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Environmental Kuznets Curves for CO_2: Heterogeneity versus Homogeneity

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Abstract

We explore the emissions–income relationship for CO_2 in OECD countries using various modelling strategies. Even for this relatively homogeneous sample, we find that the inverted-U-shaped curve is quite sensitive to the degree of heterogeneity included in the panel estimations. This finding is robust, not only across different model specifications but also across estimation techniques, including the more flexible non-parametric approach. Differences in restrictions applied in panel estimations are therefore responsible for the widely divergent findings for an inverted-U shape for CO_2. Our findings suggest that allowing for enough heterogeneity is essential to prevent spurious correlation from reduced-form panel estimations. Moreover, this inverted U for CO_2 is likely to exist for many, but not for all, countries.

Keywords: Environmental Kuznets Curves, (Semi)parametric Estimation, Heterogeneity.
JEL Code: C 33; O 50; Q 50

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1. Introduction

The typical empirical approach towards estimating the inverted-U-shaped relationship between economic growth and the environment, the so-called Environmental Kuznets Curve (EKC), has been based on the assumption of homogeneity: the same shaped EKC applies to all countries or regions involved. It is commonly assumed that *every* cross-sectional unit reacts similarly to shifts in the income parameters, even if the cross-sections are allowed to differ in their intercepts. Recently, Brock and Taylor (2004) cast doubt on this homogeneity assumption on both theoretical and empirical grounds.[1] They argue that income–emissions profiles are likely to vary across countries if countries differ in initial conditions or in structural parameters such as savings, technological change (in abatement) and population growth rates. Such divergences across countries (over time) would not be adequately captured by country- and time-specific fixed effects in an econometric modelling environment based on the homogeneity assumption. Therefore, Brock and Taylor (2004) claim that it is hardly surprising that the EKC literature has so many difficulties in demonstrating this relationship.

The literature on inverted-U-shaped patterns for CO_2 emissions is a case in point. Using the traditional parametric panel data approach with region-specific and time effects, Shafik (1994) and Holtz-Eakin and Selden (1995) report a turning point, though far out of sample ($7 million per capita). Schmalensee et al. (1998) introduce a much more flexible spline-based estimation technique (allowing for both region-specific and time effects) and report clear evidence of a *within*-sample turning point with negative income-elasticities for the highest income segment. However, with the even more flexible non-parametric panel data approach, Azomahou et al. (2001) claim that the inverted-U shape would no longer

[1] Seminal theoretical contributions to the EKC literature, such as Stokey (1998) and Andreoni and Levinson (2001), primarily focus on models of ‘representative economies’ that replicate the inverted-U-shaped relationship for all countries from the start.

hold in the CO_2 case. In their sample, the countries at the highest income levels do not reach a phase of declining per-capita emissions, which challenges the idea that countries become automatically cleaner if they reach higher income levels. Moreover, they confirm the finding of Millimet et al. (2003) that non-parametric estimation rejects the traditional parametric approach. Interestingly, Azomahou et al. (2001) do not include region- and time-specific effects, based on the rejection of a poolability test proposed by Baltagi et al. (1996).

Accordingly, much confusion exists as to whether CO_2 emissions follow an inverted U or not. The homogeneity assumption, however, has been questioned only in a few papers so far. List and Gallet (1999) demonstrate that parametric estimations for NO_x and SO_2 emissions in the USA including region- and time-specific effects do not satisfy the homogeneity assumption, although without any consequence for their basic findings on the existence of an EKC. Dijkgraaf and Vollebergh (2005) report similar estimation problems for CO_2 emissions using various parametric panel data specifications as well as the spline technique applied by Schmalensee et al. (1998). Martinez-Zarzoso and Bengochea-Morancho (2004) confirm these problems, applying the pooled mean group estimator as proposed by Pesaran et al. (1999) while assuming a cointegrated relationship between CO_2 emissions and GDP per capita. Finally, Millimet et al. (2003) report sensitivity of their semi-parametric panel data results for the homogeneity assumption, particularlyfor the case of SO_2 emissions.

These papers illustrate that heterogeneity is indeed an important issue when investigating the EKC. However, they only go as far as a linear time trend, and typically do not allow for more general (heterogeneous) time effects. In particular, full heterogeneity is not yet combined with a non-parametric approach.[2] This paper demonstrates the importance of estimating the EKC relationship for CO_2 by – at the same time – allowing for heterogeneity across regions, flexible (non-parametric) functional forms *and* general time effects. For this purpose, we use a panel for CO_2 emissions in 24 OECD countries between 1960 and 2000.

Our results are striking. First of all, we more-or-less confirm the highly different findings in the existing literature and their dependence on the estimation technique applied. However, the non-parametric results are highly sensitive to the inclusion of one country in particular, namely Luxemburg. This finding already suggests that the homogeneity assumption commonly applied in panel data estimations is not innocent. Indeed, further testing of parametric specifications as well as the non-parametric specification based on the partial linear regression (PLR) estimator following Robinson (1988) or Stock (1989) and applied by Millimet et al. (2003) confirms the importance of allowing for enough heterogeneity across countries. Unfortunately, it is not possible to apply this PLR estimator with a general time effect while allowing for heterogeneity across countries. The time effect has to be restricted to a parametric form, and, consequently, the heterogeneous PLR model does not nest the homogeneous PLR model.

Therefore, we take a different approach and propose to apply a pairwise estimation of comparable countries. Taking differences between comparable countries eliminates the time effect, and taking differences between comparable countries only requires the time effect to be the same for these comparable countries. After differencing, the country-specific regression curves can be estimated non-parametrically by applying, for example, Linton and Nielsen (1995). This procedure allows us to extend the homogeneous non-

[2] Only Dijkgraaf and Vollebergh (2005) and Martinez-Zarzoso and Bengochea-Morancho (2004) allow for linear heterogeneous time trends. However, their analyses are restricted to parametric estimations.

parametric approach with a (common) general time effect to a heterogeneous non-parametric approach allowing for general time effects, which only have to be the same for comparable countries. Applying this pairwise approach yields clear evidence for an EKC for CO_2 emissions. For many of the highest-income countries, we find support for an EKC pattern. Moreover, this finding is robust across different estimation techniques, in particular for both parametric and non-parametric estimation. Accordingly, our results yield strong support for the claim of Brock and Taylor (2004) that allowing for enough heterogeneity is essential to understanding the EKC.

The remainder of the paper is organized as follows. Section 2 describes our data-set and briefly discusses the econometric model specifications. Section 3 shows that applying commonly used estimation techniques to our data-set reproduces the mixed picture for the existence of an EKC found in the literature. Section 4 explores in detail the role of heterogeneity using both parametric and more flexible estimation techniques. Section 5 concludes.

2. Empirical strategy

2.1 Data

Our results are based on the same national-level data-set for the 24 countries with the longest membership of the OECD countries as employed by Dijkgraaf and Vollebergh (2005) with an extension of the most recent data to 2000. Thus, we concentrate exclusively on the subsample of traditional OECD countries between 1960 and 2000, which alone is responsible for 50% of overall world CO_2 emissions in 2000. The data included are the following:

C = CO_2 emissions from energy consumption, millions of metric tons of carbon

Y = GDP, millions of 1990 US dollars

N = population

E = energy consumption, million tons of oil equivalent (TOE).

Data on C are calculated from E using OECD (2000) and IEA/OECD (1991). To calculate CO_2 emissions, we use data for total primary energy supply (TPES) per fuel, corrected for non-energy use of fuels such as chemical feedstocks. The fuels incorporated in the calculations are coal, other solid fuels (for example, wood), crude oil, petroleum products and natural gas. Total energy use and emissions per country are corrected for exports and imports of fuels, as well as for stock changes and international marine bunkers.[3] Data on Y and N were taken from the OECD (2000). All figures are expressed in 1990 dollars, using purchasing power parities. Time coverage of these data is considerably more recent than that of the widely used Penn World Table, which has figures only up to 1992. The data on Germany require some additional attention due to the country's unification in 1991. The OECD has reconstructed data on Y for Germany as a whole (including the former GDR) for the years between 1970 and 1989. We further extrapolated GDP figures backward to 1960 using adjusted GDP levels for West Germany with the number of inhabitants of East Germany.

Table 1 shows some descriptive statistics. [INSERT TABLE 1] Our overall data-set contains 984 observations for all variables, and for each country we have 41 observations available. Given the importance of Luxemburg for our results, we also provide descriptive statistics for the subsample without this country. Indeed, from the scatter plot in Figure 1, the peculiar pattern of the data for Luxemburg becomes immediately clear. Not only does the country dominate the upper tail of the income distribution, but it also follows an

[3] Our procedure for calculating CO_2 emissions from OECD energy consumption data is similar to the approach followed by the Oak Ridge National Laboratory (ORNL), whose data are usually included in empirical research on CO_2 emissions (see, in particular, Holtz-Eakin and Selden (1995) and Schmalensee et al. (1998)).

atypical pattern, with declining emissions per capita over the whole range of observations. [INSERT FIGURE 1]

Finally, note that our findings are based on a subset of the countries that are usually analysed in the case of CO_2 emissions. Our panel, however, is particularly useful for a study of the homogeneity versus heterogeneity assumption at the country level because there is a wide overlap of observations on different countries at similar income levels. Moreover, the range of observations is long enough to test for each country whether its slope coefficients are sufficiently close to allow for panel-based estimations of an EKC for CO_2.[4] If a problem arises for this (high-income) subsample of OECD countries, one might expect the homogeneity assumption to be even more problematic for samples including both OECD and non-OECD countries. In addition, this panel also includes data on CO_2 emissions covering the 1990s and is by far the most reliable source of information on these emissions compared with non-OECD sources and non-energy-related CO_2 emissions.

To investigate whether unit roots might be present, we applied the IPS test for unit roots in heterogeneous panels, as proposed by Im, Pesaran and Shin (2003). In the case of GDP per capita, we rejected the hypothesis of unit roots, while in the case of CO_2 emissions, we rejected the presence of unit roots, when allowing for linear time trends. On the basis of these results, we shall restrict attention to static relationships between CO_2 emissions and GDP, but with time-specific effects.

2.2 Econometric approach

In its most general form, we consider the specification

$$c = h(y, r, t) + e, \qquad E[e| \, y, r, t] = 0 \qquad (1)$$

[4] Potential problems with unit roots are eliminated by using a deterministic trend. The findings of Lanne and Liski (2003) support our assumption that it is rather unlikely that we are missing a structural break for the limited period spanned by our data.

with c = log (C/N) and y = log (Y/N), C being CO_2 emissions from energy consumption, Y the GDP level and N population size, and with the controls r and t referring to country (or region) r and year t, respectively. Note that the control r reflects persistent country-specific differences, such as fossil-fuel availability and prices, regulatory differences and preferences, and that the control t picks up changes over time, such as changing prices or technologies. To start with, the function h is left unspecified. However, without further restrictions, this function is not identified, since for each (r,t) combination, only one (c,y) observation is available.

Homogeneity

In the traditional, homogeneous approach, one imposes a structure like the following:

$$h(y,r,t) = g(y,b) + \sum_r a_r dr_r + \sum_t l_t dt_t \tag{2}$$

with $b = (b_0, b_1, b_2, b_3)'$ such that

$$g(y,b) = b_0 + b_1 y + b_2 y^2 + b_3 y^3 \tag{3}$$

with dr_r being a dummy for country/region r and dt_t a dummy for year t. This model can be estimated using standard panel data techniques (after imposing appropriate distributional assumptions) and the typical EKC pattern follows from $\partial g(y,b)/\partial y$ first being positive and then, after the turning point (if present), becoming negative. This traditional approach is quite restrictive because it is typically assumed that *every* cross-sectional unit reacts similarly to shifts in the income parameters, even if the units are allowed to differ in their intercepts. This homogeneity assumption also characterizes more flexible estimation techniques applied in the literature, such as the spline method used by Schmalensee et al.

(1998) and the semi-parametric methods used by Galeotti and Lanza (1999) and Millimet et al. (2003).[5] These semi-parametric alternatives estimate a version of

$$h(y,r,t) = g(y) + \sum_r a_r dr_r + \sum_t l_t dt_t \tag{4}$$

with $g(.)$ left unspecified. This model has been estimated following Robinson (1988) or Stock (1989), as, for example, in the analysis of Millimet et al. (2003), who apply the semi-parametric partially linear regression (PLR) model.[6]

Heterogeneity

In the homogeneous framework, only country-specific heterogeneity intercepts are allowed, not heterogeneous slope parameters, i.e. $g(y)$ in (4) is postulated not to depend on r (except for its level). To allow for heterogeneity in the case of equation (2), one can consider the following generalization of (4):

$$h(y,\ r,\ t) = g(y,\ b_r) + \sum_r a_r dr_r + \sum_t l_t dt_t \tag{5}$$

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[5] Note, however, that Millimet et al. (2003) also relaxed this assumption by estimating the PLR model separately for each state. However, this precludes general time effects.

[6] In the case of PLR, the estimation procedure consists of three rounds. In the first round, one estimates $E(c|y)$, $E(dr_r|y)$ and $E(dt_t|y)$. In the second round, one estimates the region- and time-specific effects in

$$c - E(c|y) = \sum_r a_r (dr_r - E(dr_r|y)) + \sum_t l_t (dt_t - E(dt_t|y)) + error$$

(using $E(g(y)|y) = g(y)$, and the estimated conditional expectations from the first round). In the final round, one can estimate $g(y)$ non-parametrically from

$$c - \sum_r a_r (dr_r) - \sum_t l_t (dt_t) = g(y) + error$$

(using the estimated region- and time-specific effects from the second round). Notice, however, that in the current application, the number of parameters in the linear regression part (the region- and time-specific effects) increases with the sample size. This is not entirely according to Robinson (1988) or Stock (1989), who both assumed that the number of parameters in the linear regression part is fixed. The reason why the estimation procedure still might work is the use of panel data: in the first round, $E(dr_r|y)$ can be estimated consistently using the increasing number of time periods, while $E(dt_t|y)$ can be estimated consistently using the increasing number of regions.

and test the null hypothesis $b_r = b$; compare, for example, Dijkgraaf and Vollebergh (2005). This generalization also applies to the spline specifications.

Note, however, that in the case of equation (5), rejection of the null hypothesis $b_r = b$ might also indicate model misspecification, and, thus, does not necessarily imply non-homogeneity.[7] So, to proceed, it makes sense to consider

$$h(y,r,t) = f(y,r) + \sum_t l_t dt_t \tag{6}$$

with $f(.,.)$ left unspecified, and to test $f(y,r) = g(y)$. Specification (6) fits in the Robinson (1988) and Stock (1989) PLR framework, but there is one difficulty. In order to apply Robinson (1988) or Stock (1989), one now has to estimate in a first round

$$E[dt_t | y,r] = 0 . \tag{7}$$

But for a given country/region r, the dummy variable dt_t is always zero, except for one observation, namely year t, implying that there is not enough variation in the data to estimate (7).[8] As a consequence, non-parametric testing for homogeneity does not seem to be possible if the starting point is specification (4) as employed by, for instance, Millimet et al. (2003). The problem is lack of identification. Indeed, consider

$$h(y,r,t) = f(y,r) + G(t) \tag{8}$$

for some function $G(t)$. It is easy to see that estimating according to the Robinson/Stock PLR framework actually allows $G(t)$ to depend on r as well, i.e. one actually allows for the more general possibility $G(t,r)$ instead of just $G(t)$. But with $G(t,r)$ left unspecified, $f(y,r)$ is clearly not identified, since $G(t,r)$ can be chosen to fit the time path of per-capita emissions c of region r exactly. Only by restricting $G(t,r)$ to some parametric form, i.e. restricting the

[7] This can easily be illustrated by considering the case of two countries whose y-values do not overlap (e.g. Luxemburg and Turkey). In the case of rejection of $b_{Luxemburg} = b_{Turkey}$, homogeneity might still be present.

[8] Compare footnote 6: one cannot use the increasing number of regions any more to estimate the conditional expectation $E[dt_t | y,r] = 0$ consistently.

degrees of freedom of $G(t,r)$ to some finite number, does it become possible to identify $f(y,r)$. A typical choice would be to restrict $G(t,r)$ to a linear time trend, as Millimet et al. (2003) actually do, or to allow for higher-order terms, such as $G(t,r) = l_{r,1} \times t + l_{r,2} \times t^2 + \ldots$, etc.

However, this yields heterogeneous specifications not nesting the homogeneous variants. Moreover, the identification of $f(y,r)$ strongly depends upon the imposed parametric structure of $G(t,r)$, which is clearly undesirable. Our solution for constructing a heterogeneous extension of the homogeneous semi-parametric specification (4), without imposing any restrictions on $G(t)$ in (8), is to consider taking the difference between countries r and s at some given time t, yielding

$$c_r - c_s = f(y_r, r) - f(y_s, s) + (e_r - e_s). \quad (9)$$

The unknown regression functions $f(y_r, r)$ and $f(y_s, s)$ can be estimated by applying, for example, Linton and Nielsen (1995), imposing their regularity conditions and distributional assumptions.

Notice that this approach can easily be generalized to allow for country-specific time trends. Indeed, consider

$$h(y,r,t) = f(y,r) + G(t,r). \quad (10)$$

Again, take the difference in the function h for countries r and s at some given time t:

$$c_r - c_s = f(y_r, r) - f(y_s, s) + G(t, r) - G(t, s). \quad (11)$$

Assuming now that $G(t,r) = G(t,s)$ (for two closely related regions r and s),[9] the time effect again drops out. To compare the non-parametric specification (9) with parametric analogues, we also use parametric specifications of $h(.)$ – such as equation (3) – in order to

[9] Note that this specification implicitly accounts for potential endogeneity if the time trend captures technological change which – in turn – depends on (the level of) emissions and income (i.e. if both $c = h(y, t)$ and $t = g(e, y)$, the reduced-form estimation would typically simplify to $e = ßy$).

obtain more accuracy in our estimations of country-specific EKC patterns and possible turning points. Note that this procedure is the ultimate reduced-form estimation of the inverted-U curve, because identifying the inverted-U relation for income and emissions no longer depends on the effects of the time variables. For a pair of countries *r* and *s* with $G(t) = G(t,r) = G(t,s)$, the time effect $G(t)$ can be estimated parametrically or non-parametrically from

$$\begin{aligned} c_r - \ f(y_r, r) &= G(t) + error \\ c_s - \ f(y_s, s) &= G(t) + error \end{aligned} \tag{12}$$

using the estimated functions *f* on the left-hand sides. In this way, each pair of comparable countries will have its own time effect.

Finally, we normalize the levels of the estimated curves such that the average levels equal the sample average, since in the semi-parametric specifications the level of the curves is not identified.

3. Empirical results based on the homogeneity assumption

In this section, we reproduce earlier estimations in the literature based on the homogeneity assumption as our benchmark. Table 2 summarizes our main findings for the (pooled) parametric (log-linear) cubic specification. [INSERT TABLE 2] The response coefficients for income in the cubic specification with both time- and country-specific fixed effects are significantly different from zero at the $p<0.01$ levels. Interestingly, our results present a much more optimistic picture of an EKC pattern for CO_2 emissions than earlier results based on polynomial specifications reported by Shafik (1994) and Holtz-Eakin and Selden (1995). We find a *within*-sample turning point (TP) at $14,355, which is at 43% of the maximum panel observation. Additionally, the income coefficients are jointly significant in at $p<0.01$. Further evidence for an EKC pattern is produced with the much more flexible piecewise (linear) spline framework first applied in this context by Schmalensee et al. (1998).[10] Our findings indicate a TP at a much higher income level than the standard parametric estimation, though still *within* the sample, i.e. at 64% of the maximum value and significant at $p<0.01$.[11] These findings more-or-less confirm estimates reported by Dijkgraaf and Vollebergh (2005).

These results seem to provide overwhelming evidence for the existence of an inverted U for CO_2. Applying the semi-parametric estimation technique, however, yields a different picture. For ease of comparison, Figure 2 summarizes our main findings for the parametric cubic specification, the (linear) spline method and the standard semi-parametric PLR estimation (with 95% confidence band) as in Millimet et al. (2003).[12] [INSERT FIGURE 2] Vertical lines are added at the predicted peak of the parametric EKC and its upper and lower limits of the 95% confidence interval.

Clearly, the estimated parametric peak indicates an inverted U, as does the declining highest income spline.[13] The fitted line of the PLR estimation, however, more-or-less follows the EKC pattern produced by the (parametric) cubic specification only for income levels up to $20,000 or 59% of the maximum income level. However, we observe an emissions–income relationship that casts doubt on the existence of an inverted U for the observations in the upper tail of the income distribution. Where both the traditional

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[10] Like Schmalensee et al. (1998), we first started with a model featuring 20- and 24-segment splines and time fixed effects, where each segment contains the same number of data points. In our case, we reject simplifications to 10 and 12 splines that preserve this symmetry, but the differences are small. The same holds for simplifications from 16 to 8 splines.

[11] For the 24-spline estimation, only the first two and the last splines are significant. This finding is robust for the 20-, 16- and 12-spline specifications. Note that we only show significant splines in our figures.

[12] We report our results using the original values and not the log values.

[13] We present results only for the cubic model because the quadratic models were all clearly rejected vis-à-vis the cubic specifications. Furthermore, both the quadratic and cubic models without any fixed effects were also rejected. Response coefficients for the quadratic model, as well as for models without country-specific fixed effects and time fixed effects, are available upon request.

parametric and the spline methods generate a negative income-elasticity, the semi-parametric result is much less decisive, with a very wide confidence band for the highest income levels. Therefore, we are not as convinced as Azomahou et al. (2001), who – using the same specification but without region- and time-specific effects – conclude that the overall pattern more-or-less follows a monotonic increasing pattern of CO_2 emissions per capita with rising (per-capita) income levels and, therefore, has no TP at all. The number of observations at the upper end is small and may point both to an upward and to a downward slope for the emissions–income relationship.

Accordingly, we more-or-less reproduce the existing, though various, findings in the literature using the commonly applied estimation techniques. This confirms the main finding reported by Millimet et al. (2003) that modelling strategies matter. For our data, however, not only is the location of the TPs different, but also the answer to the question of whether or not an inverted U exists. Moreover, applying the same specification test as Millimet et al. (2003), using the semi-parametric PLR method as the alternative (see Zheng (1996) and Li and Wang (1998)), we reject the parametric but not the spline-based specification.[14] This is a bit surprising and may be due to the fact that the PLR method is highly inconclusive at the upper tail of the income distribution (taking into account the low number of observations available there). The last spline, however, closely follows the parametric estimation which is rejected. Therefore, we do not believe that the spline method is more accurate than the PLR method given the dispersion at the end of the distribution.

[14] For a reasonable range of smoothness parameters, we find, in the case of the parametric cubic specification, values of the test statistic larger than 1.64. Taking into account that in finite samples the test statistic might be skewed to the left (see also Millimet et al. (2003)), this clearly indicates rejection of the null hypothesis. In the case of the spline specification, we find negative values of the test statistic. It is, however, unlikely that the skewness of the test statistic is so far to the left that this justifies rejection of the null hypothesis.

As noted before, a closer inspection of the data shows that only one or two countries dominate the upper tail of the income distribution, in particular Luxemburg and the USA (see Figure 1). Re-estimating the specified models without the data for Luxemburg does not alter the parametric result, but has a considerable effect on the more flexible spline-based and standard PLR estimation methods. For this only slightly smaller panel, the last, downward-sloping spline becomes no longer significant, whereas the PLR model now also clearly seems to reject the inverted-U emissions–income pattern (see Figure 3). However, the uncertainty range rapidly increases in the upper tail of the distribution. [INSERT FIGURE 3]

We conclude that not only parametric but also semi-parametric results may depend on relatively few observations in the upper tail of the (income) distribution.[15,16] Indeed, the weight of the data for Luxemburg – with only 400,000 inhabitants – is entirely similar to those of countries such as the USA, Japan and Germany. Moreover, one major event – the closing-down of a large steel firm in the 1980s in Luxemburg[17] – may affect our ultimate judgement on whether or not an EKC for CO_2 exists. It goes without saying that this is undesirable. Therefore, it makes sense to investigate the role of heterogeneity in much more detail.

Further evidence that the homogeneity assumption might be problematic comes from a recent paper by Brock and Taylor (2004). They argue that income–emissions profiles are likely to differ across countries, if countries differ in initial conditions or in basic parameters such as savings, technological change (in abatement) and population

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[15] Note that the data for Luxemburg at lower income levels only affect the confidence bound given the dominance of observations with lower per-capita emissions levels at these income levels.

[16] We also explored sensitivity of the results for the exclusion of the US data as well, but that did not change the outcomes of the spline and the PLR models relative to the case without Luxemburg.

[17] Steel production was responsible for over 50% of industrial production in 1980 but was down to 3% in 2000.

growth rates. While their amended or Green Solow model still allows for an EKC relation between emissions and income per capita, Brock and Taylor (2004) claim that empirical assessments should typically have difficulties in finding this relationship if they do not allow for enough heterogeneity across countries. Estimations should allow for heterogeneity in *when* (time) and *where* (income level) the peak occurs and for differences in the growth rate of emissions. Such divergences across countries (over time) are not adequately captured by the commonly used country-specific and time fixed effects in an econometric modelling environment based on the homogeneity assumption.

4. The role of heterogeneity

4.1 Investigating the homogeneity assumption

Reduced-form parametric estimations of the EKC hypothesis focus on the role of the income parameters *ß*, while preserving as much homogeneity between different cross-sections r as possible, i.e. $b_r = b$ in equation (5). This typically has the advantage of yielding predictions: one expects a country at the lower end of the income observations to follow the same emissions–income pattern as the other cross-sections even if its emissions level is different (controlled for by country fixed effects). Therefore, homogeneity is a desirable characteristic of panel-based estimations from an econometric perspective.

However, explicit testing of the null hypothesis of homogeneous country-specific slopes (i.e. whether $b_r = b$ in (5)) of both the parametric and the spline models presented in the previous section yields a clear rejection of this core assumption at the $p<0.01$ levels, as in Dijkgraaf and Vollebergh (2005). The magnitudes of the Wald tests for the model with country fixed effects only (the estimation results of which are not included here, but are available on request) and for the model with both time and country fixed effects are Wald(69) = 3,639 and Wald(69) = 817, respectively, so that in both cases we reject the null at the $p<0.01$ level. These results do not change if one allows for more flexibility in the time parameter by including country-specific trends (see second column of Table 2). Even though this more general model performs considerably better than the commonly estimated parametric models, the homogeneity assumption on the GDP coefficients is still rejected (the Wald statistic is Wald(69) = 1,219).[18] We also find clear indications that the spline models do not allow for enough heterogeneity, even if one allows for country-specific trends. With the same income levels for the different segments applied at the country level, we find a rejection of the homogeneity assumption for the preferred models in all cases.[19] As we explained in section 2, these results may indicate that reduced-form parametric or spline-based estimations assuming homogeneity in either the income or the time parameter or both might be misleading.[20,21]

Direct testing of the homogeneity assumption in the semi-parametric Robinson/Stock framework is not possible, however. More heterogeneity in the regression function requires enough (parametric) structure on the time component, as noted before. Therefore, we extend the approach of Millimet et al. (2003) by modelling the time trend via a country-specific third-order polynomial. Fortunately, this allows us to explore to

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[18] We generate our Wald statistics by comparing the sum of squared residuals of the general model with and without heterogeneous coefficients for only the GDP variables ('traditional models') and/or for the time-specific trend variable (general model). Because in the last case all coefficients are country-specific, we estimated this model with country-specific time-series analysis.

[19] For instance, the Wald test on heterogeneous coefficients of the income variables for the 8-spline model is Wald(126) = 1,428. We found similar results for 12-, 10- and the (non-preferred) 6-spline models. Results are available upon request.

[20] We also tested whether common exogenous covariates, such as differences in temperature, geological structure (mountainous landscape) and availability of (fossil-fuel) resources, might affect our findings for the income variables. Interestingly, we succeeded in producing similar explanatory power to the (parametric) model including fixed country effects without having much effect on the income parameters. This suggests that the fixed effects capture these exogenous factors rather well. These results are available upon request.

[21] The importance of heterogeneity is further illustrated by Dijkgraaf and Vollebergh (2005), who applied an LR test to different possible panel combinations of countries, such as the inclusion of country-specific GDP variables for one country at a time. Also, a systematic test for homogeneity of all possible sub-panels (in total, nearly 380,000 combinations were checked) showed that sub-panels for which homogeneity is not rejected are rare, and never exceed a group of five countries.

some extent the consequences of heterogeneity: under homogeneity, there is not much difference between the semi-parametric PLR curve with a general time effect (time dummies), i.e. the unrestricted case, and the semi-parametric PLR curve when the time effect is modelled by means of a third-order polynomial.[22] To investigate the implications of our results for the EKC hypothesis, we also estimate the models parametrically, considering a polynomial model including a (country-specific) trend.[23] Estimated plots – similar to those presented in Figures 2 and 3 – are presented for each country separately in Figure 4. [INSERT FIGURE 4]

The results are striking. First of all, the graphs clearly indicate heterogeneity. Comparing countries with overlapping income levels or comparing a single country with the homogeneous case yields remarkable differences in many cases.

Secondly, the difference between estimation methods is much less pronounced and has even disappeared for several countries at different income levels, e.g. Turkey, Australia and the USA. For these countries, the parametric pattern fits almost entirely within the PLR bound. In some other cases, e.g. Greece and Italy, the difference is still substantial. The polynomial-based parametric and the PLR estimates point to very different development patterns over time for these countries. This also makes robust judgements more difficult as to whether a TP exists or not.

Thirdly, the TP estimates for the countries differ remarkably, if they exist at all. Now, 17 of the 24 countries have a TP within the pooled sample, and most TPs are within their own country's income range. In contrast, the PLR method yields very different results. Looking at the (weak) hypothesis that one could reject a TP for a particular

[22] These results are available on request.

[23] Too little data are available to estimate splines for each country separately.

country, the PLR method quite often does not indicate a TP at all.[24] Interestingly, the results for the highest-income countries appear somewhat more robust, and several of the highest-income countries also indicate a TP according to both methods, with Luxemburg (indeed!) and Norway as the main exceptions.

These results are clearly an improvement on the pooled estimation based on homogeneity. Moreover, they are perfectly in line with the predictions based on the Green Solow model (Brock and Taylor, 2004). However, judgements are very sensitive to the estimation techniques applied. This lack of robustness seems mainly due to the time component if one compares the estimation results from different specifications of the time trend. Whether a further reduction of the reduced form to the income parameter only might solve this problem is the subject of the next subsection.

4.2 Allowing for heterogeneity

Allowing for a fully flexible time trend is possible in the case of homogeneity, and we can check whether or not restricting this time trend to some parametric form is possible. However, in the case of heterogeneity, and restricting oneself to country-specific time-series estimation, a fully flexible time trend makes identification of the EKC pattern impossible.[25] Fortunately, there are good reasons why some closely linked countries might develop similarly over time – for instance, because they are exposed to common (technology, regulatory or price) shocks. To allow for general heterogeneity in the time

[24] The critical test for the parametric method used is an estimated within-pooled-sample TP. If we require a negative derivative for the last, say, three observations, the PLR method yields a different outcome for five countries. The judgement for the non-parametric method, however, is a bit arbitrary. For instance, if the last couple of observations for a country rise again, one is likely to reject the existence of a TP, whereas these observations may well be far below observations at lower income levels.

[25] Due to lack of robustness of panel-based inverted-U estimations (see in particular Harbaugh et al., 2001), some scholars seem to have lost confidence in pooled estimations of EKC patterns nowadays (Stern, 2004). However, without pooling, the only remaining option is country-specific time-series estimation. Separate estimation of country-specific emissions–income patterns excludes potential isomorphic patterns between countries a priori, and estimators no longer benefit from joint parameter estimation.

component of the PLR estimates, while still capturing potential common shocks between closely connected countries, we re-estimated our model by applying (9) and using the Linton and Nielsen (1995) (LN) method. This approach is based on pairwise combinations of countries that are likely to develop more-or-less closely over time. Table 3 shows the pairwise combinations we have used as our first and second choices, based on expert opinion. [INSERT TABLE 3]

In the original LN estimator, the corresponding confidence band is based on the assumption of homoskedasticity. We extend the asymptotic limit distribution by also allowing for the possibility of heteroskedasticity.[26] The results are reported in Figure 5 for both standard parametric and non-parametric panel data techniques, with 95% confidence intervals for the non-parametric estimator, both with the imposition of homoskedasticity and allowing for heteroskedasticity. [INSERT FIGURE 5]

Again, the results are remarkable. First of all, heterogeneity clearly remains present. Secondly, the difference between estimation methods has now almost disappeared. For rather obvious combinations of countries, usually neighbours, both estimation techniques generate more-or-less similar results in most cases. For instance, assuming a similar time trend for Belgium and the Netherlands yields a robust emissions–income pattern for both countries, whereas there was much more uncertainty with the previous specification. Only in a very few cases do the different estimation techniques point to different, non-robust patterns. Moreover, these are countries for which it is not always obvious to find a neighbour with common shocks, such as Finland.

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[26] The asymptotic variance of the estimator of $f\left(y_r, r\right)$ changes from the expression in Linton and Nielsen (1995) given by $s^{2}\int p_s^{2}\left(y_s\right) / p_{r,s}\left(y_r, y_s\right) dy_s$, to, referring to equation (9),

$$\int E\left(\left(e_r - e_s\right)^2 \middle| y_r, y_s\right) p_s^{2}\left(y_s\right) / p_{r,s}\left(y_r, y_s\right) dy_s,$$

with $p_s\left(y_s\right)$ the density of y_s and $p_{r,s}\left(y_r, y_s\right)$ the density of $\left(y_r, y_s\right)$. The sample analogue follows straightforwardly and is similar to Linton and Nielsen (1995).

Thirdly, with our ultimate reduction of the reduced-form estimation of the emissions–income relationship, we are finally able to judge more robustly whether a TP exists or not for particular countries. As long as the estimated patterns are robust, we can rely on the more accurate parametric method to conclude whether a TP exists or not for particular countries. This is especially helpful because the inconclusive region of the LN method sometimes becomes quite large due to cumulating uncertainties resulting in a wider confidence bound. Accordingly, using the parametric method, we find evidence for within-pooled-sample TPs for 16 of the included 24 countries, still covering most countries with the highest income levels. This provides new evidence that the earlier result of Schmalensee et al. (1998) of the existence of a within-sample TP seems to be right after all. Note also that our results provide strong support for the Green Solow model, even for a type of emission that is, at best, only indirectly regulated so far.[27]

Our results also demonstrate the important role of the time variable. We find that estimations of a reduced-form emissions–income relationship are strongly dependent on how the time effect is taken into account. This is immediately clear from a comparison of the estimations for the different countries represented in Figures 4 and 5. For instance, the downward trend in CO_2 emissions for Luxemburg in Figure 4 can be due only to the time effect because the pure emissions–income effect shown in Figure 5 is upward-sloping. Other countries also show remarkable differences between the effects. Figure 6 plots the estimated income and time effects as well as their overall in-sample prediction for Luxemburg and for some other interesting cases, i.e. Belgium, France, Sweden and the USA. [INSERT FIGURE 6]

[27] Although some countries may have already implemented some restrictive policies directly aimed at reducing CO_2 emissions, the implementation of the Kyoto protocol still has to become effective. Nonetheless, CO_2 emissions have been reduced substantially relative to income, mainly due to energy efficiency improvements (see, for instance, Kaufman (2004)).

The time effect for Luxemburg now nicely coincides with the gradual decline in steel production, whereas our (parametric) estimation of the pure income effect shows some indication of a TP only for the last couple of years. Together, these effects more-or-less cancel each other out, although the rising income effect seems to become more dominant at the end of the period. The fit between predicted and actual values is particularly bad for Luxemburg, however, which further substantiates the difficulty of finding robust within-sample predictions of the inverted U based on pooled data.

The estimations for Belgium and France are another interesting case to illustrate the strength of our approach. Our parametric estimation of the pure income effect suggests that Belgium has an inverted U and that France does not. This is an intriguing result as both the raw data and our in-sample overall prediction for France clearly suggest an inverted U for CO_2 emissions. Interestingly, we are quite confident that our result makes sense because the pure time effect for both countries strongly correlates with the consumption of fossil fuels in the energy system. In particular, diffusion of nuclear electricity generation differs between both countries as to when and how much nuclear electricity generation has come to play a role in the energy system.[28] Note also that the within-sample predictions show a much better fit for both countries than the estimations based on the pooled sample.[29] As a final observation, we include in Figure 6 the other country in the upper tail of the income distribution, i.e. the USA. Again, the income and time effects seem to follow opposite directions over time, with only some evidence for a TP in the very last observations.

5. Conclusion

[28] Interestingly, these time effects do not show up for Sweden (see also Figure 6). This country also shifted its electricity production towards nuclear-based generation, but it used to generate from another non-fossil-fuel source in the past, hydropower.

[29] This is true for almost all countries in our sample. Results are available on request.

This paper shows that panel-based estimations of the inverted-U hypothesis for CO_2 should be treated with care. Although non-parametric estimations of a rather restrictive specification for the entire panel suggest that no such pattern exists, and specification tests hold this technique to be preferable, allowing for country-specific estimations yields a very different pattern. It turns out that such inverted-U-shaped patterns do exist for several of the highest-income countries. Thus the existence of an overall inverted U for CO_2 emissions ultimately depends on the balance between high-income countries with an (expected) inverted U and high-income countries with still-growing (per-capita) emissions. We have shown that an overall inverted U seems much more likely if we control for country-related time-specific effects. Accordingly, earlier results on the existence of an inverted U for CO_2 do not seem to be wrong after all. Further research remains necessary as to whether this inverted-U pattern is strong enough to compensate for strong upward time effects in some countries.

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Figure 1: Data plot of emissions–income relationship

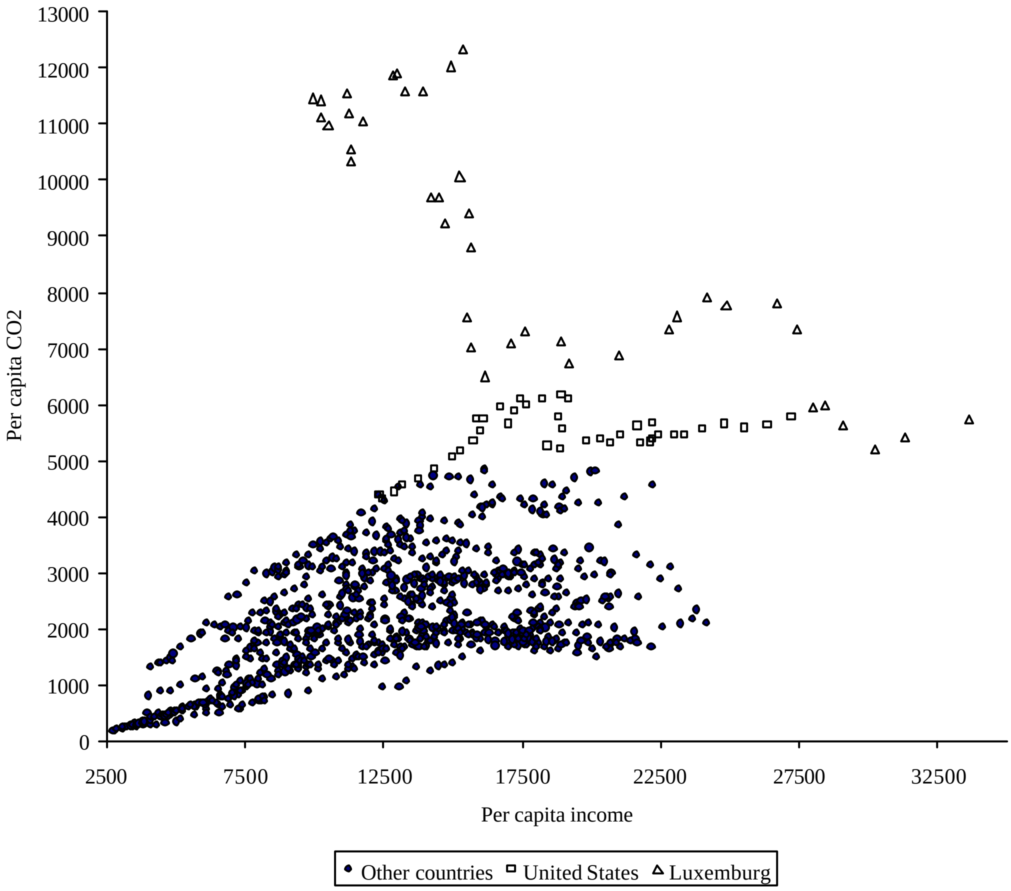
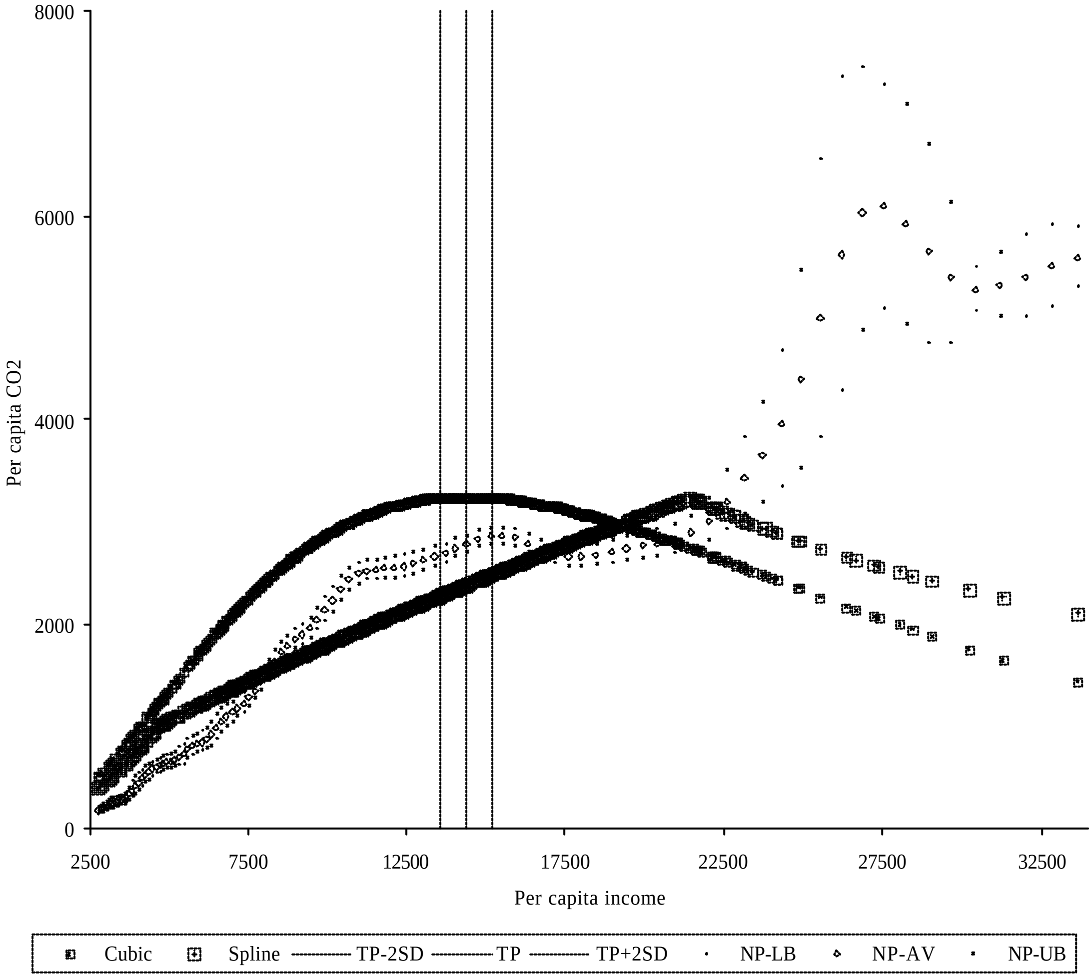


Figure 2: Estimation results for 24 OECD countries, based on the homogeneity assumption for GDP[a)]



a) Explanation legenda:

- Cubic: parametric cubic specification
- Spline: 24 piece-wise linear (significant splines only)
- TP±2SD: turning point ± 2 standard deviations
- NP-LB/AV/UB: non-parametric PLR Lower Bound, Average and Upper Bound

Figure 3: Estimation results without Luxemburg, based on the homogeneity assumption for GDP[a)]

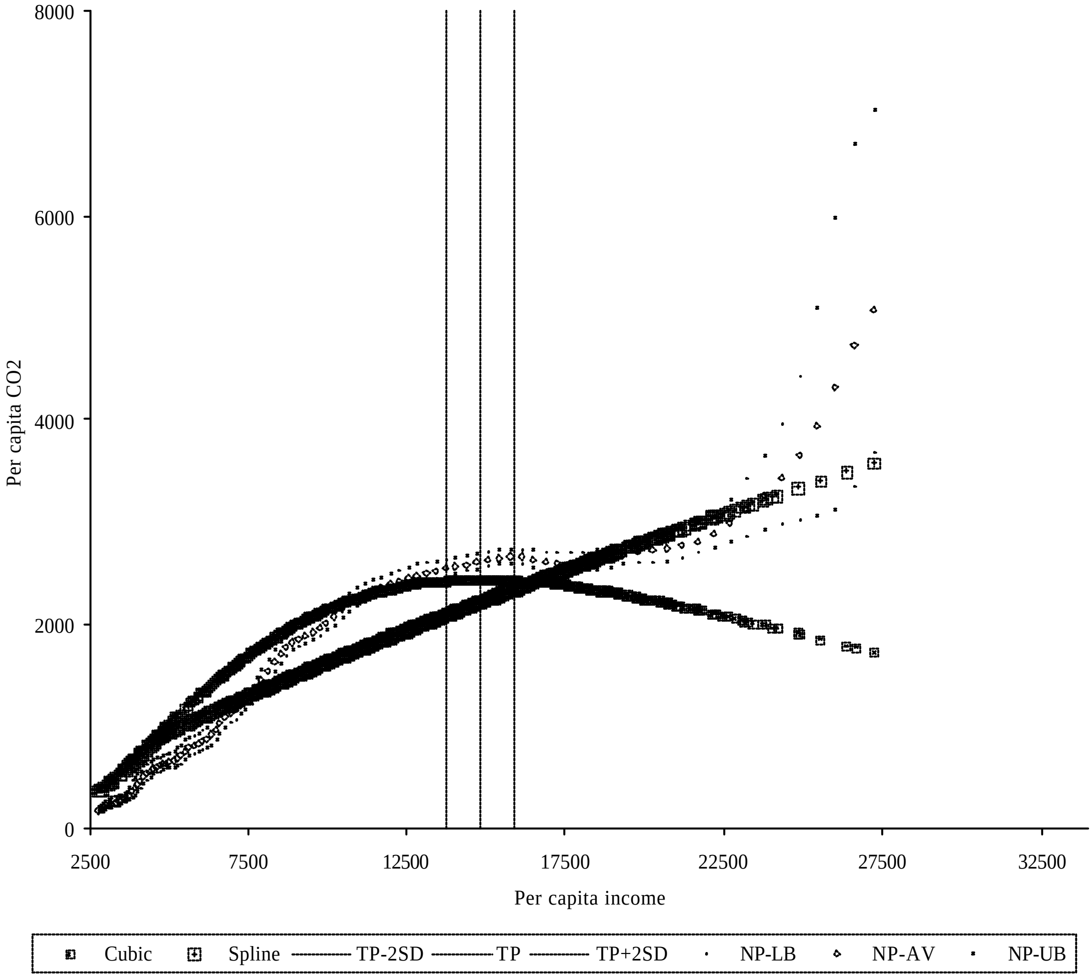
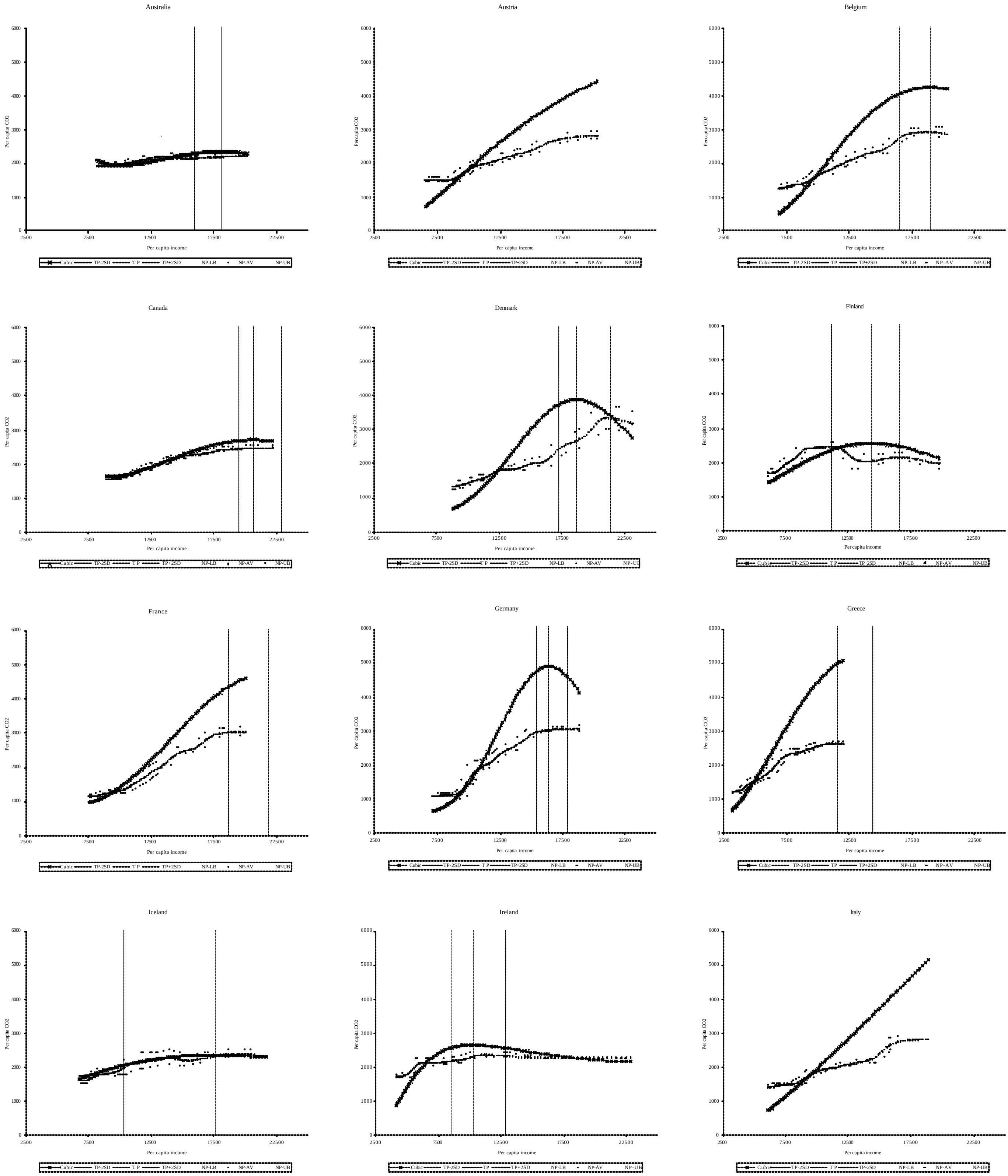
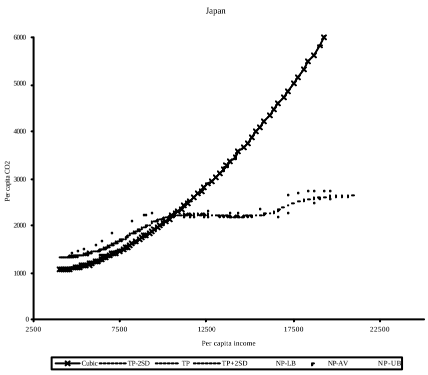
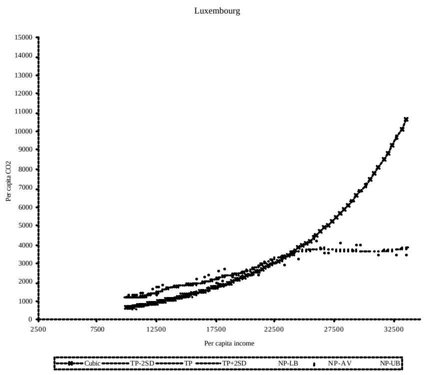


Figure 4: CO_2 emissions for OECD countries (parametric and Robinson/Stock)




Japan
Per capita CO2
Per capita income
Cubic TP-2SD TP TP+2SD NP-LB NP-AV NP-UB


Luxembourg
Per capita CO2
Per capita income
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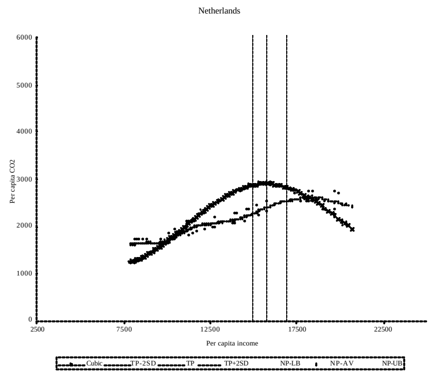
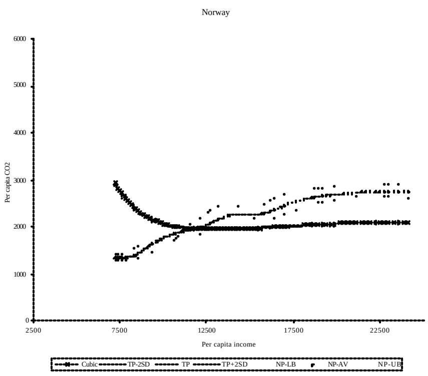
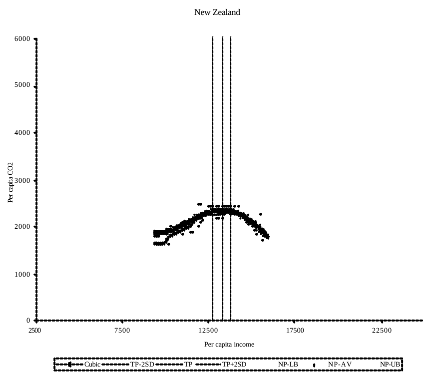
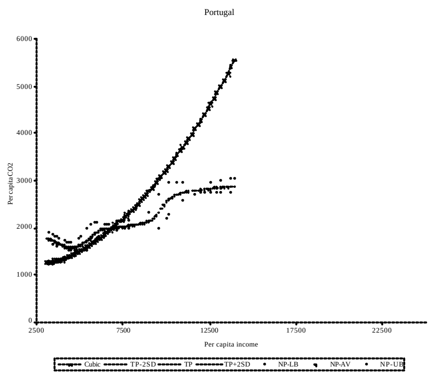

Netherlands
Per capita CO2
Per capita income
Cubic TP-2SD TP TP+2SD NP-LB NP-AV NP-UB


Norway
Per capita CO2
Per capita income
Cubic TP-2SD TP TP+2SD NP-LB NP-AV NP-UB


New Zealand
Per capita CO2
Per capita income
Cubic TP-2SD TP TP+2SD NP-LB NP-AV NP-UB


Portugal
Per capita CO2
Per capita income
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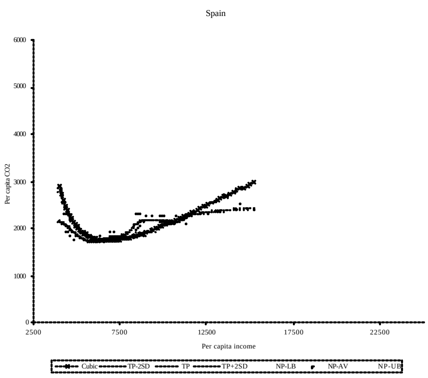
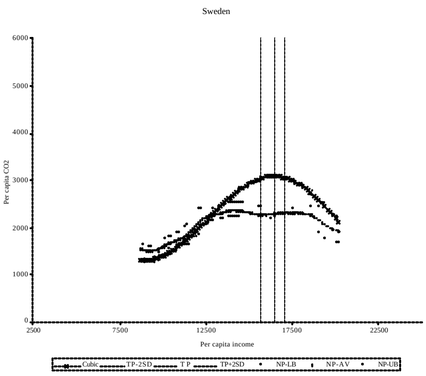

Spain
Per capita CO2
Per capita income
Cubic TP-2SD TP TP+2SD NP-LB NP-AV NP-UB


Sweden
Per capita CO2
Per capita income
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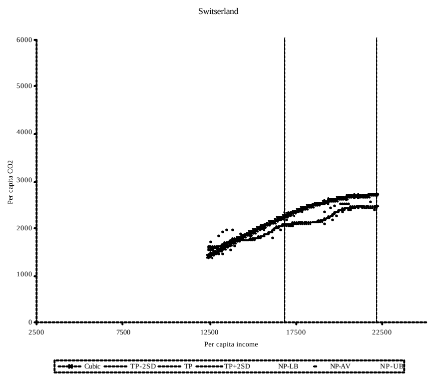
Switserland
Per capita CO2
Per capita income
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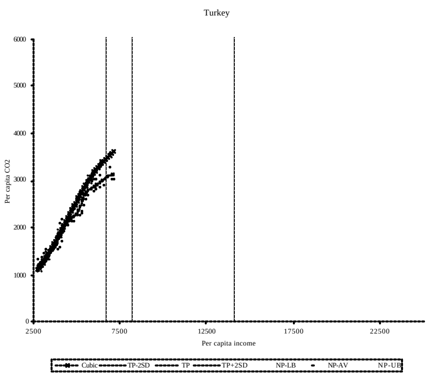
Turkey
Per capita CO2
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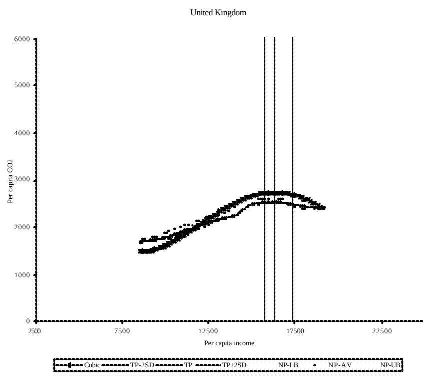

United Kingdom
Per capita CO2
Per capita income
Cubic TP-2SD TP TP+2SD NP-LB NP-AV NP-UB

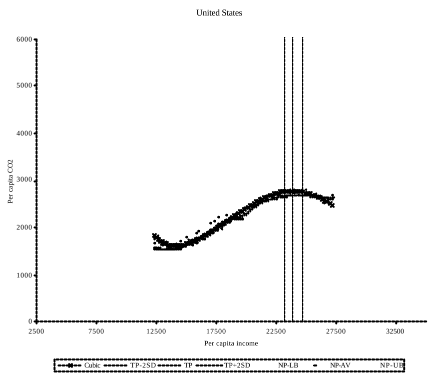
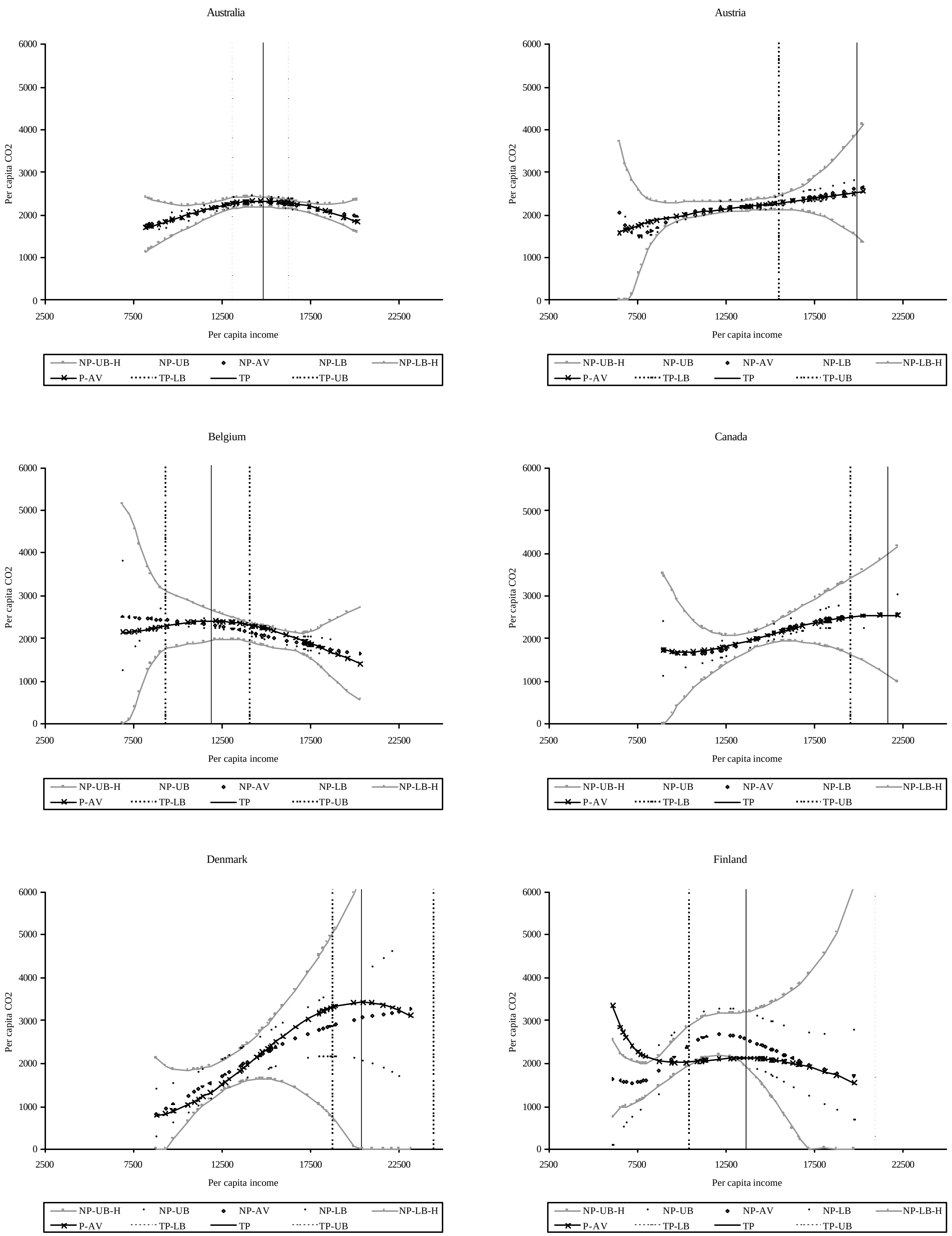

United States
Per capita CO2
Per capita income
Cubic TP-2SD TP TP+2SD NP-LB NP-AV NP-UB

Figure 5: Pairwise estimation of emissions–income relationship



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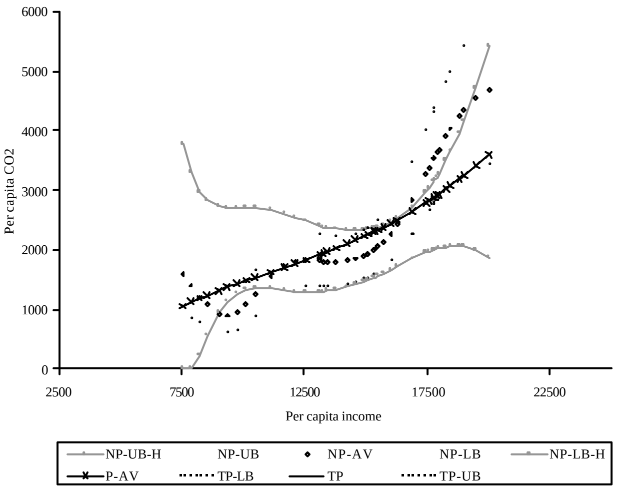
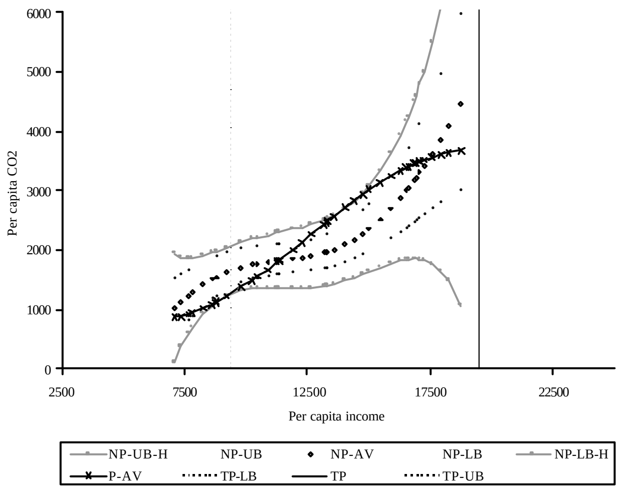
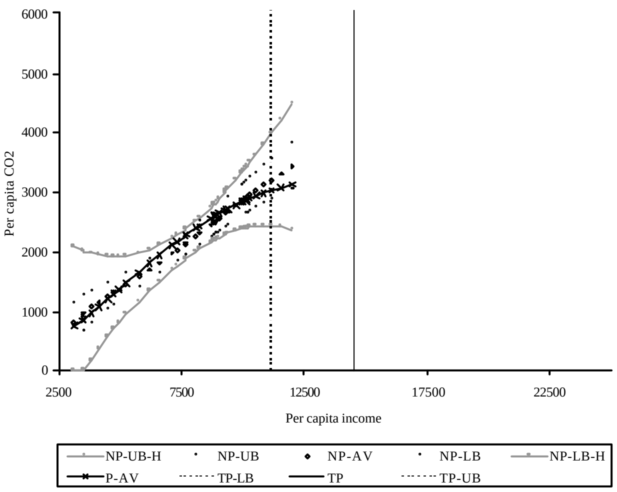


Germany



Greece



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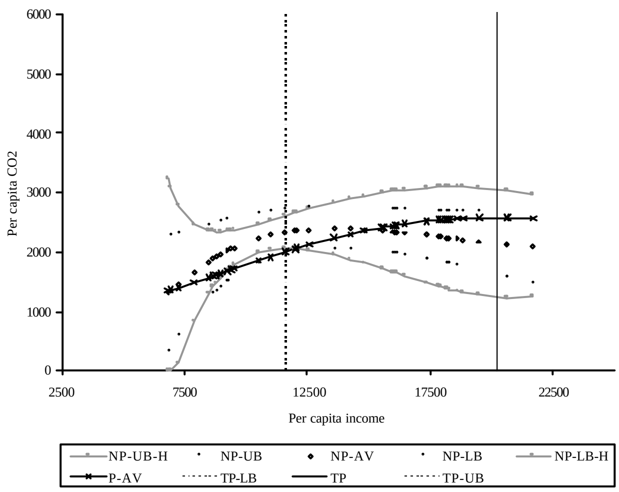
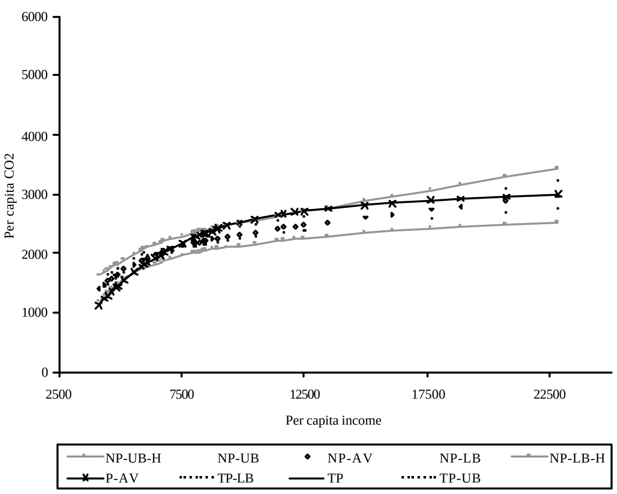
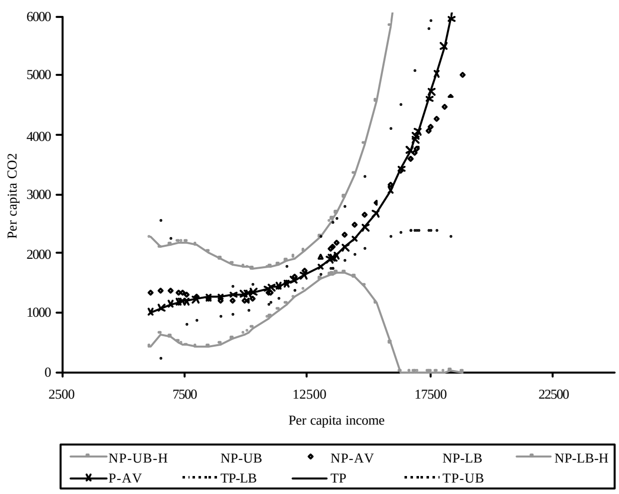


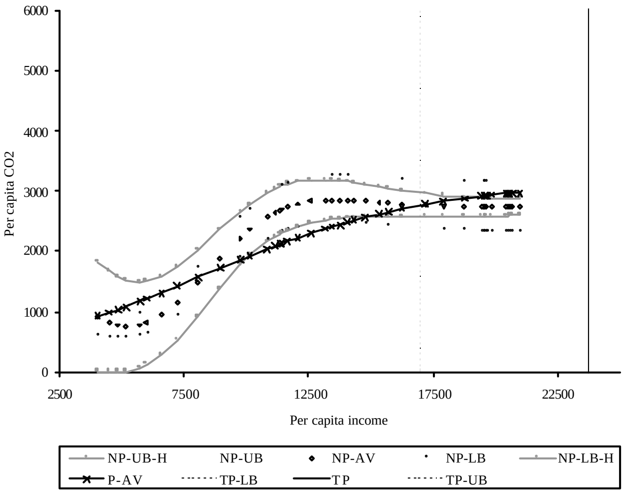
Ireland



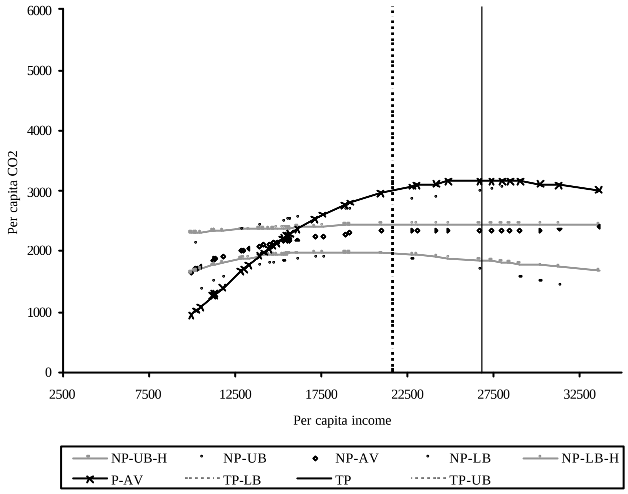
Italy



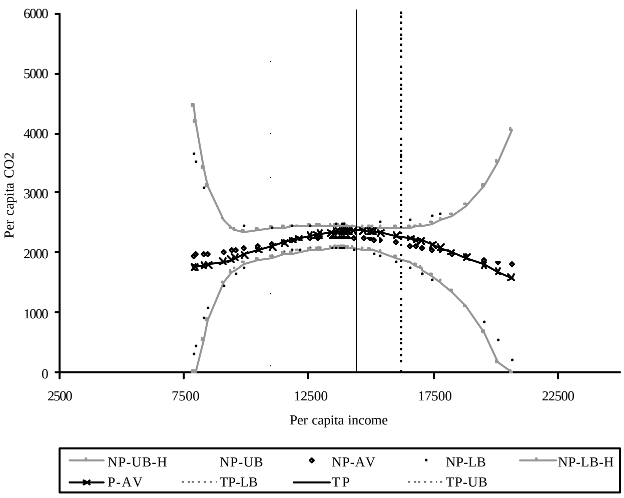
Japan



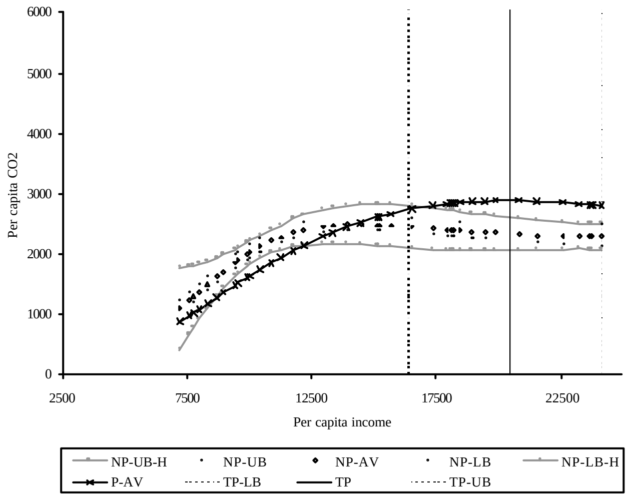
Luxembourg



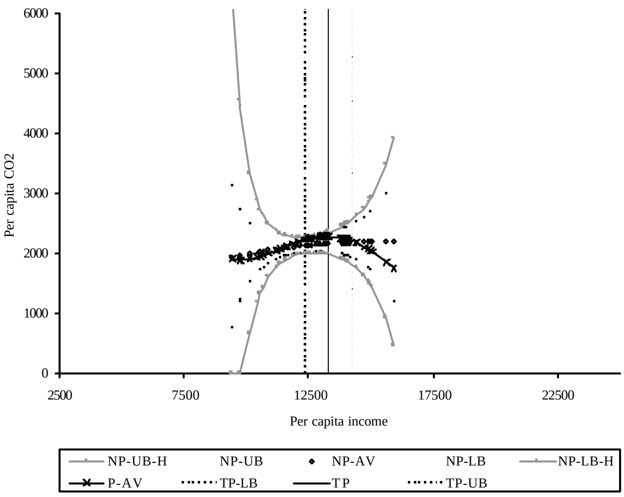
Netherlands



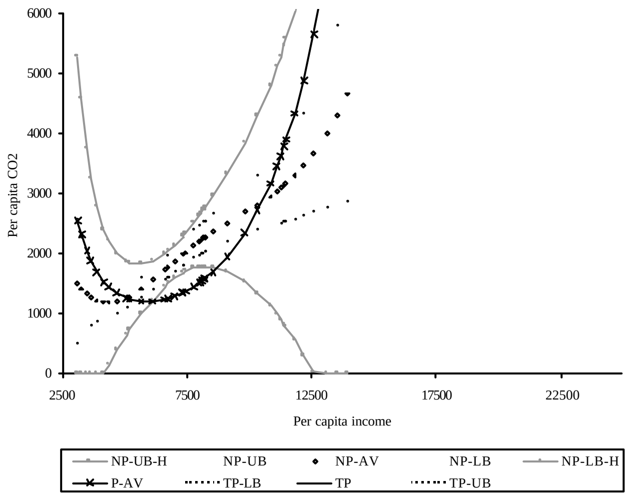
Norway

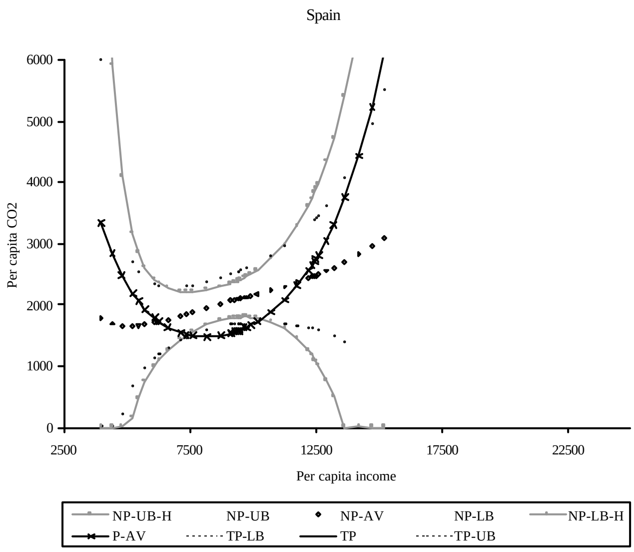


New Zealand



Portugal




Spain
Per capita CO2
Per capita income
0
1000
2000
3000
4000
5000
6000
2500
7500
12500
17500
22500
NP-UB-H
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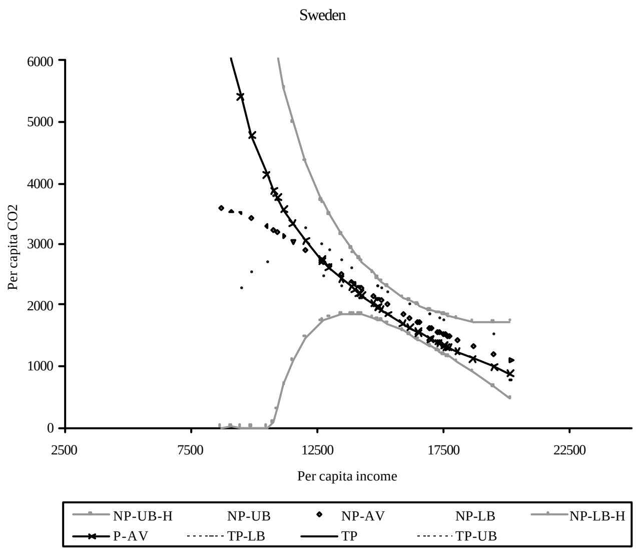
TP-LB
TP
TP-UB


Sweden
Per capita CO2
Per capita income
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1000
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3000
4000
5000
6000
2500
7500
12500
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22500
NP-UB-H
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TP-LB
TP
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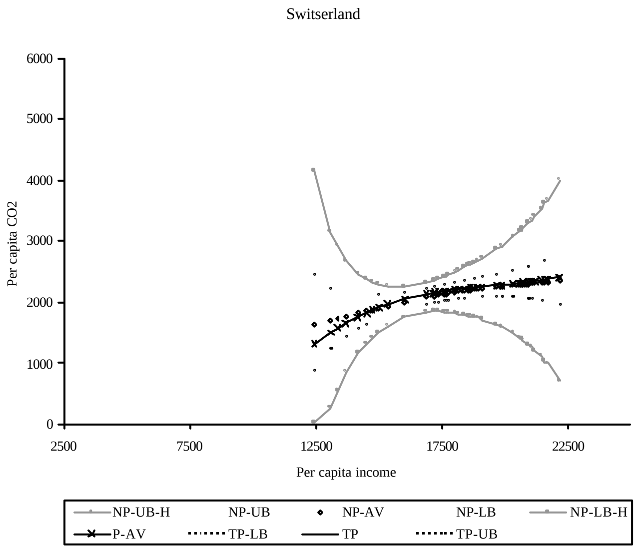
Switserland
Per capita CO2
Per capita income
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1000
2000
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6000
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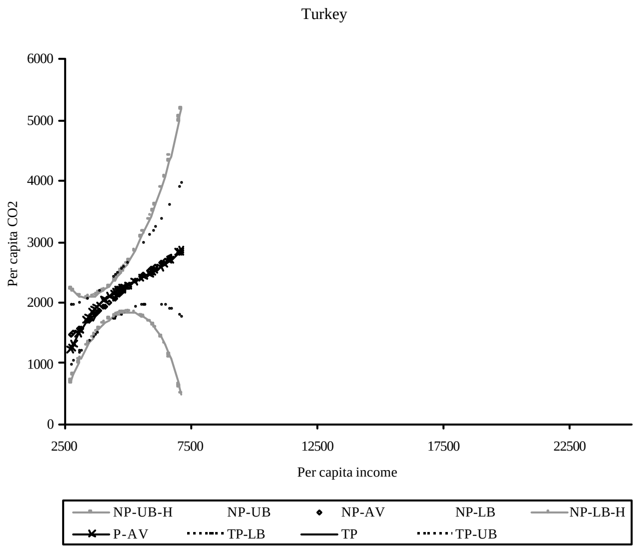
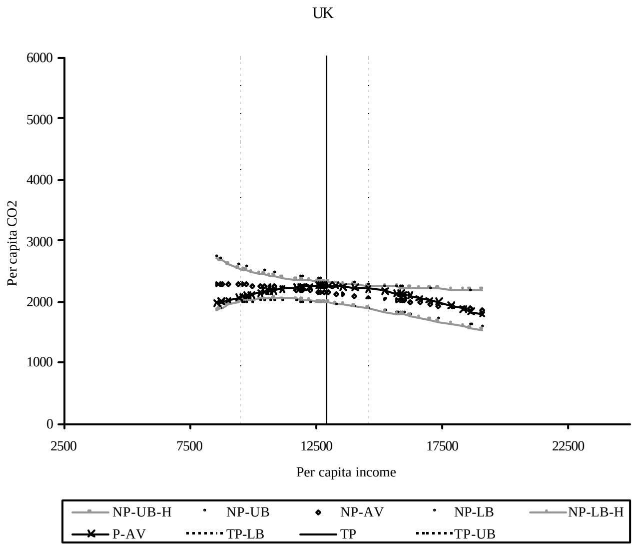
7500
12500
17500
22500
NP-UB-H
NP-UB
NP-AV
NP-LB
NP-LB-H
P-AV
TP-LB
TP
TP-UB


Turkey
Per capita CO2
Per capita income
0
1000
2000
3000
4000
5000
6000
2500
7500
12500
17500
22500
NP-UB-H
NP-UB
NP-AV
NP-LB
NP-LB-H
P-AV
TP-LB
TP
TP-UB


UK
Per capita CO2
Per capita income
0
1000
2000
3000
4000
5000
6000
2500
7500
12500
17500
22500
NP-UB-H
NP-UB
NP-AV
NP-LB
NP-LB-H
P-AV
TP-LB
TP
TP-UB

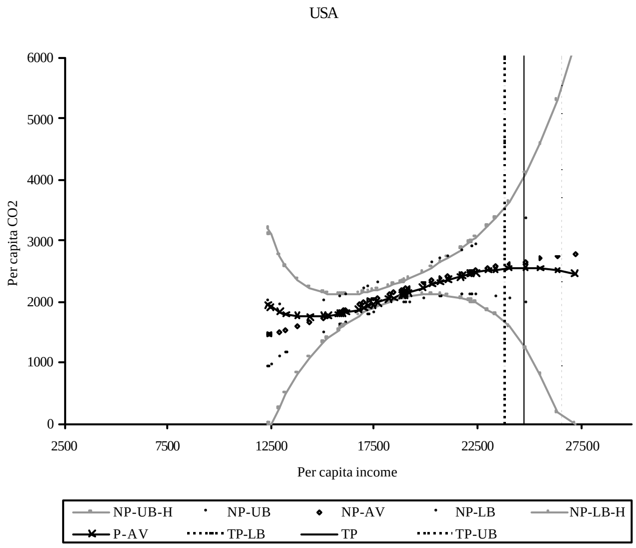

USA
Per capita CO2
Per capita income
0
1000
2000
3000
4000
5000
6000
2500
7500
12500
17500
22500
27500
NP-UB-H
NP-UB
NP-AV
NP-LB
NP-LB-H
P-AV
TP-LB
TP
TP-UB

Figure 6: The pure Kuznets curve and overall within-sample predictions for five countries

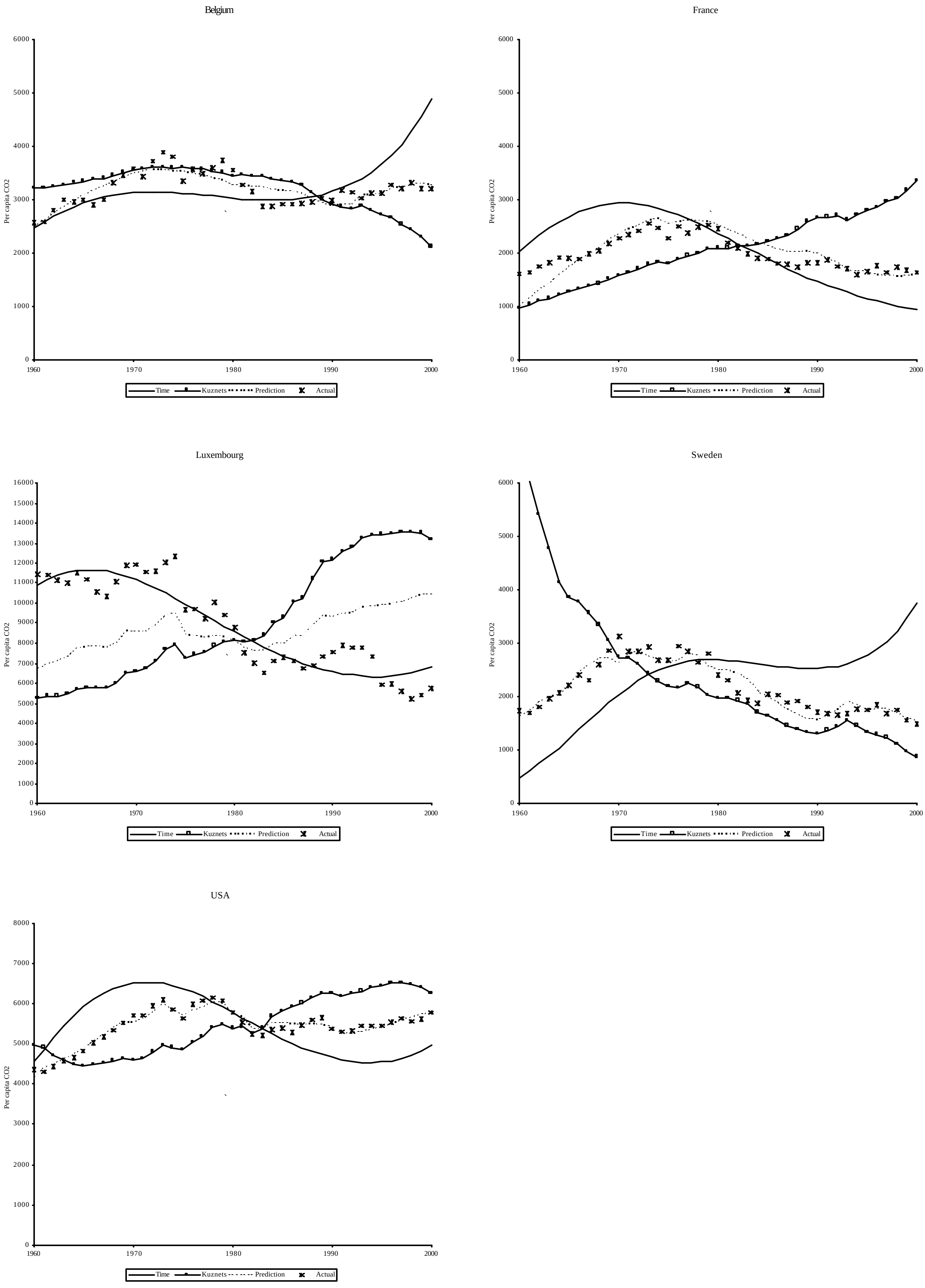


Table 1: Descriptive statistics[a,]

Variable	Mean (SD)	Minimum	Maximum
All 24 countries			
Per-capita carbon (tons)	2,606 (1,801)	167	12,333
Per-capita income (1990$)	13,172 (4,992)	2,771	33,635
Population (mln)	33 (50)	0.2	275
All countries except Luxemburg			
Per-capita carbon (tons)	2,333 (1,177)	167	6,151
Per-capita income (1990$)	12,959 (4,790)	2,771	27,234
Population (mln)	34 (51)	0.2	275

a) Descriptive statistics are for the period 1960-2000 (n = 984).

Table 2: Main test results for parametric estimations based on homogeneity[a]

	Parametric	Parametric
Independent variables		
GDP	-31.12***	-30.88***
	(7.58)	(6.12)
GDP^2	4.22***	3.80***
	(0.83)	(0.67)
GDP^3	-0.18***	-0.15***
	(0.03)	(0.02)
Fixed effects, countries	Yes	Yes
Fixed effects, years	Yes	
Country-specific trend		Yes
Homogeneity tests		
Wald (GDP variables)	817***[b]	1,219***[b]
Wald (country-specific trends)		357***[c]
Wald (all variables)		5,389***[d]

a) Dependent variable is CO_2 emissions per capita; standard errors in parentheses.
b) Wald test with H_0: $b_{1r}=b_{1r+1}$ and $b_{2r}=b_{2r+1}$ and $b_{3r}=b_{3r+1}$.
c) Wald test with H_0: $?_{irt}=?_{r+1r}$.
d) Wald test with H_0: $b_{1r}=b_{1r+1}$ and $b_{2r}=b_{2r+1}$ and $b_{3r}=b_{3r+1}$ and $?_r= ?_{r+1}$.
*** Significant at 99% confidence interval.

Table 3: Combinations of countries with similar time trends

Australia	New Zealand
Austria	Switzerland
Belgium	Netherlands
Canada	USA
Denmark	Austria
Finland	Sweden
France	Germany
Germany	France
Greece	Turkey
Iceland	Norway
Ireland	UK
Italy	France
Japan	Australia
Luxemburg	Belgium
Netherlands	Belgium
New Zealand	Australia
Norway	Iceland
Portugal	Spain
Spain	Portugal
Sweden	Finland
Switzerland	Austria
Turkey	Greece
UK	Ireland
USA	Canada