CENTRE FOR APPLIED MACROECONOMIC ANALYSIS

The Australian National University

THE AUSTRALIAN NATIONAL UNIVERSITY

CAMA Working Paper Series **February, 2010**

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CAMA Working Paper 4/2010
http://cama.anu.edu.au

Title page, including author details

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December 2009

Abstract
Recent papers by Wagner in this journal and Vollebergh *et al*. in the *Journal of Environmental Economics and Management* point out some fundamental econometric problems with traditional methods of estimating the environmental Kuznets curve (EKC) and propose alternative approaches that avoid these issues. Wagner notes that traditional methods do not take into account the presence of powers of unit root variables and cross-sectional dependence in the data while Vollebergh *et al* point out that the time effects are not uniquely identified in the EKC model. The between estimator is a simple estimator that also addresses the concerns of these authors. It makes no a *priori* assumption about the nature of the time effects and is likely to provide consistent estimates of long-run relationships in real world data situations. I apply several common panel data estimators including the between estimator to the datasets for carbon and sulfur emissions in the OECD and global sulfur emissions. The between estimates of the sulfur-income elasticity are 0.732 in the OECD and 1.067 in the global data set and the estimated carbon-income elasticity is 1.612 in the OECD and 1.509 globally.

Key Words: carbon, sulfur, environmental Kuznets curve, between estimator
JEL Codes: C23, Q53, Q56

***** I thank Elbert Dijkgraaf and Martin Wagner for providing the data used in their paper and Arik Levinson for helpful comments. The author is funded by the Australian Commonwealth Department of Environment, Water, Heritage and the Arts through the Commonwealth Environmental Research Facility Environmental Economics Research Hub

1. Introduction

Recent papers by Wagner (2008) in this journal and Vollebergh *et al*. (2009) in the *Journal of Environmental Economics and Management* point out some fundamental econometric problems with traditional methods of estimating the environmental Kuznets curve (EKC) and propose alternative approaches that avoid these issues. Wagner notes that traditional panel cointegration methods do not take into account the presence of powers of unit root variables in EKC regressions and cross-sectional dependence in the data. Conventional panel cointegration methods are not intended for use with non-linear functions of unit-roots. First generation panel unit root tests and cointegration procedures are also designed for cross-sectionally independent panels, which is a somewhat implausible assumption. Wagner uses de-factored regressions and so-called second-generation panel unit root tests to address these two issues. Vollebergh *et al.* point out that time, income, or other effects are not uniquely identified in reduced form models such as the environmental Kuznets curve (EKC) and that existing EKC regression results depend on the specific identifying assumptions implicitly imposed. The most general EKC model is given by:

$$y_{it} = h(x_{it}, i, t) + \varepsilon_{it} \tag{1}$$

where y is the environmental indicator, and x a vector of explanatory variables observed at time t in countries or states i. ε is an error term. The function *h()* is not identified without some restrictions because we only have one observation on y and x for each i and t combination. The most common EKC strategy is to assume that time and location have fixed linear effects on y that are separable from the effects of the explanatory variables:

$$y_{it} = f(x_{it}) + \alpha_i + \gamma_t + \varepsilon_{it} \tag{2}$$

where α and γ are vectors of constants that vary across countries and time periods respectively. Thus it is assumed that there is a common time effect and income coefficients in all countries and fixed differences between countries. Any remaining residual is stationary. Vollebergh *et al.*'s alternative approach assumes that the time effects are identical in each pair of most similar countries. In this paper, I propose to use the simpler between estimator – a cross section regression on the mean data for each country – as an alternative means of estimating relationships such as the EKC free from assumptions about the time effects and the econometric issues raised by Wagner. I apply the between estimator and other panel data estimators to the data sets used by Vollebergh *et al*. and Wagner.

Panel data contains two dimensions of variation – the differences between countries – the "between variation" and the differences over time within countries – the "within variation". Fixed effects estimation – also known as the "within estimator" – eliminates the average differences between countries prior to estimation. The coefficient estimates, therefore, primarily exploit the variation within the countries.[1] The between estimator first averages the data for each country over time. Therefore, the coefficient estimates only exploit variation across countries and not within countries. As explained in the following section, in the absence of a variety of misspecification issues, both these and other panel estimators should converge on identical estimates in large samples when there are no time effects (Pesaran and Smith, 1995). But in practice the various estimators diverge due to misspecification error and differences in the treatment of time effects.

In contrast to the time series and panel estimators that have been used to estimate the EKC to date, the between estimator makes no specific assumptions about the time process. To achieve identification it makes the two standard assumptions of linear regression that the regression slope coefficients are common to all countries (and implicitly time periods) and that there is no correlation between the regressors and the error term. Given these assumptions, the between estimator is a consistent estimator of the long-run relationship between the variables when the time series are stationary or stochastically trending and is super-consistent for cointegrating panels (Pesaran and Smith, 1995). Because of these properties, the between estimator should provide consistent estimates even in the presence of powers of unit root variables. Obviously, as we now only have one observation on each cross-sectional unit, cross-sectional dependence is not an issue either. Imposing common slope coefficients on all countries might be seen as overly restrictive. Several EKC studies have estimated different income coefficients in each country or state (e.g. List and Gallet, 1999; Martınez-Zarzoso and Bengochea-Morancho, 2004; Vollebergh *et al*., 2009). But all the studies that preceded Vollebergh *et al*. are more restrictive regarding the time effect. Wagner shows that allowing for heterogeneity in slope coefficients had little effect on his

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[1] Not all variation between countries is eliminated by the subtraction of country means from the data.

defactored regressions. My approach is even less restrictive than Vollebergh *et al*. regarding the time effect at the price of imposing greater restriction on the income coefficients. If we simply desire an estimate of the mean income effect in the sample as estimated by the pooled mean group estimator (Bengochea-Morancho, 2004) then the between estimator provides a consistent estimate of this (Pesaran and Smith, 1995). The simplest version of the between model assumes that the error term, u, in the following equation is normally distributed:

$$\bar{y}_i = \overline{f(x_i)} + u_i \tag{3}$$

where bars indicate the means over time. No distinction is made between the country effects and measurement error. This is a strong assumption to impose on the country effects and is a cost of allowing the time effect to be entirely unrestricted. But other assumptions are possible. u might be modeled as a combination of a one sided error term and a normal random variable so that (3) is a stochastic frontier model and/or u might be modeled as a function of explanatory variables.

Historically, the between estimator has been shunned by researchers due to a concern that omitted variables represented by the individual effects may be correlated with the included explanatory variables. As the individual effects are absorbed into the regression residual term, this would be expressed as a correlation between the error term and the regressors and lead to inconsistent estimates of the regression coefficients. The random effects estimator, which treats the individual effects as error components, suffers from the same potential bias. However, this is only one of several potential misspecifications of panel data models. Hauk and Wacziarg (2009) show that the between estimator is the best performer among potential panel data estimators even when the orthogonality assumption is violated but measurement error is present.

The paper is structured as follows. The second section reviews the econometric theory concerning potential biases in panel data estimators. It concludes that, though all estimators may suffer from biases and/or inconsistency, the between estimator is the best practical estimator. The third section briefly reviews the methods and data used. The fourth section presents the results, and the fifth concludes.

2. Econometric Theory

a. Alternative Panel Data Estimators

Differences between time series and cross-section estimates have long been discussed in the econometric literature (Baltagi and Griffin, 1984). In recent decades this interest has been transferred to panel data. A time series is simply a panel data set with only one individual and a cross-section a panel with a single time period. In addition to the estimators discussed in the introduction – within (fixed effects), random effects, and between estimates – the econometric literature reviewed in this section also discusses the average of static or dynamic time series regressions and OLS as potential estimators for panel data.[2] The standard EKC model for pollution emissions is given by:

$$\ln(E/P)_{it} = \alpha + \beta_1 \ln(GDP/P)_{it} + \beta_2 (\ln(GDP/P))^2_{it} + \alpha_i + \gamma_t + \varepsilon_{it} \tag{4}$$

where *E* is emissions, *P* is population, and *GDP* is measured in constant purchasing power parity adjusted dollars. i indexes countries and t time periods. The error term is composed of an individual component α, a time component γ, and a remainder term ε. In the general case, all three error components are considered to be random variables. The fixed effects estimator assumes that the individual and time components are fixed intercepts. Time series models might treat the time component as a linear deterministic trend.

Pesaran and Smith (1995) point out that if the true data generating process (DGP) is static, the explanatory variables are uncorrelated with the error term, and any parameter heterogeneity across individuals is random and distributed independently of the regressors, all alternative estimators should be consistent estimators of the coefficient means. It is the presence of dynamics and/or correlation between the regressors and the error term that results in differences between the estimators whether the true parameters are homogenous or heterogeneous. There is no essential difference between time series and cross-section estimates, only differences in the likely importance and impact of misspecification. In the following, I address the impact of each type of misspecification on the different estimators.

b. Coefficient Heterogeneity

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[2] There are many more potential panel data estimators including random coefficients models, maximum likelihood estimates, instrumental variable estimators etc.

Pesaran and Smith (1995) argue that, in the absence of omitted variables or measurement error, the averaged time series and between estimators are consistent, whatever the nature of coefficient heterogeneity. A traditional cross-section estimate, however, may suffer from a high level of bias because $T = 1$. In the presence of coefficient heterogeneity, FE and RE estimators for dynamic models will be inconsistent, as forcing the coefficients to be equal induces serial correlation in the disturbance, which results in inconsistency when there are lagged dependent variables. But if the true model is static, static FE and RE should be consistent in the presence of coefficient heterogeneity and in the absence of other misspecifications.

Pesaran and Smith analyze both stationary and non-stationary cases. Static time-series estimates are of course superconsistent when the variables are I(1) and cointegrate. But, if the coefficients vary across groups, the pooled estimates such as OLS or fixed effects need not be cointegrating. The between estimator, however, is also a consistent estimator of the long-run coefficients even in the absence of cointegration, as long as the explanatory variables are strictly exogenous. They estimate a labor demand model (cross-section dimension: 38, time-series dimension: 29) using heterogeneous and pooled approaches. The static cointegrating time series regressions yield an average own price elasticity of -0.30 and a variety of dynamic time series models give elasticities up to -0.45. The between estimate is -0.523 and static pooled estimates are: OLS: -0.53, RE: -0.42, and FE: -0.41. Dynamic pooled estimates are much larger in absolute value, OLS: -3.28, RE: -1.83, and FE: -0.74. The bottom line is that there are no large differences between their static estimates though BE and OLS show greater elasticities, time series smaller elasticities, and fixed effects occupies a mid-point. The dynamic pooled estimators, however, deviate significantly from the estimators that Pesaran and Smith argue are consistent.

c. Misspecified Dynamics

Baltagi and Griffin (1984) examined the effect of omitted dynamics in the case of stationary panel data. If the true data generating process (DGP) for a time series is dynamic and a static model is estimated there are omitted lagged variables. The value of the estimated coefficients depends on the correlation between the omitted lags and the current values of the variables. The greater the correlation, the closer the static coefficients will be to the sum of the dynamic coefficients – i.e. the long-run effect. The less the correlation, the closer the static estimates will be to the impact coefficients – i.e. a short-run effect. Baltagi and Griffin argued further, that in panel data, the higher the correlation between lagged dependent variables the better the between estimator would estimate the long-run coefficients. The performance of the within estimator also depends on the relative amount of between and within variation in the data as correlations between cross-sections of demeaned data are usually lower than between cross-sections of raw data. They carry out a Monte Carlo analysis of a model with a very long lag structure, random effects errors, and no correlation between the explanatory variables and those errors. In this procedure they fit dynamic models to the generated data (they do not fit static models). Estimated lag length tends to be truncated. The between estimator gets very close to the true long-run elasticity while the within estimator provides good estimates of the short-run elasticity and somewhat underestimates the long-run elasticity. The within estimator is also strongly affected by changes in the dynamic structure or length of the time series, while the between estimator is not. All this is despite the cross-section dimension being only 18 (the time-series dimension is 14). OLS is slightly biased upwards.

Van Doel and Kiviet (1994) concluded that in general "static estimators usually underestimate the long-run effect" when the variables are stationary but are consistent under non-stationarity if there is cointegration. Two more recent papers further examine the performance of static estimators for stationary data. Pirotte (1999) shows that even if the time dimension is fixed but $N \rightarrow \infty$ the between estimator converges to the long-run coefficients of a dynamic model. When there is little serial correlation the within estimator converges to short-run effects. If there are no individual effects, OLS converges to the long-run when the sum of the lag coefficients tends to unity as well as when there is less serial correlation but large individual effects. Egger and Pfaffermayr (2004) also assume an underlying stationary, dynamic DGP. Using Monte Carlo analysis, they find that when the explanatory variables are not serially correlated the static within estimator is downwardly biased even compared to the short-run effects. But when the level of serial correlation is high the within estimator converges towards the long-run effects. On the other hand, the between estimator is biased downwards if serial correlation is high and the time dimension is small. In their simulations, on the whole, the parameter estimates are ranked from smallest to largest FE, RE, OLS, BE with even BE biased down from the true value.

d. Omitted Explanatory Variables

The one-way error components model assumes that the error term in a panel model is composed of an individual effect, which varies across individuals but is constant over time and a remainder disturbance that varies over both time and individuals (Baltagi, 2008). If omitted explanatory variables are correlated with the included regressors, the regressors will be correlated with the individual effects and/or the remainder disturbance (Griliches and Mairesse, 1987). The fixed effects estimator eliminates the individual effects prior to estimation while the between estimator averages over the remainder disturbances of each individual. Therefore, panel OLS, random effects, between, and cross-section estimators will be biased if the regressors are correlated with the individual effects and the fixed effects and time series estimators will be unbiased. But if the correlation is instead with the remainder disturbance, the between estimator will be consistent (though biased when the time series dimension is small) and all the other estimators will be inconsistent.

In the case of the EKC, there may be many omitted variables but the most important is likely to be the state of technology (Stern, 2004). While a large number of EKC studies allow for a common series of time dummies, others do not include any time effects, while others still include linear or more complex trends. If a linear trend is employed and the true technology trend is not deterministic and linear, a variable has been omitted. The rate of technological change certainly varies over time and there may well be a correlation between income and the level of technology adopted. Therefore, there is likely to be a correlation between both the remainder error and the regressors and between the individual effects and the regressors. *A priori*, there is no reason to prefer one estimator over the other on these grounds.

e. Measurement Error

We also need to consider measurement error in the explanatory variables (Mairesse, 1990). As is well-known, measurement error induces a correlation between the error term and the regressors and biases the estimates downwards if the measurement error is not correlated with the regressors (Hausman, 2001). If measurement errors are non-systematic the between estimator will average them out over time and will be consistent but biased when the time series dimension is small, while the within estimator amplifies the noise to signal ratio by subtracting individual means from each time series. Hauk and Wacziarg (2009) carry out a Monte Carlo analysis of an economic growth equation to examine the effects of both measurement error and omitted variables on alternative panel estimators. They find that the between estimator is the best performer in terms of having the minimum bias relative to fixed effects, random effects, and some GMM estimators commonly used in the growth literature.

f. Conclusion

There appears to be, therefore, a consensus that the between estimator is the best estimator of long-run relations in panel data. It uses a large sample of data compared to time series estimates and is consistent for both stationary and non-stationary data in the face of misspecified dynamics and heterogeneous regression coefficients. And despite the potential for correlation between the explanatory variables and the individual effects, it appears to perform well in real world situations (Hauk and Wacziarg, 2009). Cross-section estimates may, however, be significantly biased. And there is disagreement on the properties of other estimators whose performance depends on the specific properties of the data.

It is likely that the data used in environmental Kuznets curve studies is stochastically trending but that given the overly simple nature of the EKC model cointegration is unlikely (Perman and Stern, 2003). PPP adjusted GDP and sulfur emissions are likely to be measured with significant error. There is less error in the measurement of carbon emissions. Correlation between the regressors and omitted variables is very likely but there is no *a priori* reason I believe to assume that there is a more significant correlation between the country means of the regressors and the omitted variables than there is in the variation over time in the omitted variables and the regressors. In these circumstances the between estimator is likely to be a reasonably good estimator of the long-run relationship between income and emissions and at least better than other estimators.

3. Methods and Data

Equation (4) specifies the general model. I estimate this model for sulfur and carbon emissions. I also estimate a linear version of the model (setting $\beta_2 = 0$) for the between estimator. One could also use non-parametric estimators as in Carson *et al*. (1997), but the main point of this paper is simply to demonstrate the potential of the between estimator rather than add additional complications.

I estimate models for the Vollebergh *et al*. and Wagner datasets. Vollebergh *et al*. compiled data for sulfur and carbon emissions, GDP (in real 1990 international dollars), and population for 24 OECD countries for the period 1960-2000. Wagner compiled data on carbon and GDP per capita for 100 countries for the period 1950-2000 and for 97 countries for sulfur (Puerto Rico, Gambia, and Sao Tome & Principe were dropped from the sulfur sample).

I use each of the following estimators: Between estimator, fixed effects, random effects, first differences, and pooled OLS. All the estimates apart from OLS are carried out using the PREGRESS procedure in RATS which computes standard errors taking clustering of residuals into account. OLS regressions were estimated in RATS using LINREG with the option CLUSTER. I estimated the fixed effects and random effects models with and without time effects. For OLS and the first differences estimator I estimated the model with and without a linear time trend.

Because the between estimator is a consistent estimator of the long-run relationship even in the absence of cointegration, I do not carry out tests of cointegration in this paper. The extracted time effects are almost certainly non-stationary and, therefore, emissions will not cointegrate with income, but we will have a good estimate of the income elasticity of emissions.

For the quadratic models, I computed the turning point at which the elasticity of emissions with respect to income switches from positive to negative as well as the mean and standard deviation of the elasticity of emissions with respect to GDP under the assumption that the coefficients are known.

Vollebergh *et al*. (2009) raise the influence of outliers on their simple EKC estimates. For the between estimator I re-estimated the model eliminating one country at a time to determine to what degree the results were sensitive to influential observations. I report the distribution obtained from this exercise.

4. Results

Table 1 presents the results for the EKC model applied to Vollebergh *et al*.'s OECD sulfur emissions data. The R^2 statistics are not comparable across different estimation methods between models with and without time effects for the fixed and random effects estimators. The turning points for the quadratic models are all within sample. The mean of the income elasticity indicates which of the turning points fall in the lower half or upper half of the income distribution – positive elasticities indicate that the majority of the observations are on the rising limb of the EKC and *vice versa*. The models with time trends or time effects have somewhat higher turning points and more positive mean elasticities. The first difference estimates with a time trend yield the highest turning point of $19,008 1990 PPP Dollars.

There is little difference between fixed and random effects estimates of the turning points which are a little higher than those in Stern and Common (2001) for the OECD from 1960-1990 and are the lowest of the estimates. For the model without time effects the Hausman statistic is just 0.0035 (p=1.00) and in the case of time effects 0.456 (p=0.634). This result is important because it indicates that the regressors do not appear to be correlated with the individual effects in this sample. Therefore, the between estimator is not likely to suffer from this bias either. Stern and Common (2001) estimated an income elasticity of 0.67 for the OECD from the first difference estimates, which is identical to that found here for the longer period. However, while they found that the coefficient on the time trend in the first differences regression was -0.020 here it is -0.048.

All these EKC estimates have a much higher degree of curvature than those in Stern and Common. As shown by the standard deviations of the elasticities, each country's estimated elasticity has typically moved over an implausibly wide range of values in the period of 40 years. For the random effects estimator with time effects the average income elasticity in the sample goes from 1.37 in 1960 to -1.97 in 2000. These results strongly contrast with Vollebergh *et al.*'s pairwise estimates. Figure 4 in their paper shows that the average income effect remains positive through the whole time period for both sulfur and carbon. The curve is somewhat convex down suggesting a more or less constant elasticity. The point is simply that these traditional panel estimates are very different to Vollebergh's pairwise estimates. If we believe these latter to be reasonable then it is clear that the traditional estimates are biased.

The between estimator for the quadratic model, however, clearly suffers from multicollinearity - both regression coefficients are insignificantly different from zero. The turning point is also very imprecisely estimated, though the elasticity has a narrower range than all but the first difference estimates. The estimated income elasticity for the linear model is 0.732. This finding seems congruent with Vollebergh *et al.*'s findings.

To test the effect of influential data, I estimate the linear between estimator 24 times using samples that drop a different country each time. The lowest elasticity estimated was when Turkey was eliminated (0.566) and the highest when Switzerland was eliminated (0.989). The standard deviation is 0.081. Eliminating Turkey reduced the t-statistic of the elasticity to 1.05. Omitting Switzerland increased it to 2.64.

Figure 1 presents the linear between estimate together with the income part of each of the other estimates that include time effects. The average individual and time effect has been added to the fixed effects estimate and the first differences estimate has been given an intercept so that the mean fitted value is equal to the mean fitted value of the other estimators. All four quadratic curves show an in-sample turning point but the first differences curve is flatter than the others and not so different from the linear between estimator in the upper income range. Random effects, fixed effects and OLS do not differ very substantially from each other.

Figure 3 decomposes projected sulfur emissions based on the between estimator in a similar fashion to Vollebergh *et al*. The income effect, I, in year t is the population weighted mean of the fitted regression model in the given year:

$$I_t = \frac{1}{\sum_i P_{it}} \sum_i P_{it} \exp\left(\hat{\alpha} + \hat{\beta}_1 \ln(GDP/P)_{it}\right) \tag{5}$$

where "hats" indicate the between estimates of the regression parameters in equation (4). The constant term is, therefore, included in the income effect. The time effect, T, is the population weighted mean residual:

$$T_t = \frac{1}{\sum_i P_{it}} \sum_i P_{it} \exp\left(\ln(E/P)_{it} - \hat{\alpha} - \hat{\beta}_1 \ln(GDP/P)_{it}\right) \tag{6}$$

I have not normalized the curves – the sum of the two curves is equal to average per capita emissions. The overall picture is similar to Vollebergh *et al*.'s Figure 4a. As they found, the time effect dominates change in emissions over time.

Table 2 presents the corresponding results for Vollebergh *et al*.'s carbon emissions data. The turning points are within sample for fixed and random effects models and mostly out of sample for the other estimators. For fixed and random effects the models with time effects have slightly lower turning points than those without. For the other estimators the reverse is true. The highest turning points are found for the OLS and first difference estimators with time effects ($57,505 and $51,334) and the maximum elasticity is 1.666 for the quadratic between model. The turning point for the between estimator is effectively zero and the regression suffers from multicollinearity, so I again also estimate a linear model for the between estimator. For all models, the majority of observations are on the rising limb of the EKC as shown by the positive mean income elasticities.

The two-way fixed effects estimate of the turning point is almost identical to that in Vollebergh *et al*. There is again little difference between the fixed and random effect estimates indicating that omitted variables bias is not likely to be problematic in this sample. For the one-way model the Hausman statistic is just 0.0035 (p=1.00) and for the two-way model 0.124 (p=0.940).

The coefficients on the time trends for OLS and first differences are negative but substantially smaller than the estimates reported above for sulfur. There is also much less variation around the mean of the income elasticities for all of the estimators compared to the estimates for sulfur.

The estimated mean income elasticity for the linear between model is 1.612 which is highly significantly different to zero (t = 6.322). It is also significantly greater than unity (t = 2.400). To test the effect of influential data I estimate the linear between model 24 times in each case eliminating one country from the data. Eliminating Luxembourg results in the lowest estimate of the elasticity (1.472) while the highest estimate results when Switzerland was eliminated (1.791). The standard deviation is just 0.059.

Figure 2, which was prepared in the same way as Figure 1, shows charts of the different estimates. The between estimates look plausible though the OLS ones seem to fit to the data better in a naïve sense but are close to the between estimates throughout the income range. The first differences curve is again flattest. Random effects and fixed effects do not differ very substantially from each other.

Figure 4 decomposes carbon emissions based on the linear between estimator. The picture differs from Figure 4b in Vollebergh *et al*. Those results show no net reduction in emissions due to the time effect over the sample period, though there is a reduction from the mid 1970s on. Still, the income effect in my results has increased carbon emissions by more than the time effect has reduced them. Given ongoing improvements in energy efficiency and increases in the share of energy coming from nuclear power and natural gas over this period, it is not unreasonable to expect an important time effect for carbon, albeit a smaller one than for sulfur.

Figures 5 and 6 present the residuals or time effects for twelve of the countries for the between estimates in Table 1 and 2. The residual can be interpreted as the level of technology or emissions efficiency in each country in each year. Figure 5 is comparable to Figure 2 in Stern (2005), which also shows the technology trends for sulfur emissions in some OECD countries. The differences are that the latter study controls for the input and output structure of the economy, the sample of countries is smaller, and the time series extend from only 1971 to 2000. The frontier of the most efficient countries is here made up of Turkey, Switzerland (neither of which are included in Stern (2005)) and Japan. The latter country was on the frontier for most of the period in Stern (2005). Australia and Turkey see a rise in emissions controlling for income, with Australia ending the period as the dirtiest country for its income level. Canada starts the period as the dirtiest. As found in Stern (2005), the countries end the period with the Germanic countries and Japan the cleanest and the Anglo-Saxon and Mediterranean countries the dirtiest with the exception of France. Compared to my prvious results (Stern, 2005) France is found to be relatively clean her, because Stern (2005) controls for nuclear power. It is clear that there is no particular relationship in the sample between income and efficiency. This explains why there is no significant difference between the random and fixed effects estimation.

Figure 6 shows that Switzerland has the lowest carbon emissions for its income level for every year in the sample. The UK starts the period with the highest income-adjusted carbon emissions and Australia ends it. Turkey sees rising income adjusted emissions. So here too there is no relationship between the individual effects and income. There is also less of a clear-cut relationship between cultural regions and the final level of income-adjusted emissions. The Anglo-Saxon countries are in the upper half of the distribution. But so is Germany.

Tables 3 and 4 present the regression results for the Wagner global sulfur and carbon datasets. For the sulfur data, first differences, fixed and random effects estimates are all rather similar with highly significant turning points in the $6,000-$9,000 range. The mean elasticities are all positive – as the sample mostly consists of developing economies this is not surprising. The OLS and between estimates show higher and less significant turning points and very similar elasticities close to unity. The between estimates quadratic term is significant at the 10% level and there is no multicollinearity issue evident but the turning point is insignificantly different from zero. The estimated income elasticity in the linear model is effectively the same as the mean for the quadratic model. The income elasticity may, therefore, be larger in this global sample than in the OECD sample though probably not significantly so. Wagner's defactored estimates for sulfur have positive coefficients for both the linear and quadratic income terms with a significant quadratic coefficient in five of the six models estimated. My between estimates do not support such a convex monotonic shape for the EKC but they do not support the traditional inverted-U either.

The Hausman test comparing the random and fixed effects models with no time effects has a p-value of 0.85. For the models with time effects the p-value is 0.065. The latter test suggests that correlation between the individual effects and the regressors could be an issue but not a very significant one as we see from the relatively small difference between the regression coefficients and turning points for the two models. Applying the robustness test to the linear between model results in income elasticities ranging from 1.036 (Nepal dropped) to 1.1195 (Zaire). The standard deviation is only 0.011, which shows the estimate is robust to the dropping of most countries.

For carbon (Table 4) only random and fixed effects with time effects show in sample turning points. The turning points for OLS, first differences, and between estimates are all insignificantly different from zero. The between estimate of the income elasticity of 1.509 is similar to that found for the OECD sample (Table 2). Again, Wagner (2008) finds a convex monotonic EKC for carbon for all his six models. This is not supported by my results, but the linear EKC model cannot be rejected in favor of an inverted U-curve either. The Hausman statistics have p-values of 0.95 and 0.72 for the models without and with time effects respectively. The robustness test for the linear between estimator results in elasticities ranging from 1.549 (Mongolia dropped) to 1.4765 (Nepal dropped) with a standard deviation of 0.0077. These tests suggest that the estimates are robust. In order to save space and because Wagner (2008) does not have any comparable charts I do not present any charts for the Wagner data sets. As we see that these global between estimates are similar to the OECD estimates in Tables 1 and 2 the analogs of Figures 1 to 6 would not add too much value.

5. Discussion and Conclusions

Theory suggests that the between estimator is likely to perform well as an estimator of long-run relationships unless the correlation between the individual effects and the regressors in the panel data model outweighs other sources of estimation bias. Theory and Monte Carlo experiments predict that under a range of assumptions elasticities estimated using the between estimator will be greater in absolute value. The between estimator gave higher estimates of the emissions elasticity with respect to income than other estimators for the two samples of OECD data. For sulfur, however, the results shown in Figure 3 seem reasonably similar to Vollebergh *et al*.'s results. In contrast to most past research, I found quite a large time effect for carbon in the OECD sample, but it is smaller than the effect for sulfur and increasing energy efficiency and fuel switching could explain this effect even in the absence of strict climate policies in most countries. Results for a global panel of 100 countries over 50 years also support the linear EKC model when using the between estimator with similar results from OLS estimates in this larger more representative sample. The sulfur income elasticity may be somewhat higher in the global sample than in the OECD sample but the carbon elasticity was similar in both samples. Regression using defactored observations finds that the coefficients for both the level and square of log income are significantly positive (Wagner, 2008) and likely results in a similarly high income elasticity. However, the estimates in this paper do not support a convex down relationship between emissions and income. My results, alongside those of Vollebergh *et al*. (2009), Wagner (2008), Stern and Common (2001) and others, show that lower estimates of turning points and income elasticities in the EKC literature are largely the result of biased estimates.

The between estimator is very simple to implement compared to either Vollebergh *et al*.'s approach, a structural time series approach (Stern, 2005, 2007) or a de-factored regression (Wagner, 2008) but gives somewhat similar results. None of these methods supports the traditional inverted-U shaped EKC. The estimated time effects in this paper presumably include both a permanent time effect and a transitory component. Future research could decompose the time effect into transitory and permanent components using structural time series models or non-probabilistic filters such as the Hodrick and Prescott (1997) filter. Also, as explained in the introduction the simple version of the between estimator imposes a fairly strong constraint on the nature of the country effects as the price of imposing no restrictions on the time effects. As mentioned there, more complex models such as stochastic frontier models could allow more flexibility.

Of course, the models in this paper leave more unexplained than they explain. I am not advocating the simple emissions-income model as an adequate model of emissions. However, the between estimator can provide a consistent estimate of the income-emissions elasticity. This is most important as a guide to the likely evolution of business as usual emissions of sulfur, carbon, and other pollutants. This study, together with Vollebergh *et al.* (2009) and Wagner (2008) show that as presaged by Stern and Common (2001) the common assumption that increased income results in reduced emissions is incorrect even for sulfur. Rather, reductions in emissions are time related or possibly related to other time varying variables.

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Table 1: Vollebergh et al. Sulfur Data

	Constant	ln(GDP/P)	$\ln(GDP/P)^2$	Time Trend	R^2 (adjusted)	Turning Point	Elasticity
OLS	-141.208	32.977	-1.793		0.272	9809.335	-0.754
	(23.165)	(5.198)	(0.290)			(573.342)	(1.567)
OLS with Time Trend	-111.706	25.859	-1.371	-0.036	0.389	12417.886	0.069
	(24.955)	(5.673)	(0.321)	(0.008)		(1995.649)	(1.198)
First Differences		16.409	-0.888		0.021	10246.47	-0.296
		(2.191)	(0.118)			(675.251)	(0.776)
First Differences with Time Trend		14.557	-0.738	-0.048	0.078	19007.94	0.666
		(2.138)	(0.116)	(0.006)		(3006.541)	(0.645)
Fixed Effects		32.939	-1.823		0.803	8351.104	-1.354
		(1.044)	(0.056)			(111.505)	(1.594)
Fixed Effects with Time Effects		28.011	-1.499		0.821	11407.293	-0.178
		(1.120)	(0.062)			(515.918)	(1.310)
Random Effects	-138.418	32.976	-1.825			8372.405	-1.346
	(4.832)	(1.042)	(0.056)			(110.769)	(1.595)
Random Effects with Time Effects	-122.461	28.754	-1.557			10213.833	-0.529
	(5.069)	(1.105)	(0.060)			(346.063)	(1.361)
Between Estimates Quadratic	-64.531	15.536	-0.808		0.068	14890.973	0.334
	(87.752)	(19.211)	(1.048)			(9545.615)	(0.706)
Between Estimates Linear	3.037	0.732			0.086		
	(3.870)	(0.411)					

Standard errors are in parentheses. The mean value of the elasticity is given but the standard error is the regular standard deviation not the standard error of the mean.

Table 2: Vollebergh et al. Carbon Data

	Constant	ln(GDP/P)	$ln(GDP/P)^2$	Time Trend	R^2 (adjusted)	Turning Point	Elasticity
OLS	-59.231	13.403	-0.667		0.568	22949.923	0.853
	(10.617)	(2.369)	(0.132)			(5422.287)	(0.583)
OLS with Time Trend	-42.335	9.326	-0.425	-0.021	0.633	57504.708	1.326
	(12.995)	(3.027)	(0.175)	(0.008)		(56622.970)	(0.371)
First Differences		5.934	-0.28		0.188	39128.776	0.658
		(0.852)	(0.046)			(9353.152)	(0.245)
First Differences with Time Trend		5.732	-0.264	-0.005	0.191	51334.001	0.763
		(0.856)	(0.046)	(0.002)		(16823.577)	(0.230)
Fixed Effects		13.799	-0.711		0.954	16278.272	0.421
		(0.383)	(0.020)			(264.012)	(0.621)
Fixed Effects with Time Effects		13.943	-0.727		0.956	14425.861	0.255
		(0.420)	(0.023)			(550.354)	(0.636)
Random Effects	-59.095	13.806	-0.711			16297.252	0.423
	(1.777)	(0.382)	(0.020)			(264.263)	(0.622)
Random Effects with Time Effects	-58.735	13.769	-0.711			15849.711	0.383
	(1.875)	(0.405)	(0.022)			(396.067)	(0.622)
Between Estimates Quadratic	1.74	-0.411	0.11		0.611	6.442	1.666
	(55.161)	(12.076)	(0.659)			(280.378)	(0.096)
Between Estimates Linear	-7.497	1.612			0.628		
	(2.400)	(0.255)					

Standard errors are in parentheses. The mean value of the elasticity is given but the standard error is the regular standard deviation not the standard error of the mean.

Table 3: Wagner Sulfur Data

	Constant	ln(GDP/P)	ln(GDP/P)^2	Time Trend	R^2 (adjusted)	Turning Point	Elasticity
OLS	-24.777	5.669	-0.288		0.384	18643.034	1.025
	(6.211)	(1.509)	(0.090)			(9322.573)	(0.579)
OLS with Time Trend	-24.479	5.572	-0.28	-0.005	0.387	20283.208	1.046
	(6.234)	(1.512)	(0.090)	(0.003)		(10914.660)	(0.564)
First Differences		3.242	-0.179		0.009	8419.719	0.352
		(0.657)	(0.041)			(2970.890)	(0.360)
First Differences with Time Trend		3.319	-0.185	0.004	0.009	7532.312	0.324
		(0.662)	(0.042)	(0.004)		(2556.810)	(0.373)
Fixed Effects		6.879	-0.383		0.777	7891.06	0.704
		(0.287)	(0.017)			(393.860)	(0.770)
Fixed Effects with Time Effects		6.217	-0.353		0.780	6521.895	0.515
		(0.293)	(0.017)			(410.896)	(0.711)
Random Effects	-28.379	6.889	-0.382			8115.073	0.724
	(1.175)	(0.284)	(0.017)			(406.769)	(0.769)
Random Effects with Time Effects	-26.477	6.499	-0.363			7565.021	0.637
	(1.196)	(0.287)	(0.017)			(433.156)	(0.731)
Between Estimates Quadratic	-20.256	4.469	-0.21		0.470	41445.06	1.083
	(8.155)	(2.036)	(0.125)			(63939.035)	(0.422)
Between Estimates Linear	-6.702	1.067			0.460		
	(0.952)	(0.117)					

Standard errors are in parentheses. The mean value of the elasticity is given but the standard error is the regular standard deviation not the standard error of the mean.

Table 4: Wagner Carbon Data

	Constant	ln(GDP/P)	$\ln(GDP/P)^2$	Time Trend	R^2 (adjusted)	Turning Point	Elasticity
OLS	-18.138	4.536	-0.189		0.757	154048	1.477
	(4.080)	(0.987)	(0.058)			(172844)	(0.381)
OLS with Time Trend	-18.375	4.613	-0.195	0.004	0.758	131697	1.461
	(4.133)	(1.001)	(0.059)	(0.002)		(140715)	(0.393)
First Differences		0.101	0.037		0.019	0.258	0.705
		(0.379)	(0.024)			(1.533)	(0.075)
First Differences with Time Trend		0.447	0.008	0.02	0.029	0	0.581
		(0.380)	(0.024)	(0.002)		(0.000)	(0.016)
Fixed Effects		5.161	-0.242		0.936	41678	1.253
		(0.154)	(0.009)			(4043)	(0.487)
Fixed Effects with Time Effects		4.432	-0.229		0.949	15837	0.74
		(0.141)	(0.008)			(1060)	(0.460)
Random Effects	-19.774	5.171	-0.242			42470	1.262
	(0.634)	(0.153)	(0.009)			(4127)	(0.487)
Random Effects with Time Effects	-15.142	4.498	-0.23			17144	0.781
	(0.596)	(0.140)	(0.008)			(1169)	(0.463)
Between Estimates Quadratic	-15.42	3.809	-0.142		0.791	653110	1.517
	(5.524)	(1.381)	(0.085)			(2084513)	(0.286)
Between Estimates Linear	-6.265	1.509			0.788		
	(0.636)	(0.078)					

Standard errors are in parentheses. The mean value of the elasticity is given but the standard error is the regular standard deviation not the standard error of the mean.

Figure Captions:

Figure 1. Vollebergh et al. Sulfur Data

Figure 2. Vollebergh et al. Carbon Data

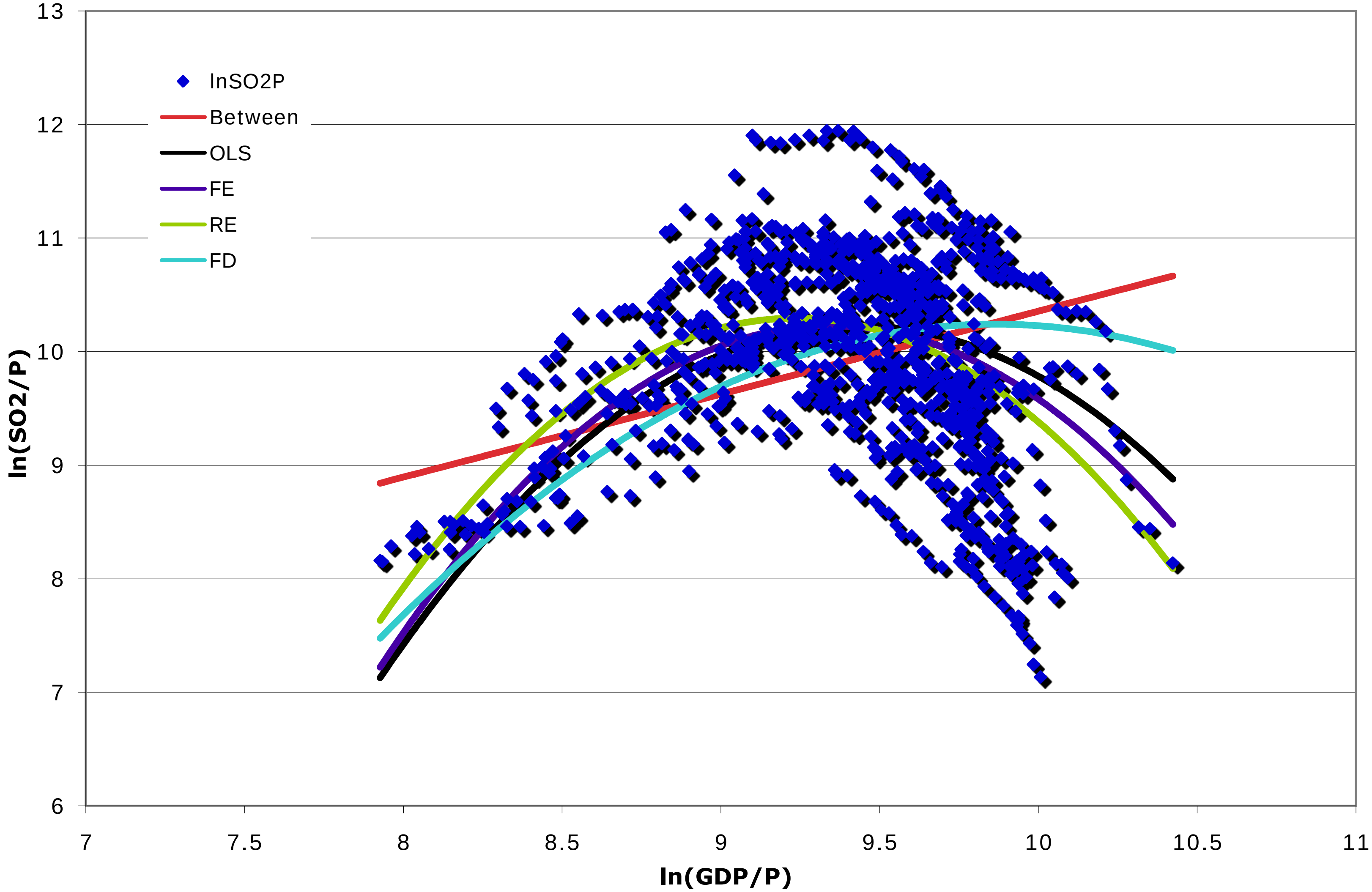
Figure 3. Income and Time Effects: Between Estimator, Vollebergh et al. Sulfur Data

Figure 4. Income and Time Effects: Between Estimator, Vollebergh et al. Carbon Data

Figure 5. Country Time Effects: Between Estimator, Vollebergh et al. Sulfur Data

Figure 6. Country Time Effects: Between Estimator, Vollebergh et al. Carbon Data

Figure(s)



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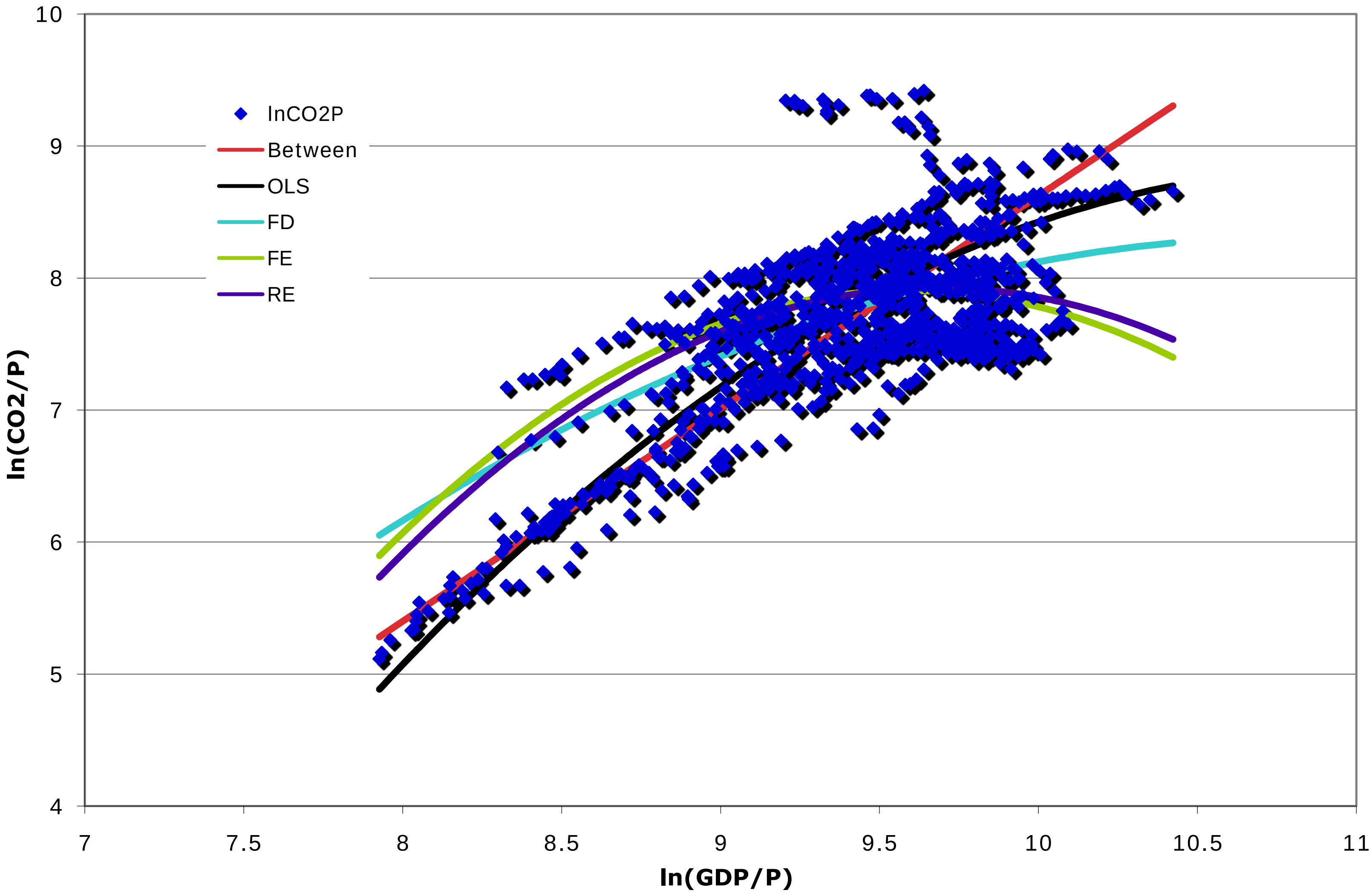
Figure(s)



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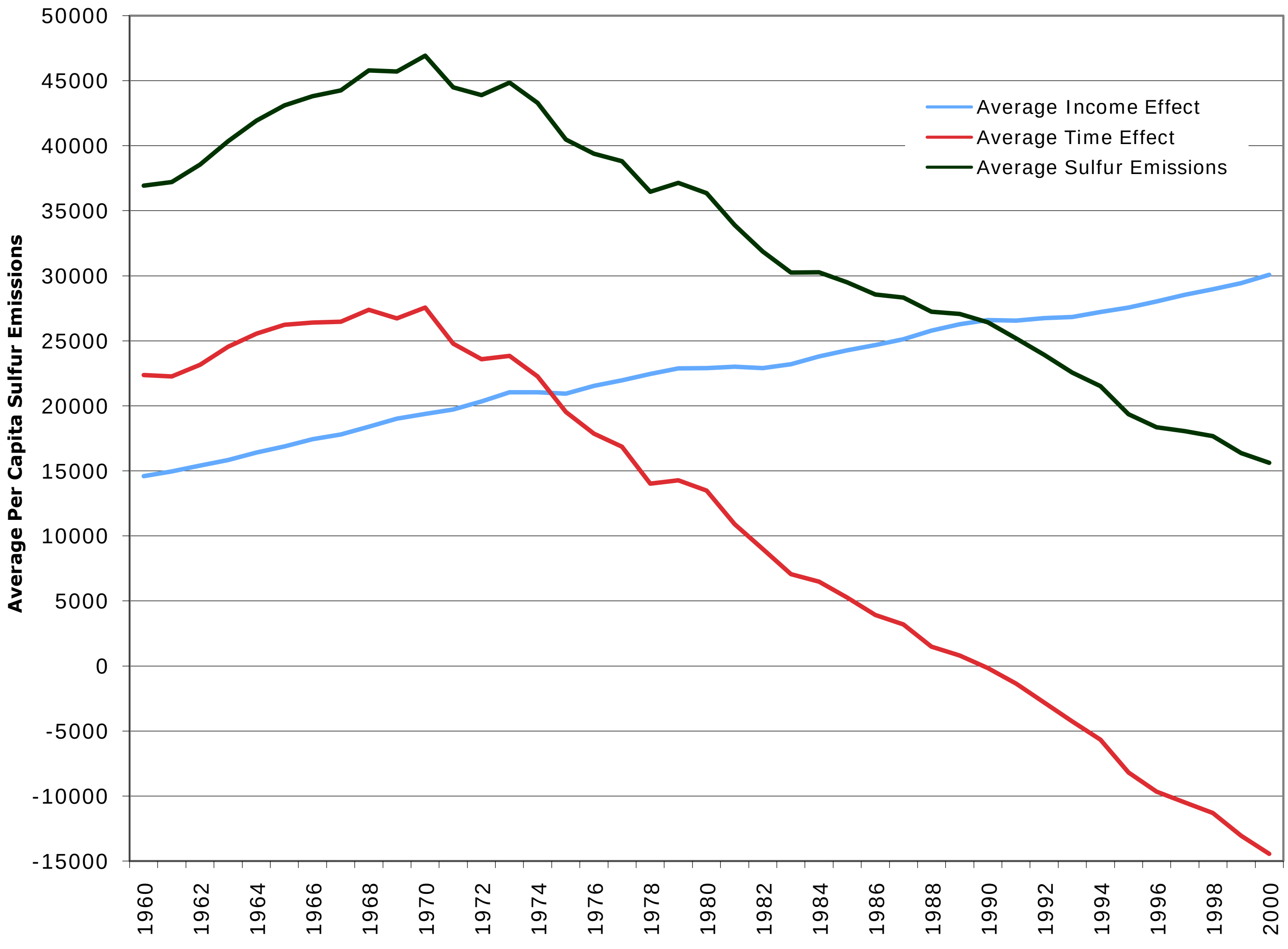
ln(CO2/P)
ln(GDP/P)

Figure(s)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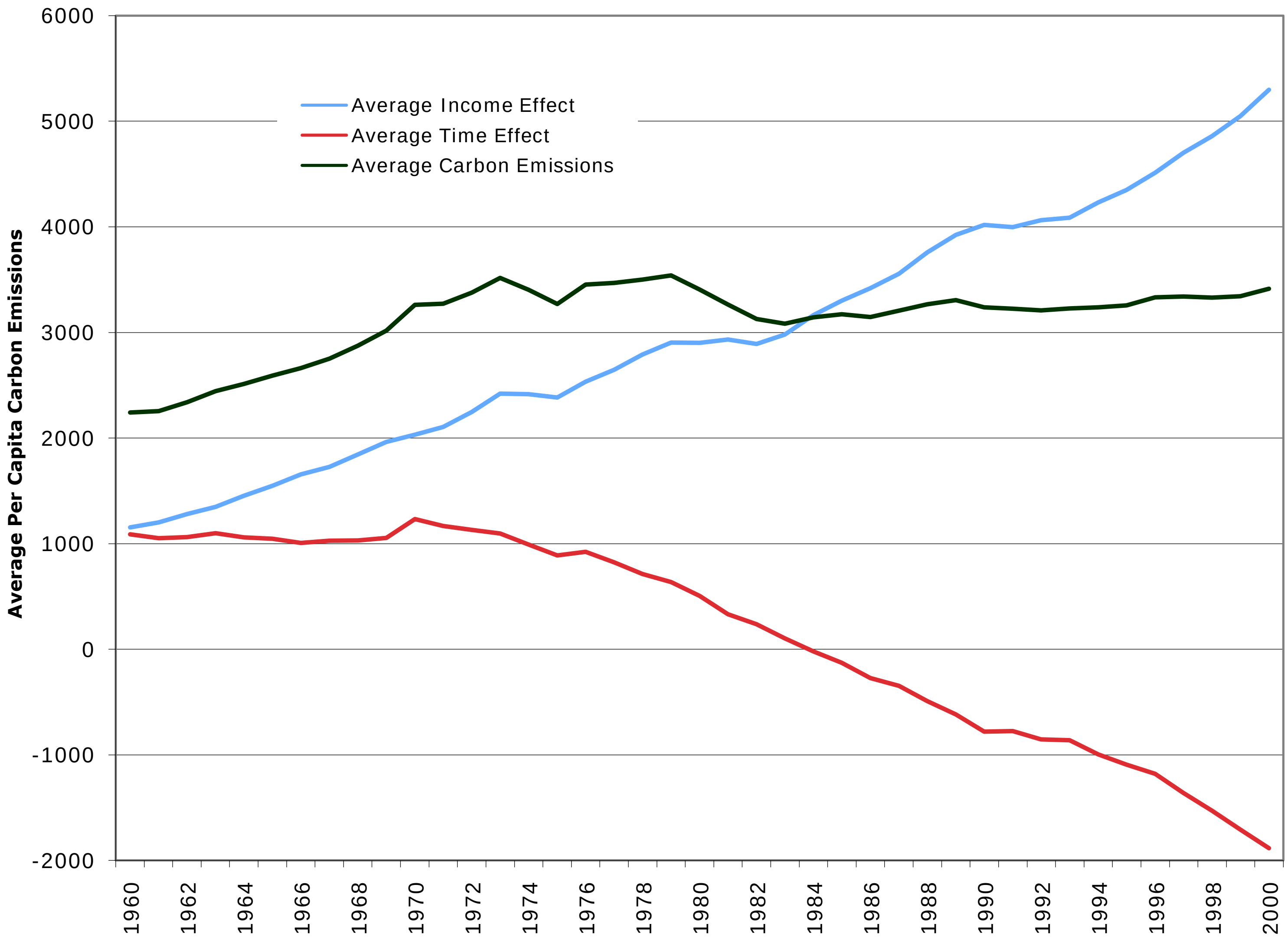
Average Sulfur Emissions

Figure(s)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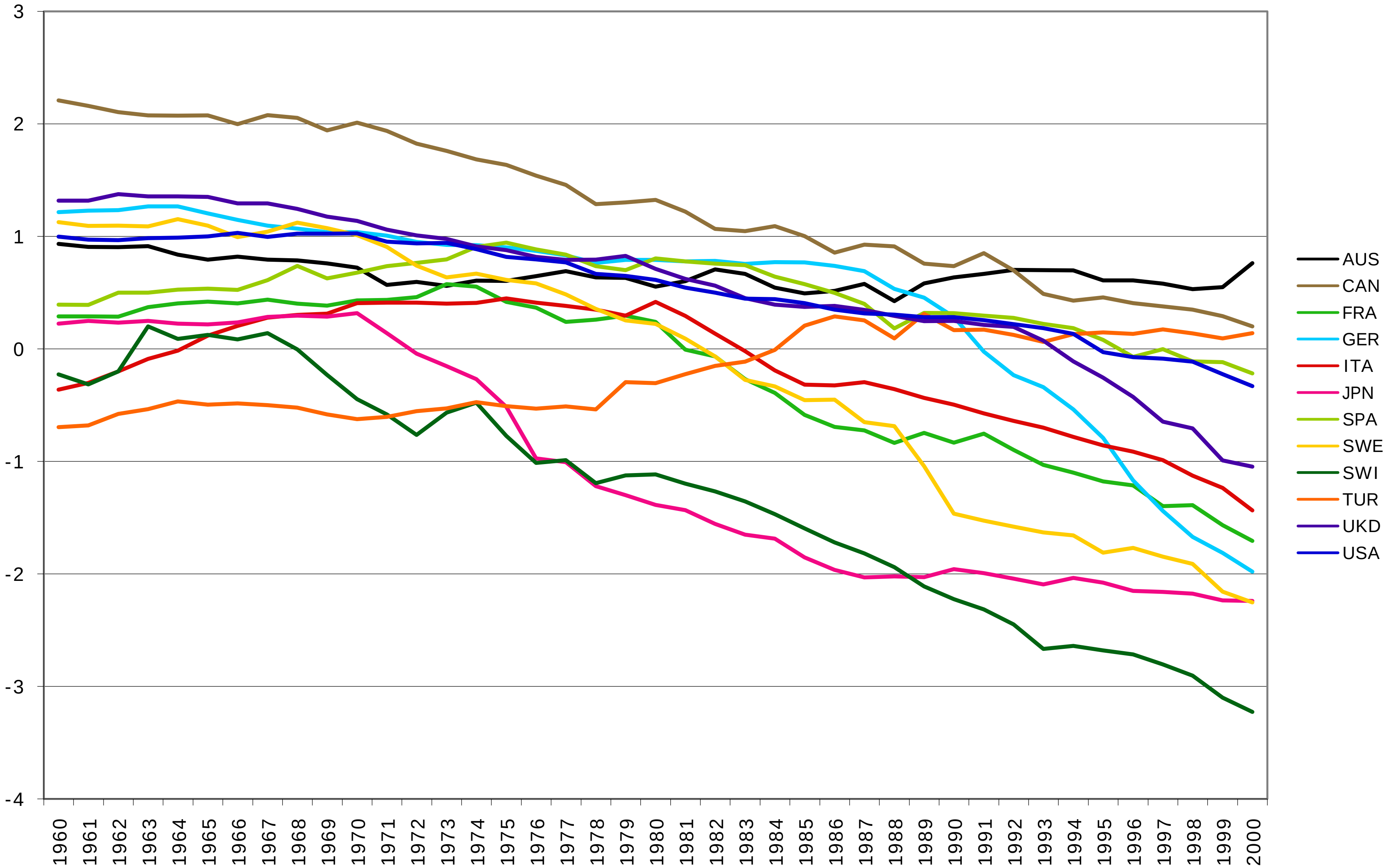
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UKD
USA

Figure(s)

Figure 7. Carbon Time Effects