepsilon_i \qquad (1)$$

where hats indicate long run growth rates, i.e. $\hat{E}_i = \left(E_{iT} - E_{i0}\right)/T$, where T is the final year of the time series in levels, 0 indicates the initial year, and i indexes countries. E is the log of emissions per capita and G is the log of GDP per capita. β is an estimate of the income-emissions elasticity. If it is insignificantly different from unity, then the IPAT/Kaya model could be treated as more than a simple accounting identity. A simple environmental Kuznets curve story would assume that this elasticity is insignificantly different from zero or at least less than unity. This is because growth in developing countries should raise emissions but

[6] Bradford *et al*. (2005) starts by assuming that the derivative of pollution w.r.t. time is a linear function of the rate of growth of income and the interaction between it and the level of income. This is a continuous time version of our equation (3) assuming that the time effect is zero. But they then integrate this function with respect to time deriving an estimation equation in levels. STIRPAT

growth in developed countries should reduce emissions or not increase them by as much.[7] α is an estimate of the mean of $\hat{E}_i$ for countries with zero economic growth and thus is the equivalent to the time effect in traditional EKC models in levels. If the elasticity of income growth is unity it is the mean rate of decline of emissions intensity $\left(\hat{E}_i - \hat{G}_i\right)$. Our second model is:

$$\hat{E}_i = \alpha + \beta\hat{G}_i + \gamma G_i + \varepsilon_i \qquad (2)$$

where G_i is the log of income per capita averaged over time in each country with the simple cross-country mean deducted.[8] This allows us to interpret the intercept term in the regression as the mean rate of change in emissions for a country with average log income and zero economic growth. Conditional on $\beta = 1$, γG_i allows us to exactly test the effect of the income level on the rate of progress in reducing the emissions intensity over time. More generally, including G_i allows us to examine the impact of the level of income on the time effect. We could still have a weak environmental Kuznets story with there being a one to one scale effect of growth but a composition/technique effect related to income levels (Grossman and Krueger, 1995). If β turns out to be significantly less than unity and γ is significantly negative in (2) then the EKC story gets stronger. However, a more clear-cut test of the EKC hypothesis would be a test of $\beta_2 < 0$ in:

$$\hat{E}_i = \alpha + \left(\beta_1 + \beta_2 G_i\right)\hat{G}_i + \varepsilon_i \qquad (3)$$

so that emissions decline when income increases above a given turning point income level. If we demean G_i then β_1 is the elasticity of emissions with respect to growth at the sample mean log income level. We can find the EKC turning point, μ, by estimating (3) without demeaning log income and computing: $\mu = \exp\left(-\beta_1/\beta_2\right)$. We use the delta method to compute the standard error of the turning point. We can combine models (2) and (3):

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[7] Assuming an equal number of developing and developed countries and no correlation between the level of income and its growth rate and a turning point for the EKC near the middle of the income range for example, would result in a zero correlation between the growth rates of income and emissions. Of course, as we change one of the conditions without changing others in compensation the correlation would be non-zero. For example, if growth rates are higher in developing countries as in the Solow model then there would be a positive correlation if the EKC model is true and the other conditions hold.

[8] All the cross-country means that we deduct from the levels variables are unweighted simple means.

$$\hat{E}_i = a + (b_1 + b_2 G_i)\hat{G}_i + gG_i + e_i \qquad (4)$$

so that there are now effects of both growth and income and their interaction. The time effect depends on the level of income. If $g < 0$ then over time the level of emissions will be reduced by more in richer countries than poorer countries in the absence of growth. In the classic EKC model in levels this would have the effect of pulling the turning point towards lower income levels over time. However, as our model is estimated with data averaged over the entire period it seems reasonable that the turning point can still be computed as above, which would represent an estimate of the average location of the turning point over the period.

Next, we test for convergence in emissions by adding the level of emissions per capita at the beginning of the sample period to equation (4):

$$\hat{E}_i = a + (b_1 + b_2 G_i)\hat{G}_i + gG_i + dE_{i0} + e_i \qquad (5)$$

where E_{i0} is the demeaned log of emissions per capita in country i in the first year in the sample period. This is our most general model. For convergence we would expect that $\delta < 0$. We also test if countries have faster or slower emissions growth depending instead on their initial emissions intensity:

$$\hat{E}_i = \alpha + (\beta_1 + \beta_2 G_i)\hat{G}_i + \gamma G_i + \delta(E_{i0} - G_{i0}) + \varepsilon_i \qquad (6)$$

The rationale here is that countries such as China had low per capita emissions at the beginning of the period but high emissions intensity. So, we test whether convergence in emissions intensity contributes to the rate of change in the level of emissions per capita. Again, the cross-country mean is subtracted from the initial log emissions intensity variable.

Finally, we also estimate short and long forms of the Green Solow Model (Brock and Taylor, 2010). The empirical implementation of Brock and Taylor's (2010) model is closely related to our model as the dependent variable is the average growth rate of carbon dioxide emissions over almost four decades (1960-1998) and the main explanatory variable is the initial level of emissions. The short form of the Green Solow Model is given by the following equation:

$$\hat{E}_i = f_0 + f_1 E_{i0} + u_i \qquad (7)$$

In order to replicate Brock and Taylor's results as closely as possible we do not subtract the mean of E_{i0}. The long form of the Green Solow Model is given by:

$$\hat{E}_i = f_0 + f_1 E_{i0} + f_2 \ln s_i + f_3 \ln(n_i + 0.05) + u_i \tag{8}$$

where s_i is the log of the average investment to GDP ratio over the sample period and n is the average rate of population growth over the period.

We estimate models using OLS with heteroskedasticity robust standard errors. We also implement White's (1980) test of general heteroskedasticity. Emissions per capita and income per capita are means computed over varying size populations. As a result the variance of these variables should be inversely related to the size of the population, which introduces grouping related heteroskedasticity (Maddala, 1977; Stern, 1994). By the delta method, the variance of the log of these means also should be inversely related to the size of the population. We test whether this is the case using the Breusch-Pagan test. We regress the squared residuals from each regression on the reciprocal of the mean over time of both population.[9] None of these tests for structured heteroskedasticity was significant at the 5% level but some were significant at the 10% level. However, the White test showed that the residual variance seems to be related to the log of emissions. At this stage we decided not to use WLS estimation, but we may do so in future research.

We assume that the explanatory variables in our regressions are exogenous. Clearly, there can be no reverse causality from growth rates to initial values. There is potentially feedback from the growth rate of emissions, especially of carbon dioxide, to the growth rate of income or the average level of GDP, assuming that it is correlated with the growth of energy use and energy use contributes to growth. Omitted variables bias is, however, clearly an important issue as there are many variables that may be correlated with GDP or GDP growth, which may help explain emissions growth. Future research will attempt to include such variables. For example, legal origin might have an effect on the level of GDP (La Porta *et al*., 2008) but also affect policy choices that drive the rate of emissions growth (Stern, 2012). Finally, measurement error is clearly a significant issue in the estimation of GDP and emissions. The usual approach is to address these issues using instrumental variables. However, in general it is hard to find plausible instrumental variables in the macro-economic context (Bazzi and Clemens, 2013). It is insufficient that a potential instrumental variable be theoretically exogenous to the dependent variable and correlated with the endogenous explanatory

[9] Breusch and Pagan (1979) allow for the residual variance to be related to any variables, not just the regressors.

variable. It must not be correlated with any omitted variable or affect the dependent variable itself directly. So even variables such as legal origin or latitude will not be suitable as instrumental variables.

Data

The Appendix describes the data sources in detail. In addition to the CDIAC data for carbon dioxide emissions from fossil fuel combustion and cement production shown in Figure 1, we carry out our analysis for carbon dioxide from fossil fuel combustion provided by the IEA (Figure 2) and sulfur emissions estimated by Smith et al. (2011) (Figure 3). The IEA and CDIAC data look broadly similar, though there are some noticeable differences for smaller countries due to the different country coverage, different emissions coverage, and differences in estimates of emissions by the different agencies. The sulfur data also look broadly similar to the carbon data except that the whole distribution of circles is shifted downwards, which suggests a negative time effect relative to carbon dioxide. Also, there is a group of smaller OECD countries with very negative emissions growth clustered immediately below the USA in the graph.

Table 1 presents some descriptive statistics for the growth rates variables and the level of income per capita. The latter are computed by taking the exponential of our average log income per capita variable, G_i, before demeaning. Statistics for the demeaned logs of the levels variables used in the regressions would not be very informative and so are not included. Mean income per capita varies by up to \$2,000 across the samples and median income is only just over half mean income. The most notable feature of the growth rates is that per capita carbon dioxide emissions are rising on average across countries by more than one percent per annum while sulfur emissions are falling at 0.7% per annum on average.[10] Variations in the rate of change across countries are much larger for sulfur emissions than for carbon emissions. The standard deviation of sulfur emissions is twice as large as that for carbon emissions. GDP per capita has grown a little faster than have carbon dioxide emissions on average with a bit less variation across countries. There do not seem to be important differences between the distribution of the GDP data across the three samples. However, the average growth rate of carbon emissions as measured by CDIAC is lower than the emissions measured by the IEA. Based on these simple statistics the naïve estimates of

[10] The mean growth rates of the global totals will differ from these as these are unweighted means.

the elasticity with respect to income would be 0.75, 0.90, and -0.39 for the three datasets. As we will see from the next section, separating the total effect into time and income effects greatly modifies such a conclusion.

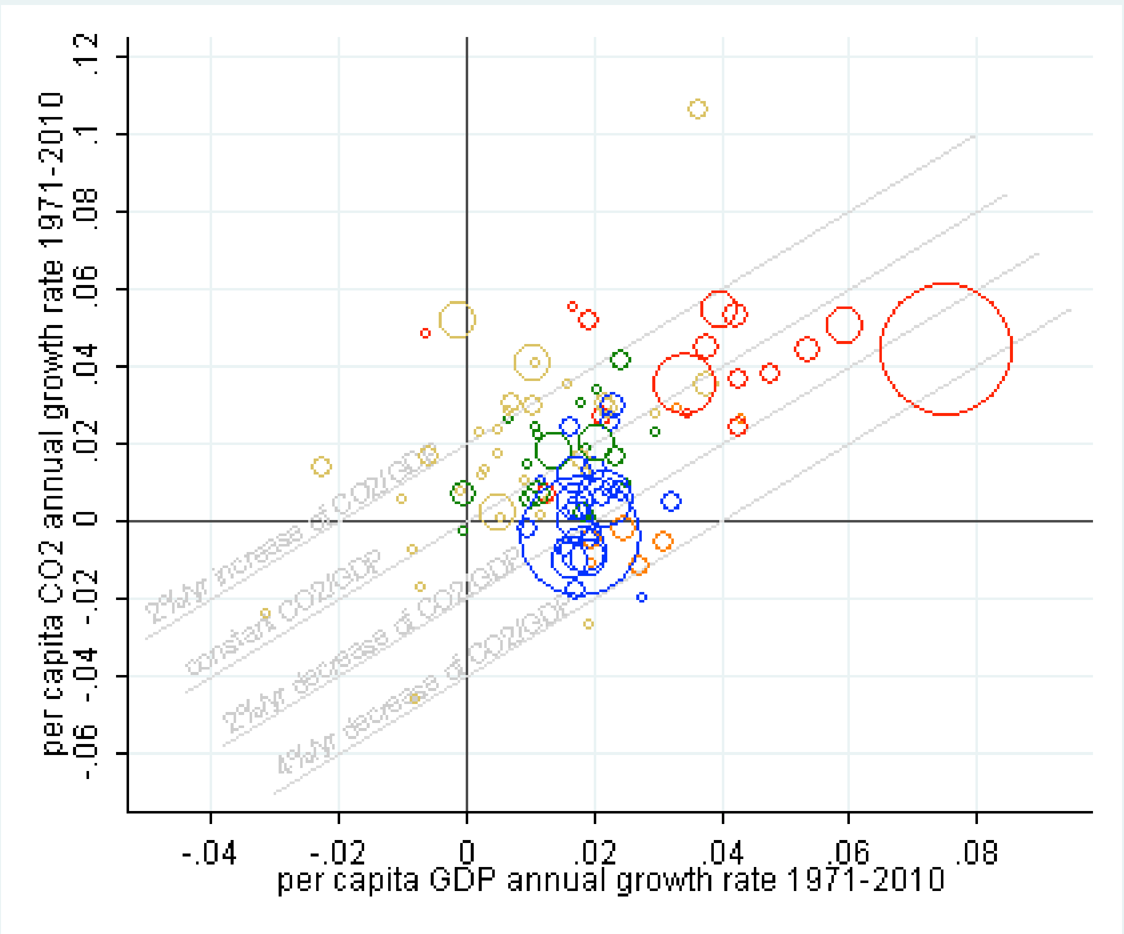

Figure 2: **Growth Rates of Per Capita Income and Per Capita Carbon Dioxide Emissions from Fossil Fuel Combustion**. The figure shows the relation between the average annual growth rates of per capita income and per capita emissions from 1970 to 2010. Points along the grey lines have either constant emissions intensity or emissions intensity increasing by 2% or declining at 2%, 4% per annum. The size of the circles is proportional to countries' emissions in 2010. The colors represent economic regions - See Figure 1 for key. Sources: IEA and Penn World Table 8.0.

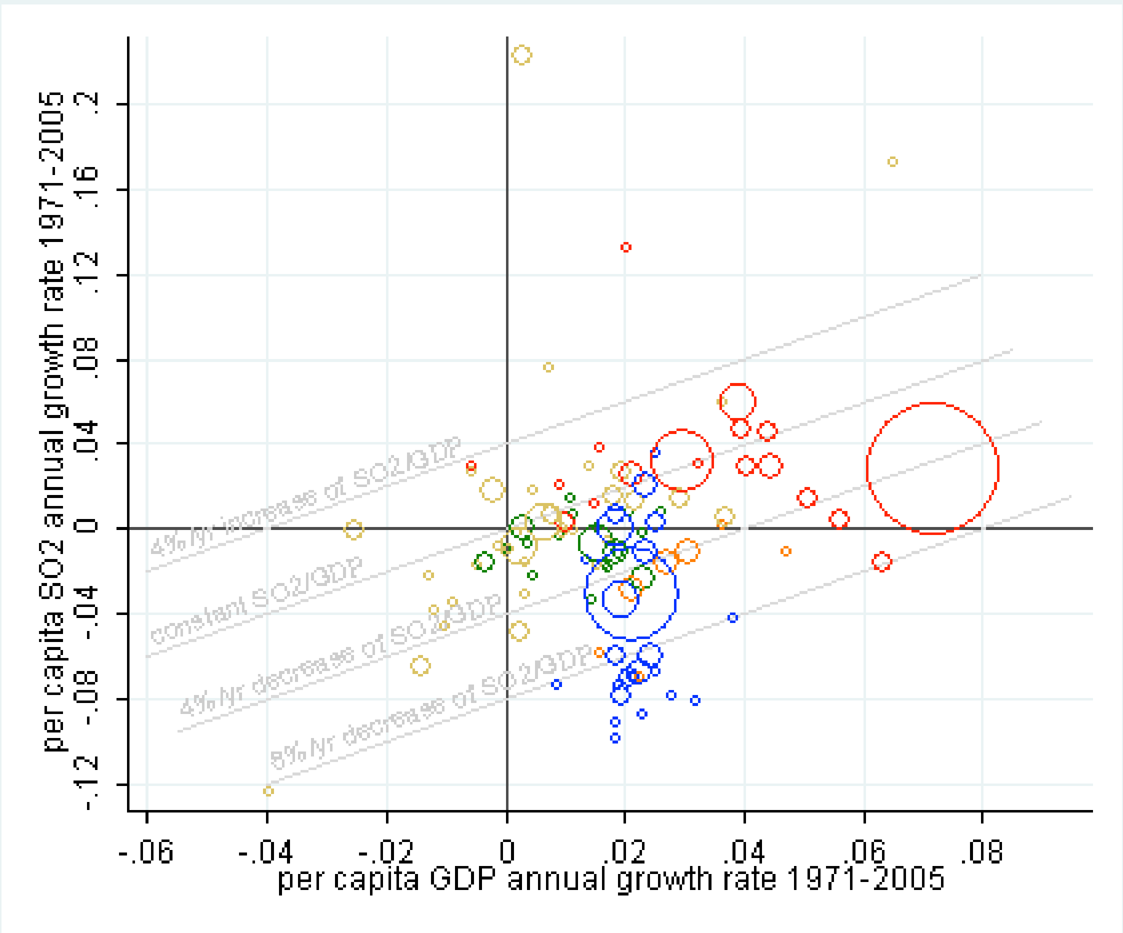

Figure 3: **Growth Rates of Per Capita Income and Per Capita Sulfur Dioxide Emissions**. The figure shows the relation between the average annual growth rates of per capita income and per capita emissions from 1970 to 2010. Points along the grey lines have either constant emissions intensity or emissions intensity increasing by 4% or declining at 4% or 8% per annum. The size of the circles is proportional to countries' emissions in 2010. The colors represent economic regions - See Figure 1 for key. Sources: CDIAC and Penn World Table 8.0.

Table 1. Descriptive Statistics

Variable	Mean	Standard Deviation	Minimum	Median	Maximum
Emissions per capita growth rate:					
CDIAC CO_2	0.013	0.025	-0.043	0.010	0.121
IEA CO_2	0.016	0.022	-0.046	0.014	0.106
SO_2	-0.007	0.050	-0.124	-0.005	0.223
GDP per capita growth rate:					
CDIAC sample	0.017	0.018	-0.031	0.017	0.077
IEA sample	0.018	0.016	-0.031	0.018	0.075
SO_2 emissions sample	0.017	0.018	-0.040	0.018	0.072
GDP period mean income per capita:					
CDIAC sample	\$8,696	\$9,809	\$407	\$4,458	\$48,771
IEA sample	\$10,629	\$10,560	\$407	\$6,126	\$48,771
SO_2 sample	\$9,687	\$9,814	\$377	\$5,563	\$45,419

Results

Tables 2 to 4 present the results of the regression analysis for equations 1-6 for the three datasets and Table 5 presents the results for the short and long forms of the Green Solow Model (equations 7 and 8) for all data sets. Looking first at the diagnostic statistics, none of the Breusch-Pagan test statistics for a specific theory-based structure of heteroskedasticity are statistically significant at the 5% level. [11] Therefore, we have only used OLS and not carried

[11] Possibly measurement errors are also greater in smaller countries causing a faster than linear decline in the variance as population increases.

out WLS estimation. However, many of the White test statistics for heteroskedasticity of an unknown form are highly significant, especially for the models involving initial emissions.

Table 2. Per Capita Carbon Dioxide Emissions Growth Rate 1971-2010: CDIAC Data

Variable/ Statistic / Test	Eq (1)	Eq (2)	Eq (3)	Eq (4)	Eq (5)	Eq (6)
Constant	-0.0015 (0.0021)	-0.0031 (0.0022)	0.0002 (0.0022)	-0.0013 (0.0022)	0.0041** (0.0018)	-0.0004 (0.0017)
$\hat{G}_i$	0.8338*** (0.1171)	0.9257*** (0.1212)	0.8113*** (0.1103)	0.8768*** (0.1186)	0.5798*** (0.0813)	0.8351*** 0.0774)
G_i		-0.0056*** (0.0015)		-0.0035** (0.0015)	0.0162*** (0.0029)	0.0033** (0.0014)
$G_i\hat{G}_i$			-0.2601*** (0.0675)	-0.1695** (0.0742)	-0.2381*** (0.0641)	-0.2049*** (0.0603)
E_{i0}					-0.0137*** (0.0018)	
E_{i0} - G_{i0}						-0.0136*** (0.0017)
EKC income per capita turning point (1000's of $)			100 (93)	781 (1,984)	50 (44)	260 (365)
$\bar{R}^2$	0.3460	0.4143	0.4165	0.4319	0.6639	0.6700
White test χ^2 (2k+0.5((k^2)-k))	7.4541 (0.0241)	8.7376 (0.1200)	10.2258 (0.0691)	17.3806 (0.0264)	26.3912 (0.0151)	25.5000 (0.0198)
BP test: inverse of population χ^2 (1)	2.8493 (0.0914)	1.7864 (0.1814)	2.6102 (0.1062)	1.8842 (0.1699)	0.2821 (0.5953)	0.4317 (0.5112)

Notes: 136 data points. Figures in parentheses are standard errors for the regression coefficients and the EKC turning point and p-values for test statistics. k is the number of non-constant regressors. Significance levels of regression coefficients: * 10%, ** 5%, *** 1%. The sample mean is subtracted from all levels variables so that the intercept term can be interpreted as the time effect for a country with the sample mean level of log income and emissions.

Table 3. Per Capita Carbon Dioxide Emissions Growth Rate 1971-2010: IEA Data

Variable/ Statistic / Test	Eq (1)	Eq (2)	Eq (3)	Eq (4)	Eq (5)	Eq (6)
Constant	0.0059** (0.0030)	0.0054 (0.0033)	0.0068** (0.0029)	0.0069** (0.0030)	0.0091*** (0.0020)	0.0031 (0.0022)
$\hat{G}_i$	0.5727*** (0.1229)	0.6024*** (0.1384)	0.5581*** (0.1312)	0.5533*** (0.1378)	0.4285*** (0.0789)	0.7590*** (0.1015)
G_i		-0.0028 (0.0020)		0.0004 (0.0021)	0.0213*** (0.0036)	0.0049*** (0.0017)
$G_i\hat{G}_i$			-0.2462*** (0.0832)	-0.2569*** (0.0937)	-0.2479*** (0.0612)	-0.1946*** (0.0602)
E_{i0}					-0.0174*** (0.0025)	
E_{i0} - G_{i0}						-0.0174*** (0.0025)
EKC income per capita turning point (1000's of $)			57 (59)	51 (57)	33* (20)	293 (436)
$\overline{R}^2$	0.1636	0.1778	0.2347	0.2270	0.5987	0.5945
White test χ^2 (2k+0.5((k^2)-k))	0.0199 (0.9901)	4.0807 (0.5379)	1.4203 (0.9221)	4.3126 (0.8279)	39.8443 (0.0001)	39.9317 (0.0001)
BP test: inverse of population χ^2 (1)	2.7968 (0.0945)	3.6740 (0.0553)	1.0299 (0.3102)	0.9273 (0.3356)	0.1142 (0.7355)	0.3044 (0.5811)

Notes: 99 data points. Figures in parentheses are standard errors for the regression coefficients and the EKC turning point and p-values for test statistics. k is the number of non-constant regressors. Significance levels of regression coefficients: * 10%, ** 5%, *** 1%. The sample mean is subtracted from all levels variables so that the intercept term can be interpreted as the time effect for a country with the sample mean level of log income and emissions.

Table 4. Per Capita Sulfur Dioxide Emissions Growth Rate 1971-2005

Variable/ Statistic / Test	Eq (1)	Eq (2)	Eq (3)	Eq (4)	Eq (5)	Eq (6)
Constant	-0.0181** (0.0071)	-0.0216*** (0.0081)	-0.0139** (0.0058)	-0.0154** (0.0062)	-0.0107** (0.0049)	-0.0180*** (0.0044)
$\hat{G}_i$	0.6571** (0.3151)	0.8563** (0.3472)	0.6506** (0.2732)	0.7084** (0.2860)	0.3682** (0.1800)	0.7734*** (0.1644)
G_i		-0.0137*** (0.0041)		-0.0039 (0.0032)	0.0192*** (0.0057)	-0.0030 (0.0028)
$G_i\hat{G}_i$			-0.8909*** (0.1651)	-0.7970*** (0.1594)	-0.5166*** (0.1092)	-0.4598*** (0.1093)
E_{i0}					-0.0230*** (0.0047)	
E_{i0} - G_{i0}						-0.0231*** (0.0049)
EKC income per capita turning point (1000's of $)			11.2*** (3.5)	13.1** (5.2)	11.0*** (4.3)	29.1* (16.4)
$\bar{R}^2$	0.0465	0.1377	0.2556	0.2541	0.5894	0.5807
White test χ^2 (2k+0.5((k^2)-k))	0.6657 (0.7169)	3.5163 (0.6209)	1.0221 (0.9608)	3.0118 (0.9336)	74.1625 (0.0000)	70.5298 0.0000)
BP test: inverse of population χ^2 (1)	1.4012 (0.2365)	3.4053 (0.0650)	1.8025 (0.1794)	2.1154 (0.1458)	1.5712 (0.2100)	1.3440 (0.2463)

Notes: 103 data points. Figures in parentheses are standard errors for the regression coefficients and the EKC turning point and p-values for test statistics. k is the number of non-constant regressors. Significance levels of regression coefficients: * 10%, ** 5%, *** 1%. The sample mean is subtracted from all levels variables so that the intercept term can be interpreted as the time effect for a country with the sample mean level of log income and emissions.

The adjusted R-squared increases substantially as more variables are added for all three datasets and particularly for the models including initial emissions, emphasizing the importance of the convergence mechanism in explaining emissions growth rates.

Looking at equation (1), all three datasets have a positive and statistically significant estimate of the emissions income elasticity. For the CDIAC and sulfur datasets the elasticities are not significantly different from unity (p=0.158 and p=0.279 for a two sided test), however, in the latter case the estimated elasticity is quite far from unity but the standard error is large, reflecting the low R-squared in this regression. The time effect for CO_2 is insignificant for the CDIAC dataset and significantly positive for the IEA dataset (0.59% p.a.). For sulfur it is significantly negative (-1.81% p.a.). This explains the differences between the estimated elasticity of income here and the naïve estimates discussed in the previous section. Therefore, not controlling for other variables, growth increases emissions for both sulfur dioxide and carbon dioxide and depending on the dataset, perhaps on a one to one basis. However, over time, sulfur emissions fall in all countries irrespective of their income level and may rise (for IEA data) or not change (CDIAC) for carbon.

Equation (2) adds the level of GDP as an explanatory variable. This has the effect of increasing the growth elasticity and strengthening the time effect where negative. Both the CDIAC data set and the sulfur data set have significantly negative effects of the level of GDP, indicating that the time effect is more negative in higher income countries.

Equation (3) tests the EKC hypothesis. In each case, the interaction term is significantly negative but the growth elasticity at the sample mean of log income does not change much compared to equation (1). For carbon dioxide the turning point income level is out of sample and statistically insignificant. Therefore, we can conclude that the elasticity decreases with higher income but we do not have evidence of an actual turning point. For sulfur, however, the turning point is $11.2k with a standard error of $3.5k. For both carbon dioxide samples there is now a significantly positive time effect, while for sulfur the time effect becomes less negative.

Adding the level of income to equation (3), resulting in equation (4), makes little difference for the IEA and sulfur data. For the CDIAC data this term is significantly negative. Adding the level of initial emissions in equation (5) changes all the results quite a bit. Initial emissions per capita have a strong negative effect in all the datasets, which indicates that countries conditionally converge in emissions over time. The income elasticity declines somewhat, the time effect is less negative, and the effect of the level of income becomes positive so that over time emissions are increasing more in higher income countries controlling for growth and the convergence effect. The EKC turning point for the IEA data is within the sample range and just significant at the 10% level.

The final model, equation (6), uses initial emissions intensity instead of initial emissions per capita. This formulation suggests that, controlling for other factors, emissions are partly driven by convergence across countries in emissions intensity rather than convergence in the level of emissions. The results are quite sensitive to this alternative specification.[12] The effect of initial emissions intensity on emissions growth is, however, almost identical to that of initial emissions per capita. On the other hand, the growth elasticity and the EKC turning point are substantially increased compared to equation (5) and the effect of the level of income significantly reduced.

Table 5. Green Solow Model

Data Source:	CDIAC		IEA		SO_2	
Variable/ Statistic / Test	Eq (7)	Eq (8)	Eq (7)	Eq (8)	Eq (7)	Eq (8)
Constant	0.0128*** (0.0019)	0.0128*** (0.0018)	0.0161*** (0.0020)	0.0161*** (0.0019)	-0.0067* (0.0036)	-0.0067** (0.0033)
E_{i0}	-0.0059*** (0.0012)	-0.0084*** (0.0013)	-0.0054*** (0.0012)	-0.0074*** (0.0018)	-0.0181*** (0.0031)	-0.0187*** (0.0031)
s_i		0.0203*** (0.0057)		0.0252*** (0.0087)		0.0402*** (0.0111)
$\ln(n_i + 0.05)$		-0.0298** (0.0116)		0.0214** (0.0104)		0.0554** (0.0267)
$\bar{R}^2$	0.1872	0.3087	0.1489	0.2694	0.4388	0.5287
Sample Size	136	136	99	99	103	103

Notes: Figures in parentheses are standard errors for the regression coefficients. Significance levels of regression coefficients: * 10%, ** 5%, *** 1%. Sample means are not subtracted from levels variables. The sample mean is subtracted from all levels variables so that the intercept term can be interpreted as the time effect for a country with the sample mean level of log income and emissions.

For the Green Solow Model (GSM), comparing the results using the CDIAC data in Table 5 with Table 2 in Brock and Taylor (2010) the results for the short form model (equation 7) are very close to Sample A in Brock and Taylor and the results for the long-form model are extremely close to Sample C in Brock and Taylor both in terms of the regression coefficient and their significance levels as well as the adjusted R-squared. This is despite the different temporal and geographical coverage of our sample and suggests that the relationship is quite stable and robust. However, the adjusted R-squared for either GSM estimated with the CDIAC data is lower than that for any of our models in Table 2. So, the GSM seems to be

[12] It is not a simple re-parameterization because we use initial GDP in the emissions intensity variable and average period GDP in the interaction and levels income terms.

only part of the story of carbon emissions growth and the growth rate of GDP is very important in explaining the growth rate of emissions. The results for the IEA data differ from those for the CDIAC data - the sign of population growth is reversed, so that higher population growth increases the growth rate of per capita emissions. This is also the case for sulfur emissions and for Sample B in Brock and Taylor (2010) though there the coefficient is statistically insignificant. This suggests that the model is not really very well specified.

On the other hand, for sulfur emissions, the GSM explains more of the variation than the Environmental Kuznets Curve model (equation (3), Table 4) with adjusted R-squared values of 0.44 (equation (7)) and 0.53 (equation (8)) compared with adjusted R-squared values of 0.16 to 0.23 for equations (1) to (4) in Table 4. Only equations (5) and (6) have a superior explanatory power than the GSM. The convergence mechanism is clearly more important in the case of sulfur than it is in the case of carbon.

Discussion

Using a new formulation of the emissions income relationship in terms of growth rates we found that the effect of growth on emissions at the sample mean log income level is strongly positive. However, the interaction term with the level of income is robustly significantly negative across our three data sets so that the elasticity declines as income increases. For carbon dioxide, the EKC turning point is very high or out of sample, for sulfur it is around \$11k-\$13k in 2005 PPP Dollars except in our preferred model (6) where it is \$29k with a standard error of \$16k (p=0.076). There is a strong negative time effect for sulfur ranging from -1.07% p.a. to -2.16% p.a., depending on the specification. Time effects for carbon are not robust across datasets and specifications. The effect of the level of income, independent of its interaction, is not robust across specifications.

As mentioned in the introduction, recent papers (Wagner, 2008; Vollebergh *et al*., 2009; Stern, 2010), which estimate models in levels using more sophisticated approaches that address some of the econometric issues with traditional estimators, find that the income effect is monotonic. Using the between estimator, Stern (2010) found constant income elasticities of as high as 1.61 for carbon dioxide and 0.73 for sulfur dioxide. The time effect for sulfur was very strong, decreasing emissions over time by more than twice as much as income increased them, while the time effect for carbon was about half the size of the income effect. These effects are very similar to those found by Vollebergh *et al*. (2009). Stern (2010) found a turning point for sulfur of \$14.9k with a standard error of \$9.5k and hence the linear estimate was preferred. Wagner's (2008) defactored regression approach found a monotonic and convex down emissions income relationship for both carbon and sulfur dioxide.

The results in the current paper find smaller elasticities and time effects for carbon dioxide than Stern (2010). In many cases the carbon dioxide time effect is positive. This suggests that Stern's (2010) results are biased by omitted variables that are differenced away in the current analysis. Perhaps, this could be the cause of the similar results found by Wagner (2008) and Vollebergh *et al*. (2009), who also use models in levels. However, we do not reject the monotonic form of the carbon EKC. For sulfur, we find a similar turning point to that found using a quadratic model and BE in Stern (2010). Here, the standard error is smaller and so the turning point is statistically significant. This suggests that Stern (2010) committed a type II error in not rejecting the linear specification for sulfur. However, in equation (6) the turning point becomes much higher, three times mean income, though still in sample. So the presence of an relevant in sample turning point for sulfur, which was first questioned by List and Gallet (1999) and Stern and Common (2001), is still an open question.

We also find strong evidence of conditional beta convergence across countries in either emissions per capita or emissions intensity. This is clearly a separate effect to the scale and income per capita effects we find in our models, as the latter terms are highly significant in the presence of the convergence term. So, neither a structural interpretation of the IPAT model, nor a simple EKC model, or a simple convergence model, is on its own sufficient to explain the data. Our estimates of the Green Solow Model for carbon emissions have lower adjusted R-squared values than any of our models that include the growth rate of GDP. So, though convergence is important it is not as important as growth in explaining carbon emissions. However, for sulfur emissions we find the reverse. Convergence has greater explanatory power than growth or the environmental Kuznets curve effect.

The results of our analysis so far do not let us differentiate between alternative deeper determinations of the cause of the differences in emissions growth rates across countries. This is the norm for "reduced form" approaches in this literature. For example, we find that carbon emissions grow more slowly with economic growth in richer countries and that sulfur emissions possibly decline. This could be for a variety of reasons, among others:

- Productivity increases that result in economic growth are associated with improvements in energy and environmental efficiency in the production of specific products. Energy efficiency improvements are a component of total factor productivity growth (Saunders, 1992). High-income countries tend to be more energy efficient (Stern, 2012).

- Economic growth is associated with structural change to less emissions intensive economic sectors such as some parts of the service sector. Henriques and Kander (2010) find that the contribution of such structural change to environmental improvement is modest.

- Changes in trade patterns with economic growth result in the decline of emissions intensive industries in developed countries and their growth in developing countries. This offshoring or pollution haven hypothesis has been very controversial. Most mainstream economic researchers find little evidence that this is an important driver of improvements in emissions intensity with growth (Levinson, 2010).

- Rising incomes cause switches to lower-carbon energy sources for a variety of energy security, environmental, and economic reasons (Burke, 2010, 2013). Nuclear power, for instance, has been more likely to have been adopted in higher-income countries, as these countries typically have electricity demand of sufficient scale, the required human and institutional capital, and concerns about energy security and/or local air pollution. Similarly, it seems obvious that increased incomes have led to policies that have directly reduced sulfur emissions in some countries. But developed countries have converged into clubs of higher and lower sulfur emissions that seem more driven by cultural or legal origin reasons (Stern, 2005, 2012).

Similarly, convergence in emissions intensity may be driven by global convergence in technology for non-environmental reasons, or because countries with high emissions intensities act to improve their environments and/or reduce their dependence on imported energy.

Conclusions

This paper introduced a new method for estimating income-emissions relations, which we believe is both more econometrically robust and allows researchers to test various alternative hypotheses within a single framework. The results show that scale, environmental Kuznets, convergence, and, for sulfur, time effects are important in explaining emissions growth. Though the elasticity of emissions with respect to income declines, for carbon the emissions-income relationship is monotonic. For sulfur, our specifications found an in sample turning point, but for our preferred specification the turning point is three times mean income. We also found that the Green Solow Model convergence effect is more important than GDP growth or the EKC effect in explaining sulfur emissions but that the latter is true for carbon emissions. Future extensions of this research will attempt to explain more of the variation in the decline in emissions intensity.

Appendix: Data Sources

GDP, population, and the investment to GDP ratio data are sourced from the Penn World Table (PWT) version 8.0 (Feenstra *et al*., 2013). PWT 8.0 provides GDP data adjusted for purchasing power parity for 167 countries between 1950-2011, though not all countries have a complete time series for these years. For the period we are interested in, 1971-2010, there are complete time series for 143 countries. Following the advice of Feenstra *et al*. we compute the growth rates of GDP using the series RGDPNA, which uses the growth rate of real GDP from each country's national accounts to extrapolate GDP from 2005 to other years. RGDPNA is set equal to the variables CGDPO and RGDPO in 2005. The latter variables are so-called output side measures of real GDP that takes into account the effect of changes in the terms of trade in order to better represent the real production capacity of the economy.

Also following the recommendations of Feenstra *et al*., to measure the level of GDP we use the variable CGDPO which is measured at constant 2005 millions of purchasing power parity adjusted dollars. This variable measures the output side GDP across countries using the reference price vector for each year and then adjusting for US inflation over time. The only choice for the investment share of GDP is csh_i.

These data can be downloaded from www.ggdc.net/pwt.

We use two sources of data on carbon dioxide emissions – the Carbon Dioxide Information Analysis Center (CDIAC) (Boden *et al*., 2013) and the International Energy Agency (IEA). CDIAC produces annual data at global and national scales with data available for 249 countries for varying periods between 1751-2010. These data include emissions from the combustion of fossil fuels, gas flaring, and cement production. These data can be downloaded from:

http://cdiac.ornl.gov/trends/emis/overview_2010.html

Data are measured in thousand metric tons of carbon, which we convert to carbon dioxide by multiplying by 44/12. When we match CDIAC data to PWT data we obtain a balanced dataset for 136 countries between 1971-2010.

The IEA carbon dioxide emissions dataset covers emissions from fuel combustion from 1960 onwards for developed countries and 1971 onwards for developing countries. These data can be downloaded from the OECD iLibrary, which is a subscription database. Data are measured in million metric tons of CO_2. As we take logarithms and then demean the data, this difference in measurement units does not affect our regression results. When combined with the PWT data we obtain a balanced dataset for 99 countries between 1971-2010.

Anthropogenic sulfur dioxide emission data are (Smith *et al*., 2011). Dataset provides annual estimates of anthropogenic sulfur dioxide emissions for 142 countries between 1850-2005. When combined with PWT data, we obtain a balanced dataset for 103 countries between 1971-2005. Data are measured in thousands of metric tonnes of SO_2.These data can be downloaded from:

http://sedac.ciesin.columbia.edu/data/set/haso2-anthro-sulfur-dioxide-emissions-1850-2005-v2-86

Because of the coverage of the Penn World Table some countries are excluded from all our combined datasets. These include Russia and the other successor states of the erstwhile Soviet-Union, and the successor states of Yugoslavia. Other countries with large populations that are excluded are Bangladesh and Pakistan.

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