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Modeling the Emissions-Income Relationship Using Long-Run Growth Rates

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Abstract

We adopt a new representation of the relationship between emissions and income using long-run growth rates. Our approach allows us to test multiple hypotheses about the drivers of per capita emissions in a single framework and avoid several of the econometric issues that have plagued previous studies. We find that for carbon dioxide emissions, scale, convergence, and resource endowment effects are statistically significant. For sulfur emissions, the scale and convergence effects are significant, there is a strong negative time effect, and non-English legal origin and higher population density are associated with more rapidly declining emissions. The environmental Kuznets effect is not statistically significant in our full sample for either carbon or sulfur.

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JEL Classification
Q56, O44.

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Abstract

We adopt a new representation of the relationship between emissions and income using long-run growth rates. Our approach allows us to test multiple hypotheses about the drivers of per capita emissions in a single framework and avoid several of the econometric issues that have plagued previous studies. We find that for carbon dioxide emissions, scale, convergence, and resource endowment effects are statistically significant. For sulfur emissions, the scale and convergence effects are significant, there is a strong negative time effect, and non-English legal origin and higher population density are associated with more rapidly declining emissions. The environmental Kuznets effect is not statistically significant in our full sample for either carbon or sulfur.

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1. Introduction

This paper is inspired by Figure 1,[1] which shows a strong positive correlation between the long-run average growth rate of per capita carbon dioxide emissions and the long-run growth rate of gross domestic product (GDP) per capita. Fast-growing economies typically see increases in CO_2 emissions while slow-growing or declining economies tend to have declining emissions. The Figure shows a fairly strong linear relationship between the rate of economic growth and the rate of growth of emissions, with the remaining variation reflecting differences in the rate of change in emissions per dollar of GDP. The parallel lines in the Figure each indicate a constant rate of decline or increase in emissions intensity. Emissions intensity was declining in slightly more than half of the countries. Some quickly-growing economies such as China saw significant declines in emissions intensity, in many cases at a faster rate than in most developed countries. The Figure also shows a number of slow-growing non-OECD countries have had declining emissions and other OECD countries rising emissions, suggesting that a simple environmental Kuznets curve (EKC) story – that economic growth in poor countries increases emissions while economic growth in rich countries reduces emissions – cannot fully explain the data. The Figure suggests a new and simple econometric approach: regressing the long-run growth rate of per capita emissions on the long-run growth rate of income per capita and using additional variables to explain the variation around the trend.

In this paper, we assess the determinants of long-run emissions growth rates using this new econometric approach, making two main contributions. First, our approach has important econometric advantages over the conventional panel data representation, discussed in the following. Second, our approach allows us to unify the main existing models – IPAT, the environmental Kuznets curve, and the convergence approach – and allows us to directly test the relevance of each.

By formulating our model in long-term growth rates we avoid most of the econometric problems troubling the existing literature. First, we circumvent the unit root problem raised by Wagner (2008), as unit roots are differenced.[2] The second advantage of our approach is

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[1] A similar chart is presented in Blanco *et al.* (2014, Section 5.3.3) as a description of past trends in income and greenhouse gas emissions.

[2] We also include the average level of GDP in all but our first two models. This variable is not differenced but this does not introduce any unit root issues as our estimations do not utilize the time series.

that by taking average growth rates over a long period of time we filter out short-run effects and put more weight on the long-run components of variability.[3] Third, we also solve the identification of time effects issue raised by Vollebergh *et al*. (2009). Conventional EKC approaches effectively detrend the dependent and independent variables and attribute the effects of any common trend to the time effect. Our model identifies the time effect as the mean long-run emissions growth rate when GDP growth is zero and other variables are at their sample mean. Fourth, our approach also reduces the main problem associated with the between estimator (BE) proposed by Stern (2010) – that omitted variables correlated with the levels of both emissions and income per capita may result in biased estimates of the effect of income. In our new approach, the means of these variables are removed by differencing.

Our second main contribution is that we provide a simple unified approach that can be used to compare and test the leading alternative theories about the relation between income and emissions. We find that there is a significant effect of economic growth on long-run growth in both carbon and sulfur emissions. We find that there is no significant income turning point for either carbon or sulfur emissions, so that there is little support for the environmental Kuznets curve. Instead, growth and convergence effects largely explain changes in emissions. In our most general model, the elasticity of emissions with respect to income is not significantly different to unity, supporting an IPAT-style view of emissions trajectories, albeit one which also leaves room for the importance of convergence effects and the effects of some exogenous variables. For sulfur, negative time effects are also important.

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

[3] Chirinko *et al*.'s (2011) Interval Difference Estimator to estimating production function parameters similarly emphasizes long-run change and avoids several econometric problems common to panel data estimation. Our approach is also related to the "fresh specification" for the EKC of Bradford *et al*. (2005) who start 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.

2. Prior Research

There has been an extensive debate on the drivers of pollution emissions and other environmental impacts. Three main approaches have dominated the literature. Our new approach allows us to test all three.

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).[4]

The 1980s saw the introduction of the sustainable development concept which argued that, in fact, development was not necessarily damaging to the environment and that poverty reduction was essential to protect the environment (WCED, 1987). In line with this sustainable development idea, in the early 1990s Grossman and Krueger (1991, 1995) introduced the second main approach to modeling the income-emissions relationship – the environmental Kuznets curve (EKC) – which proposes that environmental impacts first increase and then decrease over the course of economic development.[5] Proponents of the EKC argue that though economic growth at first increases 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 Development Report*, which relied on research by Shafik (1994). However, this showed that carbon emissions did not seem to follow an inverted U-shaped curve, a conclusion also reached by Holtz-Eakin and Selden (1995). Figure 2 uses the CDIAC dataset featured in Figure 1 to confirm the lack of a cross-country carbon EKC.

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[4] 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.

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

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 also 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.[6] On the other hand, using a set of simple cross-section carbon dioxide EKC regressions, Chow and Jie (2014) find a highly significant coefficient on the square of the log of GDP per capita (t = -22.9), claiming that this is conclusive econometric evidence for the carbon EKC. However, the mean turning point in their sample is in fact $378k.

A cross-country EKC could emerge from a combination of scale and time effects. Growth of emissions in faster-growing countries will outpace the efficiency improvements that come with time so that emissions would rise in fast-growing countries and decline in slow-growing countries. 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.[7] Stern (2004) proposed that perhaps the high economic growth rate of these economies better explains their increasing emissions than their middle-income status does, connecting the IPAT approach – the hypothesis that increases in the scale of the economy always lead to more emissions, *ceteris paribus*, though improvements in technology can offset this effect – to the apparent EKC. This hypothesis explains the results of Stern and Common (2001) and others mentioned above.

The third main approach to the evolution of emissions over time is to hypothesize that they are converging to a common level. There are three main approaches to testing for convergence: sigma convergence, which tests whether the variance of the variable in question declines over time; stochastic convergence, which tests whether the time series for different

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[6] 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.

[7] 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.

countries cointegrate; and beta convergence, which tests whether the growth rate of a variable is negatively correlated to the initial level of the variable. Using beta and stochastic convergence tests, Strazicich and List (2003) found convergence among the developed economies. Using sigma convergence approaches, Aldy (2006) also found convergence for the developed economies but not for the world as a whole. Using stochastic convergence Westerlund and Basher (2008) reported convergence for a panel of 28 developed and developing countries over a very long period, but recent research using stochastic convergence finds evidence of club convergence rather than global convergence (Herrerias, 2013). By contrast, using the beta convergence approach Brock and Taylor (2010) find statistically significant convergence across 165 countries between 1960 and 1998. Figure 3 shows convergence for carbon dioxide emissions in our CDIAC sample. There is a clear tendency for emissions to grow in countries with a low initial level of emissions and *vice versa*.

Brock and Taylor's (2010) theoretical Green Solow model is essentially the IPAT decomposition with the addition of economic models to explain the A and T terms (and the treatment of population as an exogenous variable). They explain affluence or income per capita using the Solow (1956) growth model, 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.[8] 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 14-42% of the variance in average national 1960-1998 CO_2 emissions growth rates. Stefanski (2013) challenges Brock and Taylor's findings, arguing that GDP growth rates have declined over time at a slower rate than emissions intensity growth rates have. Therefore, it does not make sense to argue that emissions growth has slowed mainly due to Solow-style convergence of GDP growth rates. Though Stefanski (2013) does not suggest modeling emissions growth rates as a function of convergence in emissions intensity, there is a very strong negative relationship between countries' initial level of emissions intensity and their subsequent emissions intensity growth rate (Figure 4), which we will include in our model.

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

3. Hypotheses, Models, and Methods

Our basic model is:

$$\hat{E}_i = \alpha + \beta\hat{G}_i + \varepsilon_i \tag{1}$$

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 β is insignificantly different from unity, then the IPAT/Kaya model could be treated as more than a simple accounting identity. A simple EKC story would assume that this elasticity is insignificantly different from zero or at least less than unity depending on the location of the turning point. α is an estimate of the mean of $\hat{E}_i$ for countries with zero economic growth and thus is equivalent to the time effect in traditional EKC models in levels. If the elasticity of emissions with respect to income is unity α is the mean rate of decline of emissions intensity $\left(\hat{E}_i - \hat{G}_i\right)$. Our second model is:

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

where G_i is the log of income per capita averaged over time in each country with the simple cross-country mean deducted.[9] This allows us to interpret the intercept as the mean rate of change in emissions for a country with average log income and zero economic growth. Including G_i allows us to examine the impact of the level of income on the time effect. If $\gamma < 0$, then emissions decline faster over time the higher the level of income (holding the rate of economic growth constant). We could still have a weak EKC story even if $\beta = 1$ if γ is significantly negative, so that there is a composition or technique effect related to income levels (Grossman and Krueger, 1995). However, a more clear-cut test of the EKC hypothesis would be a test of $\beta_2 < 0$ in:

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

so that emissions decline when income increases above a given income turning point. If we demean G_i then β_1 is the elasticity of emissions with respect to income at the sample mean

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

log income level. We can find the EKC turning point, μ, by estimating (3) without demeaning log income and computing $\mu = \exp(-\beta_1/\beta_2)$. We use the delta method to compute the standard error of the turning point. We can combine models (2) and (3):

$$\hat{E}_i = \alpha + (\beta_1 + \beta_2 G_i)\hat{G}_i + \gamma G_i + \varepsilon_i \tag{4}$$

so that there are now effects of both economic growth, income, *and* their interaction. The time effect depends on the level of income. If $\gamma < 0$ then over time the level of emissions will be reduced by more in richer countries than poorer countries in the absence of economic 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 using the beta convergence approach by adding the level of emissions per capita at the beginning of the sample period to equation (4):

$$\hat{E}_i = \alpha + (\beta_1 + \beta_2 G_i)\hat{G}_i + \gamma G_i + \delta E_{i0} + \varepsilon_i \tag{5}$$

where E_{i0} is the demeaned log of emissions per capita in country i in the first year in the sample period. For convergence we would expect that $\delta < 0$. However, countries such as China that have had large decreases in emissions intensity initially had low per capita emissions but high emissions intensity. Figure 4 shows that the correlation between the initial emissions intensity and the subsequent growth is higher than that between initial emissions per capita and its subsequent growth rate illustrated in Figure 3. Therefore, we also formulate our model in terms of beta convergence in emissions intensity:

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

Again, the cross-country mean is subtracted from the initial log emissions intensity variable.[10]

For the sake of comparison with the previous literature, we also estimate short and long forms of the Green Solow Model (Brock and Taylor, 2010). The empirical implementation of

[10] If we subtract the growth of GDP from both sides of (6) then we have a model of convergence in emissions intensity with GDP growth and levels terms added.

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, which tests for beta convergence. However, this model omits the economic growth variable. The short form of the Green Solow Model is given by the following equation:

$$\hat{E}_i = \phi_0 + \phi_1 E_{i0} + u_i \tag{7}$$

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:

$$\hat{E}_i = \phi_0 + \phi_1 E_{i0} + \phi_2 \ln s_i + \phi_3 \ln(n_i + 0.05) + u_i \tag{8}$$

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.

Our most general model is an extended version of equation (6):

$$\hat{E}_i = \alpha + (\beta_1 + \beta_2 G_i)\hat{G}_i + \gamma G_i + \delta(E_{i0} - G_{i0}) + \sum_j \psi_j X_{ji} + \varepsilon_i \tag{9}$$

where the X_j are additional explanatory or "control" variables. In the following, we discuss the additional variables that we add and the reasons for doing so. A wide variety of "control" variables have been considered in the EKC literature. Some of these are genuinely exogenous or predetermined, whereas others are variables that typically change in the course of economic development and might be seen as factors through which the development process drives emissions changes. Examples of the latter are democracy, free press, good governance, and lack of corruption, which have been found to both improve economic performance and reduce environmental pressure (Pellegrini and Gerlagh, 2006a, 2006b). Similarly, variables such as industrial structure are clearly driven by income growth or develop alongside GDP as part of the development process. Controlling for these could be a way to test the effect of different channels of the influence of income on emissions growth. However, in this paper we are interested in testing the overall effect of income and economic growth on emissions growth and so our main analysis only includes variables that are pre-determined or exogenous to the development process. We also mention results for models including additional variables.

The exogenous variables included in equation (9) are as follows. We include a dummy for non-English legal origin, as there is evidence that legal origin is relevant for emissions of sulfur (Stern, 2012). We also include a dummy for centrally-planned economies on the expectation that reform in the formerly centrally-planned countries spurred reductions in emissions (although our estimates do not in the end provide significant support for this). We control for the effect of climate using country averages of temperatures over the three summer months and the three winter months. Temperatures probably have a greater effect on the level of emissions than on growth in emissions but, controlling for income level, emissions may grow more rapidly in countries with larger cooling or heating requirements. We also include the log of estimated fossil fuel endowments in 1971 (Norman, 2009), as countries that are poor in fossil fuel endowments might exhibit larger transitions to low-emission energy sources such as nuclear power and renewables. Differences in fossil fuel endowments have been found to be an important cause of heterogeneity in emissions-income paths in prior work (Burke, 2012, 2013; Stern, 2012). We considered taking into account the potential for hydroelectric power by controlling for freshwater resources per capita (Burke, 2010, 2013). However, this variable was statistically insignificant in all our regressions. Finally, we include the average of the log of population density. For a given level of emissions per capita, higher population density implies higher pollution concentrations and so we would expect this variable to affect action on reducing sulfur emissions (*ceteris paribus*). Higher population density also reduces energy use through lower transportation costs and smaller living- and work- spaces. This might affect the growth of carbon dioxide emissions.

We estimate models using OLS with heteroskedasticity-robust standard errors. We also implement three heteroskedasticity tests. First, we use White's (1980) test of general heteroskedasticity. Second, because emissions per capita and income per capita are means computed over populations of various sizes, 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 (Breusch and Pagan, 1979), which involves regressing the squared residuals from each regression on the reciprocal of the mean over time of population.[11] Third, it is possible that, due to measurement errors, the variance of the error term is not linearly related to the size of the population, but instead to a power of it. To test this we use the Harvey (1976) test where we regress the log of the squared residuals on the log of population. As this process uses only a single regressor, we report the result as the regression coefficient and its standard error. We also estimated models using WLS where the error variance is assumed to be proportional to $P_i^{-\eta}$, where P is population and η is the estimated regression coefficient from the Harvey test auxiliary regression.

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 either 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 economic growth. Omitted variables bias is an important issue as there are many variables that may be correlated with GDP or GDP growth, and which may help explain emissions growth. Finally, measurement error is a significant issue in the estimation of GDP and emissions. The usual approach to these issues is using instrumental variables. However, it is hard to find plausible instrumental variables in the macro-economic context (Bazzi and Clemens, 2013), especially for long-run growth rates or levels of the variables. It is insufficient that a potential instrumental variable be theoretically exogenous to the dependent variable and correlated with the endogenous explanatory variable. It must also not be correlated with any omitted variable or affect the dependent variable itself directly. So even variables such as legal origin will not be suitable as instrumental variables.

4. Data

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 5) and sulfur emissions estimated by Smith *et al*. (2011) (Figure 6). The IEA and CDIAC data look broadly similar, but the datasets have different country coverage and there are some noticeable differences for smaller countries. Long-run growth in sulfur emissions is also positively correlated with economic growth, although the entire distribution of circles is shifted downwards, suggesting a strong negative time effect. Also, there is a group of smaller OECD countries with very

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

negative emissions growth clustered immediately below the USA in the graph. The Appendix describes the data sources in detail. Blanco *et al.* (2014) discuss the uncertainty in emissions data. For carbon emissions from fossil fuels and cement production the uncertainties are in the order of ±8%. For sulphur dioxide, uncertainties of the level in individual countries range from ±5% to ±36% depending on the country and source of emissions (Smith *et al.*, 2011).

Table 1 presents descriptive statistics for the growth rates of income and emissions per capita and the level of income per capita. Statistics for the demeaned logs of the levels variables used in the regressions would not be very informative and so are not included. The first five columns present statistics for the distribution of the country-level income growth rates and mean (over time) income levels. The sixth column presents data for the global aggregate income and emissions per capita.[12] The final column provides population-weighted means of the country-level growth rates and levels.

Mean income per capita varies by $2,000 across the samples and median income is around half mean income. Global aggregate per capita income varies by much less and is close to the median for the IEA and sulfur datasets. The CDIAC dataset contains a larger number of small low-income countries than the other two datasets and, therefore, its median income is lower. Per capita carbon dioxide emissions are rising on average across countries by more than 1% per annum while sulfur emissions are falling at 0.7% per annum on average. Variations in the rate of change across countries are much larger for sulfur emissions than for carbon emissions, as the standard deviation of the sulfur emissions growth rate is twice as large as that for carbon emissions. GDP per capita has grown a little faster than carbon dioxide emissions on average, with a bit less variation across countries. There do not seem to be important differences between the distributions of the GDP growth rates 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 the emissions elasticity with respect to income would be 0.75, 0.90, and -0.39 for the three datasets. As we will see, separating the total effect into time and income effects greatly modifies the last of these estimates.

The growth rates of global aggregate emissions are much lower than the unweighted country mean, while the population-weighted means are much higher. This is because, due to

[12] These data are for the aggregate of emissions, population, and GDP of the countries in our sample and thus are not truly global as some countries are omitted from each of our samples.

convergence, countries with higher initial emissions saw slower growth in emissions, while China and India, which have the largest populations, had rapid economic growth and rapid growth in emissions.

5. Results

Tables 2-4 present the results for equations (1)-(6) for the three datasets, Table 5 presents the results for the short and long forms of the Green Solow Model (equations (7) and (8)) for all data sets, Table 6 presents the results for equation (9) for all models, and Tables 7 and 8 present the results for equation (9) split into two sub-periods.

Looking first at the diagnostic statistics, with the exception of equation (9) for sulfur for the full sample, none of the Breusch-Pagan test statistics for a specific theory-based structure of heteroskedasticity are statistically significant at the 5% level. The Harvey test finds that there is significant heteroskedasticity at the 1% or 5% level for equations in some cases. In every case, the estimated coefficient is very far from the -1 assumed by the Breusch Pagan test. For the equations where the Harvey test does not find significant heteroskedasticity at the 5% level or higher, the WLS estimates are obviously very close to the OLS estimates, while for the other equations the two sets of estimates are qualitatively not very different. Therefore, we only report the OLS results and not the WLS results. Many of the White test statistics for heteroskedasticity of an unknown form are highly significant, which justifies the use of heteroscedasticity-robust standard errors.

The adjusted R-squared increases substantially as more variables are added for all three datasets and particularly for the models including initial emissions (5) and (6), emphasizing the importance of the convergence mechanism in explaining emissions growth rates. Results for equation (9) are not strictly comparable to those for equations (1) to (6) as the samples for the former exclude two or three countries, but they do show quite large increases in the R-squared for the IEA and sulfur datasets.

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, 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, GDP growth increases emissions for both sulfur dioxide and carbon dioxide and for the CDIAC and sulfur data the elasticity is not significantly less than unity. 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. Both the CDIAC data set and the sulfur data set have significantly negative effects on the level of GDP, indicating that the time effect is more negative in high-income countries. In addition, the point estimates of the emissions-income elasticity increase and the time effect becomes negative for these two datasets.

Equation (3) tests the EKC hypothesis. In each case, the interaction term is significantly negative but the emissions-income 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 the IEA carbon dioxide sample there is now a significantly positive time effect, while for sulfur the time effect becomes less negative.

Adding the level of income makes little difference for the IEA and sulfur data (equation (4)). For the CDIAC data this term is significantly negative. Adding the level of initial emissions in equation (5) changes all the results substantially. Initial emissions per capita have a strongly negative effect in all the datasets, which indicates that countries conditionally converge in emissions over time. The emissions-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 long-run GDP 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.

Equation (6) uses initial emissions intensity instead of initial emissions per capita. The results are quite sensitive to this alternative specification.[13] 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 emissions-income elasticity and the EKC turning point are substantially increased compared to equation (5). The effect of the level of income is significantly reduced.

Table 5 presents results for the Green Solow Model (GSM). The results for the short form (equation 7) are very close to those for Sample A in Table 2 of Brock and Taylor (2010) and the results for the long form are extremely close to their Sample C results 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. 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 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 very well specified.

On the other hand, for sulfur emissions, the GSM explains more of the variation than the EKC 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 more important in the case of sulfur than for carbon.

Table 6 presents the results of the extended model presented in equation (9). The time effects are similar to those in equation (6) – not significant for carbon, and significantly negative for sulfur (if a bit smaller here). The effect of GDP growth is increased and now is not significantly different from unity, the EKC effect is reduced and only statistically significant for the CDIAC data at the 10% level, and the convergence effect remains strong and of

[13] 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.

similar magnitude. The estimated EKC turning points are all out of sample and statistically insignificant.

The coefficients of the additional variables are very different for the carbon dioxide and sulfur dioxide models. Legal origin has no significant effect on carbon emissions growth but countries with non-English legal origin saw much more rapid decline in sulfur emissions than the English legal origin countries, confirming previous findings (Stern, 2005, 2012). This difference between CO_2 and SO_2 is easy to explain as to date sulfur emissions have typically received more active policy attention than carbon emissions. Formerly centrally planned status has a significantly positive effect on SO_2 emissions growth *ceteris paribus*. As there was a rapid decline in energy intensity in these countries following liberalization, we would expect emissions to decline more rapidly in reforming economies. However, as we see in Table 7 they grew much more rapidly in the centrally-planned economies prior to reform and this effect dominates. Summer temperature has a positive effect on both carbon and sulfur emissions growth, perhaps because of growing use of air conditioning in hot countries. The coefficient is largest for sulfur emissions, which are largely produced by electricity generation. Higher winter temperatures have a negative effect on emissions growth but this effect is smaller in absolute value than the effect of higher summer temperatures. This is probably because countries with cold winters have always heated living and workspaces over this period and probably have moved towards greater efficiency together with increased heating during this period.

A larger fossil fuel endowment increases the rate of growth of carbon emissions as we would expect (Burke 2012, 2013; Stern, 2012) but does not have a significant effect on sulfur emissions.[14] Population density has strong negative effects on sulfur emissions and smaller and insignificant effects on carbon emissions. Greater density means that for given emissions per capita, emissions concentrations will be higher and we expect as a result there will be greater policy action to reduce emissions. Higher density should also be associated with

[14] We also tested adding the interaction between fossil fuel endowments and the rate of economic growth to the regression. For CO_2, the coefficient of the interaction term was significant and the coefficient of the levels term of fossil fuel endowment was insignificant. For sulfur the interaction term was not significant. Other coefficients did not change much and so we chose to just present the model as in equation (9).

lower energy use in transport and smaller living- and work- spaces and perhaps in the growth of the energy use associated with these activities.[15]

To explore whether effects varied over time we split the sample period in half and re-ran equation (9) on the two sub-periods separately. Tables 7 and 8 report these results. The findings that economic growth and emissions convergence are significant drivers of emissions growth and that there is either no meaningful EKC turning point or a high EKC turning point are robust across the separate sample periods. But our cutting of the sample into two time periods reveals some interesting stories. Looking first at the CDIAC dataset, the time effect becomes negative and the effect of GDP growth strengthens in the second period. The EKC effect also becomes more negative though it is still not statistically significant. These effects are less pronounced for the IEA data. For both carbon datasets the effects of the endowments and temperature are reduced.

For sulfur dioxide in the first period the time effect and environmental Kuznets curve effect are insignificantly negative and both become significantly negative in the second period. The turning point also moves into the sample range but is still statistically insignificant. As might be expected, the coefficient for centrally-planned economies is very positive and significant in the first period and becomes negative though insignificant in the second period. The effect of winter temperatures disappears in the second period.

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[15] Though energy prices are not exogenous, there is interest in their effect on the growth of emissions. We use the log of the retail price of road-sector gasoline as a proxy of country-by-country fossil fuel prices (in the absence of data for other fuel prices for our large international sample). Adding this variable to equation (9) for the CDIAC data the coefficient is -0.0100 (0.0027). The main changes in the other parameters are as follows. The coefficient on the EKC effect becomes completely insignificant. The coefficient on the fossil fuel endowment becomes much smaller and only just significant at the 10% level. Therefore, greater fossil fuel endowments are correlated with lower gasoline prices and the small EKC effect that was present also appears to be related to higher fuel prices in richer countries. Results for the IEA data are similar, though the fossil fuel endowment is still highly significant ($p = 0.013$) for this data set. The gasoline price has a negative but insignificant coefficient in the sulfur dataset. Due to the large literature on the relationship between trade and the environment, which also inspired the first study of the EKC (Grossman and Krueger, 1991), we also tested for the effect of trade openness. When added to equation (9) its coefficient is positive. This effect is not statistically significant at the 5% level for carbon emissions but is for sulfur emissions (with a coefficient of 0.0178 (0.0048)). The main change to the other parameter values is that the EKC effect becomes significant but the income turning point is still out of sample ($179k) and insignificant.

6. Discussion

Using a new formulation of the emissions-income relationship in terms of long-run growth rates we find that the effect of income growth on emissions is strongly positive, and close to unity. Though the interaction term between income growth and the level of income is significantly negative across our three data sets for our simpler models, this is generally not the case when we add exogenous controls. Furthermore, in this extended model, any EKC income turning point is well out of sample and/or statistically insignificant for all three datasets. We conclude that there is no significant EKC effect in the full sample for either carbon or sulfur.

There is a strong negative time effect for sulfur ranging from -1.07% p.a. to -2.16% p.a., depending on the specification (-1.20% in our full model). Time effects for carbon are not robust across datasets and specifications. The effect of the level of income, independent of its interaction with income growth, is also not robust across specifications.

We find strong evidence of convergence across countries in either emissions per capita or emissions intensity. So, while the EKC story receives little support, neither a simple structural interpretation of the IPAT model, nor a simple convergence model, is on its own sufficient. Our estimates of the Green Solow Model for CDIAC carbon emissions have lower adjusted R-squared values than any of our models that include the growth rate of GDP. We therefore conclude that, though both are important, economic growth explains more of the variation in carbon emissions growth rates than does convergence. However, for sulfur emissions we find the reverse: convergence has greater explanatory power than GDP growth or the EKC effect. Though we find that convergence is important for both sulfur and carbon dioxide emissions our analysis does not explain why emissions per capita or emissions intensity is converging across countries. Convergence could be due to globalization leading to economic structures and the technologies used across countries becoming more similar over time or due to countries with high emissions intensities taking policy action to improve their environments and/or reduce their dependence on imported energy.

Our results provide smaller elasticities of emissions with respect to income and smaller time effects for carbon dioxide than Stern (2010). This suggests that Stern's (2010) results are biased by omitted variables. Perhaps this is also the case for the results of Wagner (2008) and Vollebergh *et al*. (2009), who also use models in levels.

Our finding that there is no statistically significant turning point for sulfur emissions provides support to similar conclusions first drawn by List and Gallet (1999) and Stern and Common (2001) (albeit using a very different approach). Using our full sample the EKC parameter is statistically insignificant and the turning point is out of sample and insignificant. Using data from just 1988 to 2005 we find that the coefficient of the growth-income interaction is significant and the turning point is (just) in-sample, although it is estimated with large standard errors and so is not statistically significant.

No new method can address all potential issues. The fact that long-run GDP growth rates filter out non-stationary dynamics, short-run relations, time varying time-effects and variables that might explain variation in the initial level of emissions across countries also means that we cannot use our approach to assess these (important) issues. For example, variation in countries' initial levels of emissions is left unexplained. This omission is shared with the panel data approach with country fixed effects. Also, we do not consider the effect of the business cycle on emissions (Bowen and Stern, 2010; Jotzo *et al.*, 2012; York, 2012; Li *et al.*, 2014). The approach we follow is focused on its purpose of identifying the long-term effects of economic growth on emissions.

Appendix: Data Sources

<u>GDP, Population, Area, Investment to GDP Ratio, Trade Openness</u>

These 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 the period we are interested in, there are complete 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 output side measures of real GDP that take 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 output-side GDP across countries using the reference price vector for each year and then adjusting for US inflation over time.

The Green Solow model uses the investment share of GDP for which we use csh_i. We also compute population growth rates and population density from the Penn World Table data. Trade openness is calculated as the average ratio of the sum of merchandise exports and imports to GDP over the period.

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

Emissions

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 for 249 countries for varying periods between 1751-2010. These are for emissions from the combustion of fossil fuels, gas flaring, and cement production and can be downloaded from: http://cdiac.ornl.gov/trends/emis/overview_2010.html. Emissions are 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 from Smith *et al*. (2011), who provide annual estimates 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.

Centrally Planned Economies

We identify centrally planned economies using a dummy variable equal to one for those countries on the list of transition economies in Table 3.1 in IMF (2000). In our sample, these countries are: Bulgaria, Hungary, Poland, Romania, Albania, Cambodia, China, Laos, and Vietnam.

Legal Origin

We treat English legal origin as the default and assign zero-one dummies for German, French, and Scandinavian legal origin using the classification of La Porta *et al*. (2008). The data are available from:

http://scholar.harvard.edu/shleifer/publications/economic-consequences-legal-origins

Temperature

Average temperature in degrees Celsius for 1960-1990 by country and month are available from Mitchell *et al*. (2003). The data are available from:

http://www.cru.uea.ac.uk/~timm/climate/index.html

We average the temperature of the three summer months – June to August in the Northern Hemisphere and December to February in the Southern Hemisphere – to obtain a summer temperature variable. We average the temperature of the three winter months to obtain a winter temperature variable. This should give a better idea of the demand for cooling and heating than simply using the temperature of the hottest and coldest months.

Energy Endowments

We multiply Norman's (2009) ratio of the value of fossil fuel stocks to GDP in 1971 by GDP per capita at market exchange rates in 1971 (World Bank) to derive the value of per capita fossil fuel endowments in 1971. As there are many zero values, we add one dollar to this value before taking logs. As the median value for countries with non-zero resources is $359 this does not change the data for countries with significant resources by very much.

Gasoline Prices

Data on the average gasoline pump price are provided by the *World Development Indicators* for various years between 1991 and 2010 in nominal US Dollars. We convert these into 2005

US dollars per liter using the US GDP deflator and then take an average of the price for each country over the years available for that country.

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Table 1. Descriptive Statistics

	Country					Global Aggregate	Population Weighted Mean
	Mean	Standard Deviation	Min	Median	Max		
Emissions per capita mean annual growth rate 1971-2010:							
CDIAC sample	0.013	0.025	-0.043	0.010	0.121	0.005	0.025
IEA sample	0.016	0.022	-0.046	0.014	0.106	0.006	0.027
SO_2 sample	-0.007	0.050	-0.124	-0.005	0.223	-0.019	0.005
GDP per capita mean annual growth rate 1971-2010:							
CDIAC sample	0.017	0.018	-0.031	0.017	0.077	0.020	0.036
IEA sample	0.018	0.016	-0.031	0.018	0.075	0.020	0.036
SO_2 sample	0.017	0.018	-0.040	0.018	0.072	0.021	0.034
GDP period mean income per capita 1971-2010:							
CDIAC sample	$9,303	$10,508	$423	$4,833	$55,963	$7,184	$7,184
IEA sample	$11,324	$11,311	$423	$6,584	$55,963	$7,087	$7,087
SO_2 sample	$10,207	$10,360	$383	$5,819	$48,875	$6,636	$6,636

Note: Growth rates are presented in fractions rather than percentages as that is the way the data are used in our regression analysis. The first five columns present unweighted statistics for our sample when computing the statistics for each country separately first. In the sixth column (global) we first compute the total emissions, GDP, and population for our sample of countries and we then compute the mean annual growth rate and mean per capita level of this global aggregate. In the final column we compute the growth rates using population-weighted regressions of the country-level growth rates on a constant.

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) [-1.42]	0.9257*** (0.1212) [-0.61]	0.8113*** (0.1103) [-1.71]	0.8768*** (0.1186) [-1.04]	0.5798*** (0.0813) [-5.17]	0.8351*** (0.0774) [-2.13]
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)
Harvey test: estimated parameter and standard error	-0.2623** (0.1260)	-0.2604*** (0.0976)	-0.2041*** (0.0809)	-0.2471** (0.1026)	-0.1058 (0.0971)	-0.0296 (0.0953)

Notes: 136 data points. Figures in parentheses are standard errors for the regression coefficients and the EKC turning point and p-values for the White and Breusch-Pagan test statistics. Figures in square brackets are the t-statistic for the difference between the coefficient and unity. 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 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) [-3.48]	0.6024*** (0.1384) [-2.87]	0.5581*** (0.1312) [-3.37]	0.5533*** (0.1378) [-3.24]	0.4285*** (0.0789) [-7.24]	0.7590*** (0.1015) [-2.37]
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)
Harvey test: estimated parameter and standard error	-0.0209 (0.1325)	-0.0917 (0.1261)	-0.0395 (0.1495)	0.0026 (0.1419)	-0.2536* (0.1413)	-0.2478* (0.1389)

Notes: 99 data points. Figures in parentheses are standard errors for the regression coefficients and the EKC turning point and p-values for the White and Breusch-Pagan test statistics. Figures in square brackets are the t-statistic for the difference between the coefficient and unity. 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 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) [-1.09]	0.8563** (0.3472) [-0.41]	0.6506** (0.2732) [-1.28]	0.7084** (0.2860) [-1.02]	0.3682** (0.1800) [-3.51]	0.7734*** (0.1644) [-1.38]
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)
Harvey test: estimated parameter and standard error	-0.2308 (0.1528)	-0.3070** (0.1503)	-0.2890** (0.1379)	-0.2606 (0.1707)	-0.1973 (0.1314)	-0.1764 (0.1320)

Notes: 103 data points. Figures in parentheses are standard errors for the regression coefficients and the EKC turning point and p-values for the White and Breusch-Pagan test statistics. Figures in square brackets are the t-statistic for the difference between the coefficient and unity. 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 can be interpreted as the time effect for a country with the sample mean level of log income and emissions.

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)
$\overline{R}^2$	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.

Table 6. Extended Model (Equation (9))

Data set	CDIAC Carbon Dioxide	IEA Carbon Dioxide	Sulfur Dioxide
Constant	-0.0023 (0.0023)	-0.0011 (0.0032)	-0.0120** (0.0057)
$\hat{G}_i$	0.9147*** (0.0840) [-1.02]	0.9074*** (0.1032) [-0.90]	0.9777 *** (0.1542) [-0.12]
G_i	0.0013 (0.0015)	0.0020 (0.0016)	-0.0021 (0.0026)
$G_i\hat{G}_i$	-0.1170* (0.0670)	-0.0129 (0.0716)	-0.1594 (0.1267)
$E_{i0} - G_{i0}$	-0.0154*** (0.0020)	-0.0169*** (0.0026)	-0.0215*** (0.0040)
Centrally Planned	-0.0056 (0.0051)	-0.0060 (0.0063)	0.0298** (0.0142)
French Legal Origin	0.0008 (0.0025)	0.0025 (0.0027)	-0.0145** (0.0058)
German Legal Origin	0.0022 (0.0042)	0.0028 (0.0036)	-0.0322*** (0.0107)
Scandinavian Legal Origin	-0.0033 (0.0044)	-0.0011 (0.0045)	-0.0437*** (0.0160)
Summer Temperature	0.0009*** (0.0003)	0.0015*** (0.0003)	0.0032*** (0.0011)
Winter Temperature	-0.0004* (0.0002)	-0.0003** (0.0002)	-0.0010*** (0.0004)
Log Fossil Fuel Endowment per Capita 1971	0.0011*** (0.0003)	0.0014*** (0.0004)	-0.0012 (0.0009)
Log Population Density	-0.0003 (0.0010)	-0.0003 (0.0010)	-0.0099*** (0.0023)
EKC income per capita turning point (1000's of $)	1.1E04 (5.4E04)	2.8E31 (1.1E34)	2,492 (12,958)
$\bar{R}^2$	0.6983	0.7123	0.6981
White test χ^2 $(2k+0.5(k^2-k))$	99.26 (0.0222)	67.56 (0.6264)	NA
BP test: inverse of population χ^2 (1)	0.0000 (0.9922)	0.1167 (0.7327)	7.3549 (0.0067)
Harvey test: estimated parameter and standard error	-0.1050* (0.059)	-0.2529 (0.1555)	-0.2300*** (0.0715)
Sample size	134	97	100

Notes: Figures in parentheses are standard errors for the regression coefficients and the EKC turning point and p-values for White and Breusch-Pagan test statistics. Figures in square brackets are the t-statistic for the difference between the coefficient and unity. 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 except dummy variables so that the intercept can be interpreted as the time effect for a country with English legal origin, a sample-mean level of log income and emissions, and that is not centrally planned. See the Appendix for further information on variable definitions.

Table 7. Equation (9) Period 1

Data set	CDIAC Carbon Dioxide	IEA Carbon Dioxide	Sulfur Dioxide
Constant	-0.0011 (0.0041)	0.0058 (0.0041)	-0.0064 (0.0093)
$\hat{G}_i$	0.8072*** (0.0919) [-2.10]	0.8029*** (0.1097) [-1.80]	0.8616*** (0.2089) [-0.66]
G_i	0.0015 (0.0030)	0.0040 (0.0026)	-0.0063 (0.0041)
$G_i\hat{G}_i$	-0.0482 (0.0753)	0.0372 (0.0846)	-0.0407 (0.2015)
$E_{i0} - G_{i0}$	-0.0235*** (0.0036)	-0.0207*** (0.0037)	-0.0312*** (0.0094)
Centrally Planned	-0.0089 (0.0117)	0.0030 (0.0096)	0.0754*** (0.0248)
French Legal Origin	0.0050 (0.0046)	-0.0012 (0.0045)	-0.0226** (0.0092)
German Legal Origin	0.0078 (0.0103)	-0.0069 (0.0075)	-0.0542** (0.0222)
Scandinavian Legal Origin	-0.0100 (0.0091)	-0.0088 (0.0091)	-0.0692*** (0.0223)
Summer Temperature	0.0017*** (0.0006)	0.0029*** (0.0006)	0.0037*** (0.0013)
Winter Temperature	-0.0010*** (0.0003)	-0.0011*** (0.0003)	-0.0023*** (0.0006)
Log Fossil Fuel Endowment per Capita 1971	0.0020*** (0.0007)	0.0025*** (0.0006)	-0.0012 (0.0012)
Log Population Density	0.0018 (0.0018)	0.0012 (0.0016)	-0.0124*** (0.0042)
EKC income per capita turning point (1000's of $)	7.3E07 (1.9E09)	0.0000 (0.0001)	7.5E09 (7.8E11)
$\bar{R}^2$	0.5458	0.5684	0.5801
White test χ^2 (2k+0.5(k^2-k))	110.34 (0.0050)	61.85 (0.7168)	98.62 (0.0137)
BP test: inverse of population χ^2 (1)	0.0846 (0.7711)	0.0395 (0.8426)	0.1187 (0.7304)
Harvey test: estimated parameter and standard error	-0.1848** (0.0950)	-0.1527 (0.1345)	-0.1208 (0.0942)
Sample	1971-1990	1971-1990	1971-1988

Notes: Figures in parentheses are standard errors for the regression coefficients and the EKC turning point and p-values for White and Breusch-Pagan test statistics. Figures in square brackets are the t-statistic for the difference between the coefficient and unity. 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 except dummy variables so that the intercept can be interpreted as the time effect for a country with English legal origin, a sample-mean level of log income and emissions, and that is not centrally planned. See the Appendix for further information on variable definitions.

Table 8. Equation (9) Period 2

Data set	CDIAC Carbon Dioxide	IEA Carbon Dioxide	Sulfur Dioxide
Constant	-0.0051* (0.0029)	-0.0025 (0.0041)	-0.0221*** (0.0077)
$\hat{G}_i$	1.0198*** (0.1040) [0.19]	0.8772*** (0.1086) [-1.13]	0.8108*** (0.1936) [-0.98]
G_i	0.0006 (0.0017)	0.0004 (0.0017)	0.0042 (0.0044)
$G_i\hat{G}_i$	-0.1256 (0.0953)	-0.0132 (0.0741)	-0.4421*** (0.1379)
$E_{i0}-G_{i0}$	-0.0125*** (0.0034)	-0.0161*** (0.0043)	-0.0133*** (0.0042)
Centrally Planned	-0.0066 (0.0098)	-0.0001* (0.0002)	-0.0076 (0.0233)
French Legal Origin	-0.0022 (0.0037)	0.0030 (0.0042)	-0.0095 (0.0078)
German Legal Origin	-0.0015 (0.0068)	0.0018 (0.0049)	-0.0249 (0.0168)
Scandinavian Legal Origin	0.0013 (0.0059)	0.0036 (0.0062)	-0.0724*** (0.0172)
Summer Temperature	0.0008 (0.0003)	0.0014*** (0.0005)	0.0046*** (0.0010)
Winter Temperature	0.0000 (0.0005)	0.0001 (0.0003)	-0.0007 (0.0006)
Log Fossil Fuel Endowment per Capita 1971	0.0010* (0.0005)	0.0010** (0.0005)	-0.0004 (0.0013)
Log Population Density	-0.0017 (0.0018)	-0.0012 (0.0013)	-0.0092*** (0.0030)
EKC income per capita turning point (1000's of $)	17,159 (1.2E05)	5.0E29 (1.9E32)	38.0k (31.9k)
$\bar{R}^2$	0.5351	0.4977	0.5613
White test χ^2 (2k+0.5(k^2-k))	105.52 (0.0077)	66.00 (0.8318)	457.62 (0.0000)
BP test: inverse of population χ^2 (1)	0.0071 (0.9327)	0.1085 (0.7419)	0.0184 (0.8921)
Harvey test: estimated parameter and standard error	-0.0273 (0.1123)	-0.1010 (0.1398)	-0.0766 (0.0769)
Sample	1990-2010	1990-2010	1988-2005

Notes: Figures in parentheses are standard errors for the regression coefficients and the EKC turning point and p-values for White and Breusch-Pagan test statistics. Figures in square brackets are the t-statistic for the difference between the coefficient and unity. 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 except dummy variables so that the intercept can be interpreted as the time effect for a country with English legal origin, a sample-mean level of log income and emissions, and that is not centrally planned. See the Appendix for further information on variable definitions.

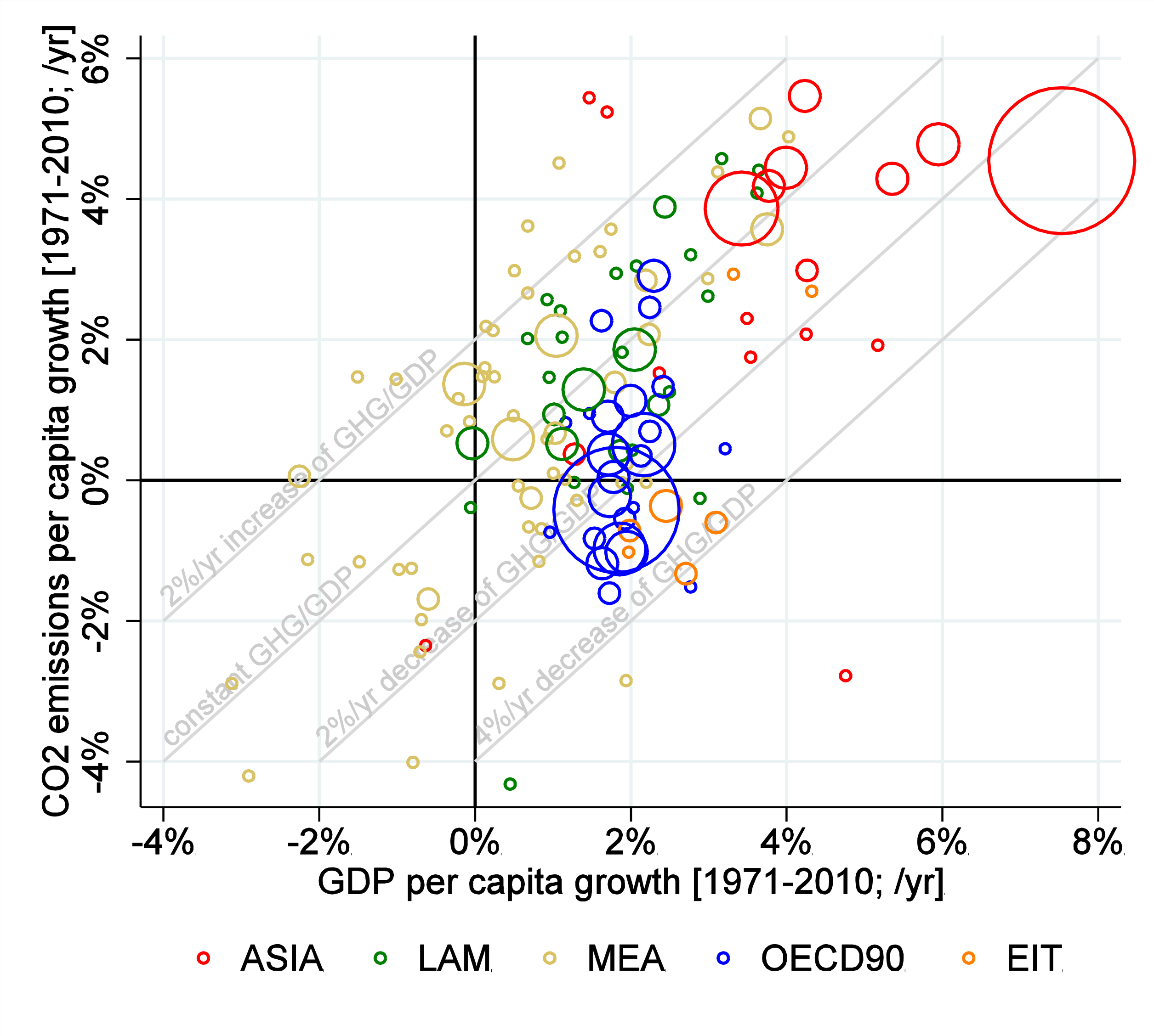

Figure 1: Growth Rates of Per Capita Income and Per Capita Carbon Dioxide Emissions from Fossil Fuel Combustion and Cement Production. The figure shows the relation between the average annual growth rates of per capita income and per capita emissions from 1971 to 2010. Points along the grey lines have 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' total emissions in 2010. Regional labels are: ASIA = developing Asia, LAM = Latin America, MEA = Middle East and Africa, OECD90 = OECD members as of 1990, EIT = Eastern Europe and the former USSR. The upper right large red circle is China and the large blue circle is the USA. Sources: CDIAC and Penn World Table 8.0.

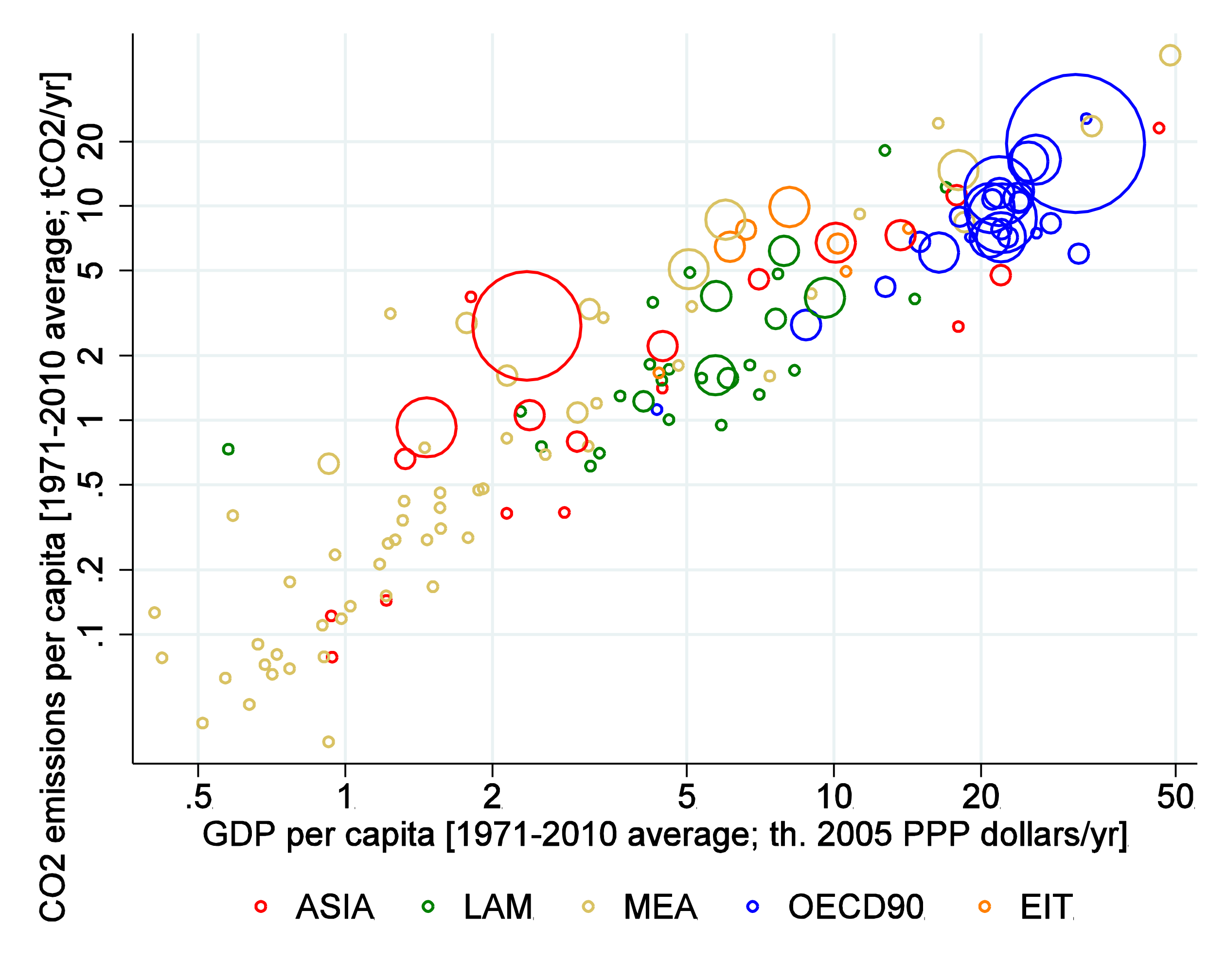

Figure 2: Levels of Per Capita Income and Per Capita Carbon Dioxide Emissions from Fossil Fuel Combustion and Cement Production. The figure shows the relation between average per capita income and per capita emissions from 1971 to 2010. The size of the circles is proportional to countries' average total emissions from 1971 to 2010. Regions and data sources as in Figure 1. The large red circle is China and the large blue circle on the upper right is the USA.

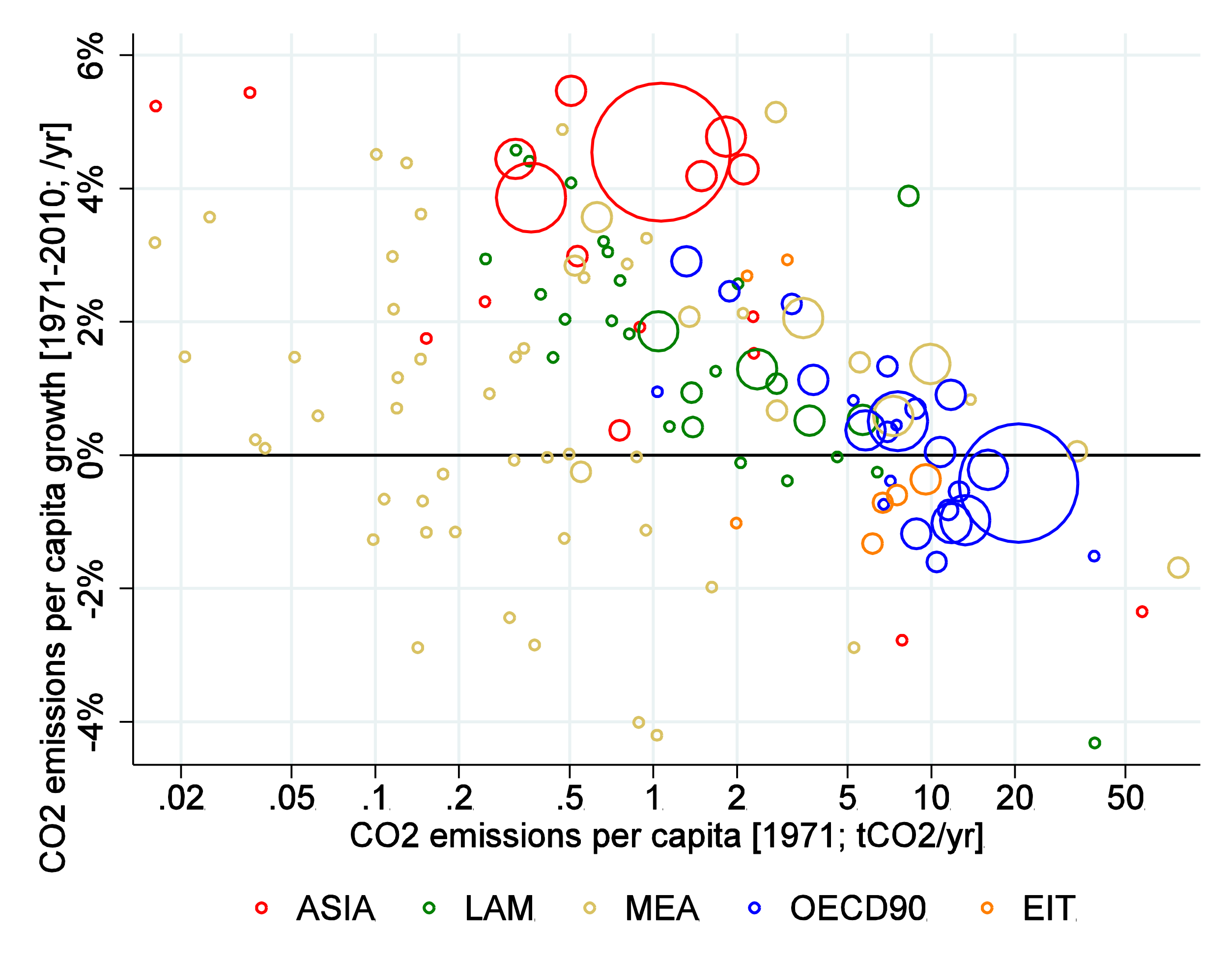

Figure 3: Convergence in per Capita Carbon Dioxide Emissions from Fossil Fuel Combustion and Cement Production. The figure shows the relation between the growth rate of per capita emissions from 1971 to 2010 and the level of emissions in 1971. The size of the circles is proportional to countries' average total emissions in 2010. Regions and data sources as in Figure 1. The large red circle is China and the large blue circle on the upper right is the USA. The dashed grey line is a simple unweighted regression fit.

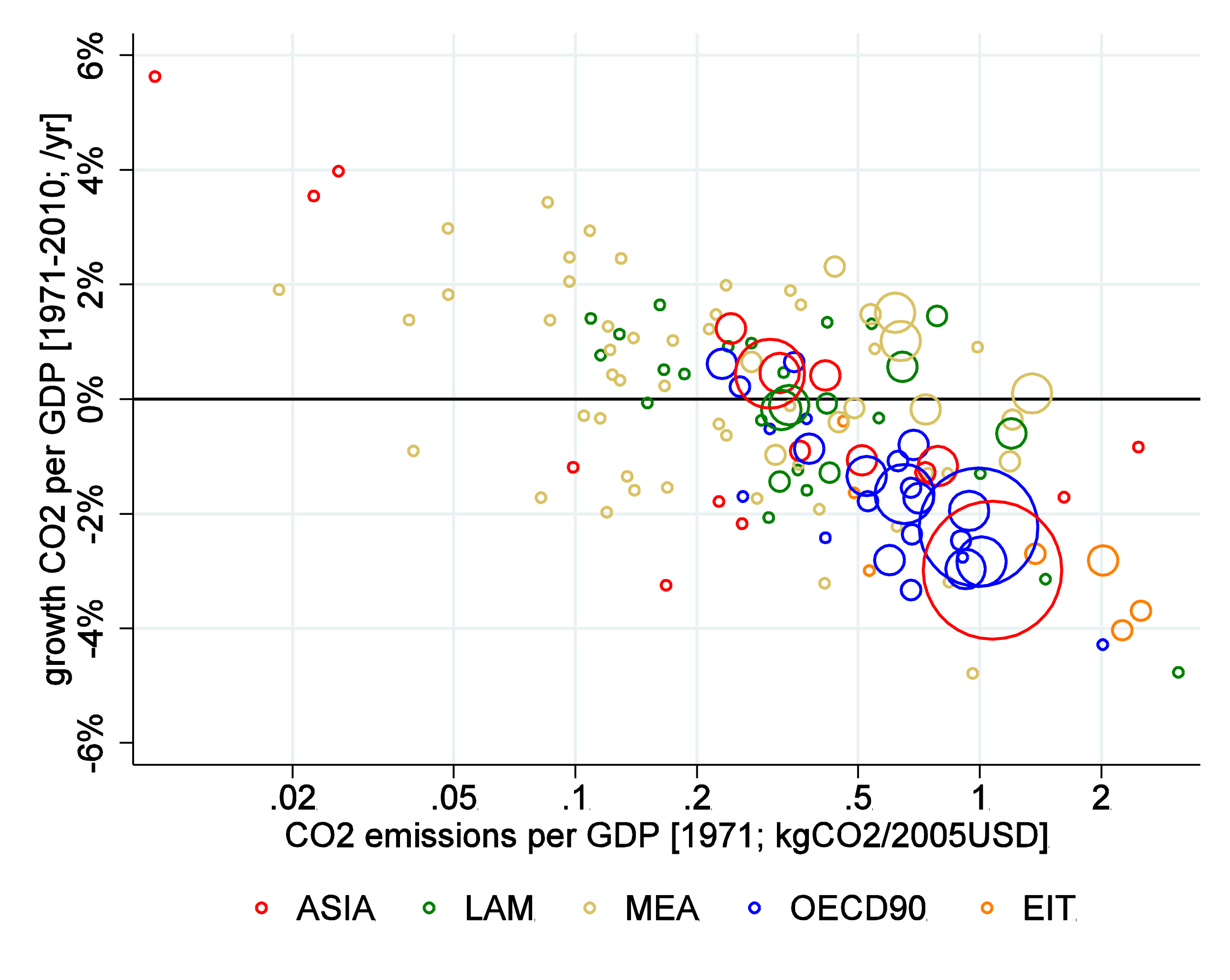

Figure 4: Convergence in Carbon Dioxide Emissions Intensity. The figure shows the relation between the growth rate of emissions intensity of GDP from 1971 to 2010 and the level of emissions intensity in 1971. The circles are proportional to countries' total emissions in 2010. Regions and data sources as in Figure 1.

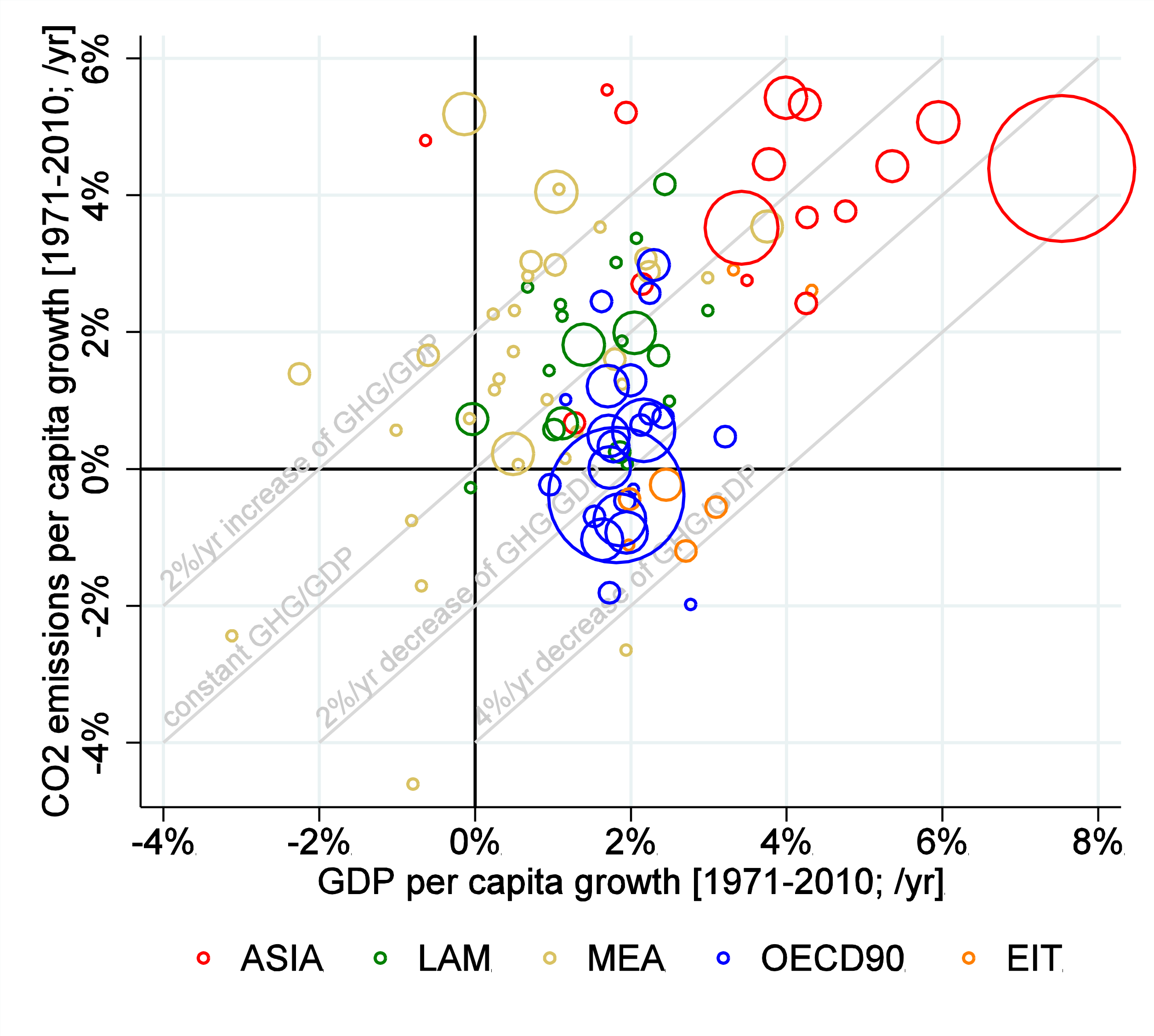

Figure 5: **Growth Rates of Per Capita Income and Per Capita Carbon Dioxide Emissions from Fossil Fuel Combustion**. The figure shows the relation between the average annual growth rates of per capita income and per capita emissions from 1970 to 2010. Points along the grey lines have either constant 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. Regions as in Figure 1. Sources: IEA and Penn World Table 8.0.

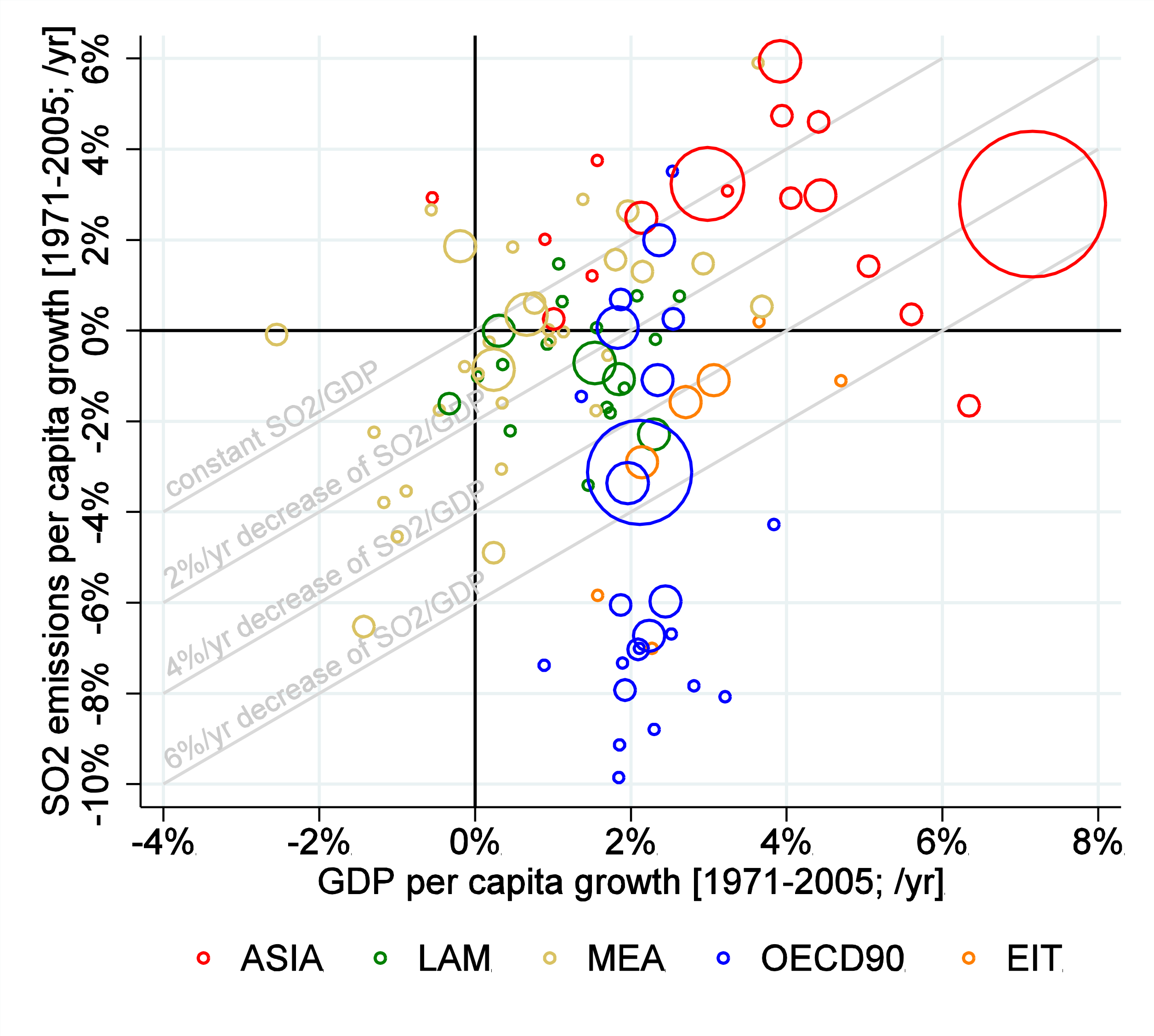

Figure 6: **Growth Rates of Per Capita Income and Per Capita Sulfur Dioxide Emissions**. The figure shows the relation between the average annual growth rates of per capita income and per capita emissions from 1970 to 2010. Points along the grey lines have either constant emissions intensity or emissions intensity increasing by 4% or declining at 4% or 8% per annum. The size of the circles is proportional to countries' total emissions in 2010. Regions as in Figure 1. Sources: CDIAC and Penn World Table 8.0.