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Herman R.J. Vollebergh[1]
Bertrand Melenberg[2]
Elbert Dijkgraaf[1,3]

[1] *Erasmus University Rotterdam, and Tinbergen Institute;*
[2] *CentEr, Tilburg University;*
[3] *SEOR-ECRi.*

Tinbergen Institute
The Tinbergen Institute is the institute for economic research of the Erasmus Universiteit Rotterdam, Universiteit van Amsterdam, and Vrije Universiteit Amsterdam.

Tinbergen Institute Amsterdam
Roetersstraat 31
1018 WB Amsterdam
The Netherlands
Tel.: +31(0)20 551 3500
Fax: +31(0)20 551 3555

Tinbergen Institute Rotterdam
Burg. Oudlaan 50
3062 PA Rotterdam
The Netherlands
Tel.: +31(0)10 408 8900
Fax: +31(0)10 408 9031

IDENTIFYING REDUCED-FORM RELATIONS WITH PANEL DATA*

Herman R.J. Vollebergh[†] Bertrand Melenberg[‡] Elbert Dijkgraaf[§]

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Abstract

The literature that tests for U-shaped relationships using panel data, such as those between pollution and income or inequality and growth, reports widely divergent (parametric and non-parametric) empirical findings. We explain why lack of identification lies at the root of these differences. To deal with this lack of identification, we propose an identification strategy that explicitly distinguishes between what can be identified on the basis of the data and what is a consequence of subjective choices due to a lack of identification. We apply our methodology to the pollution-income relationship of both CO_2 and SO_2 emissions. Interestingly, our approach yields estimates of both income (scale) and time (composition and/or technology) effects for these reduced-form relationships that are insensitive to the required subjective choices and consistent with theoretical predictions.

Keywords: Identification; Panel Data; Reduced-Form (Semi-)Parametric Estimation; Emission-Income Relationships

JEL Codes: C33; O50; Q40

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[†] Tinbergen Institute and Department of Economics, Erasmus University Rotterdam

[‡] CentER and Department of Economics, Tilburg University

[§] SEOR-ECRi, Tinbergen Institute, Erasmus University Rotterdam

I Introduction

The possible existence of inverted-U shaped relationships has been investigated in the economics literature for a number of important topics. Well-known examples include Kuznets' (1955) estimate of the link between inequality and growth, Grossman and Kruegers' (1995) estimation of the link between environmental quality and economic growth, and, recently, Aghion et al.'s (2005) inverted-U estimation of the relationship between innovation and competition. The existence of an inverted U is particularly attractive because it suggests that trade-offs may disappear, for instance, if a country experiences enough growth over time.

Such inverted U-shaped links between a dependent and independent variable are typically estimated using panel data. It is crucial to proper inference to impose (identifying) assumptions that separate the effect of the independent variable from the unobserved effects [Heckman, 2000]. Panel data are particularly useful here as they offer the advantage of allowing for controls at the individual or cross-sectional level and for time controls to capture these unobserved effects. It would be rather unfortunate, however, if the imposition of such identifying assumptions on the controls also affected estimation results such as acceptance or rejection of the existence of the postulated reduced-form relationship. Nevertheless, this is precisely the problem that hinders estimation in the type of reduced-form models studied in this paper.

The fundamental underlying problem is lack of identification. Both cross-sectional and time controls can be specified at different degrees of heterogeneity, raising the fundamental dilemma of how much flexibility to allow.[1] With too much flexibility, as with an individually specific and fully flexible time trend, no variation will be left for the independent variable. With too little flexibility, too much variation might be captured by the independent variable. In other words, the choice over flexibility in terms of heterogeneity at the individual level as well as in terms of the time trends might determine to a large extent the possible shape of the relationship between dependent and independent variables.

To illustrate, suppose one allowed sufficiently flexible individual-specific time trends alongside more restrictive versions. Then, clearly, models in which sufficiently flexible time trends capture all variations in the dependent variables cannot (or can

[1] Note that this dilemma exists irrespective of the estimation technique applied. Both parametric and non-parametric estimation techniques require identifying assumptions on the controls to enable estimation. Parametric estimations require in addition a choice to be made about how much flexibility to allow in specifying the independent variable. See also section II

hardly) be distinguished from models where the time trends are limited *a priori* and the link function captures the remaining variation between the dependent and independent variable. By restricting attention to models where at least the time trend is somehow limited in its flexibility, one essentially ignores this identification problem. Moreover, since different *a priori* restrictive choices are likely to result in different inferences, one's inference might become subjectively based instead of data driven, possibly even to a large extent. This raises the fundamental concern that different *ex ante* subjective choices of flexibility might explain the sometimes widely divergent empirical findings based on the same data.[2]

The identification strategy we propose in this paper is to make this lack of identification explicit from the very beginning. We achieve this by using a framework for making inferences based on a distinction between what can be identified and, thus, estimated on the basis of the data, and what is the consequence of a subjective choice related to identification assumptions. As a starting point for our analysis, we choose the minimal requirement of a common (flexible) time trend between two cross-sectional units. Time trends that are fully flexible at the individual level cannot be distinguished from individual- and time-specific idiosyncratic error terms since no variation is left for the independent variable even in a non-parametric setting, and for that reason they will be excluded. The requirement of a common and flexible time trend suffices to (exactly) identify the parameter of interest, namely the individual-specific link functions between dependent and independent variables, but only for a *given* pair of cross-sectional units. For this given pair of cross-sectional units we can estimate the link function by allowing *full* flexibility, both in the common time trend and in terms of the individual-specific link between the dependent and independent variables.

Accordingly, the data allow proper inference on the existence of inverted U-shaped links of two cross-sectional units sharing the same time trend, just by analyzing the time series of the pairwise difference of these two given cross-sectional units. But in a panel with N cross-sectional units we have potentially $N(N-1)/2$ possible common time trends, and for each country there are $N-1$ possible link functions.[3] Here, we reach the limits of what the data can tell us: on the basis of the data alone, we cannot infer which pairs of cross-sectional units share the same

[2] Since lack of identification is the source of the problem, specification tests do not help to solve the problem.

[3] Phrased positively: the data allow full flexibility by allowing $N-1$ possible link functions per cross-sectional unit, cf. Pesaran [2007].

time trend. In other words, given that a particular pair of cross-sectional units share a common time trend, we are able to (exactly) identify the individual-specific link functions between dependent and independent variables, but which pairs of cross-sectional units share a common time trend is not identified.[4] To proceed we need a method to select cross-sectional units sharing the same time trend that is not data driven, but will be *subjectively* based [Manski, 2000]. We model this subjective selection by using priors over pairs of cross-sectional units. By means of a robustness analysis in terms of different but reasonable prior choices, we investigate the sensitivity of the outcomes to the subjective choices.

We apply our approach to the search for an inverted U-shaped relationship between environmental quality and economic growth, first elaborated by Grossman and Krueger's [1995]. We focus on two often-studied and important examples of reduced-form estimation in this so called Environmental Kuznets Curve (EKC) literature, i.e., the possible existence of an inverted U for CO_2 and SO_2 emissions and income (growth) at the country level.[5] We choose this application, since the literature demonstrates substantial uncertainty as to whether an inverted-U relationship exists or not.[6] The results for CO_2 vary from an estimated within-sample turning point in the spline-based approach applied by Schmalensee et al. [1998] to the non-existence of an inverted U-shape for the more flexible non-parametric panel data estimations as recently reported by Azomahou et al. [2006]. Also, the debate on the robustness of estimations across specifications for the heavily regulated SO_2-emissions continues, as in Stern and Common [2001] and Millimet et al. [2003]. Furthermore, Harbaugh et al. [2002] have demonstrated the sensitivity of the existence of an inverted U-shaped relationship, in particular in ambient air pollution, to the specification of functional (parametric) forms, the inclusion of additional covariates and the use of different data-sets. By using two balanced panels of OECD countries between 1960 and 2000, we avoid issues of unbalancedness or other potential data measurement problems altogether. Moreover, the time dimension is

[4] We only have two observations per time period to estimate the common time trend. Consistent estimation of a fully flexible time trend is then impossible.

[5] Ideally, one would like to estimate an inverted U between environmental quality and income or economic growth [Grossman and Krueger, 1995]. Emissions are, at best, indirect measures of environmental quality. However, balanced panel data on air quality (relevant for SO_2) are not available, neither are data on climate change due to the uniformly mixing pollutant CO_2 given the long time delay between emission and effect.

[6] Notice that this uncertainty is not restricted to the typical reduced-form EKC estimation. See, for instance, Huang [2004] for a recent reduced-form analysis of the traditional Kuznets' analysis.

sufficiently large to apply time-series estimation and testing techniques.

Our benchmark empirical findings confirm the existing non-robustness in the literature for both our applications, when comparing different model specifications. We find that the lack of robustness between parametric and non-parametric modeling and estimation approaches is mainly due to differences in the econometric specification, including, in particular, the time component (compare, for example, Millimet et al. [2003] and Azomahou et al. [2006]). Next, we use our alternative approach allowing for inference on the existence of an inverted U-shaped relation between CO_2 and SO_2 emissions and income (growth) by considering the pairwise equality of the time effect between any two cross-sections within the panel. To test the inference sensitivity of the relationship between the dependent and independent variables for our approach, we introduce and compare three explicit priors. Interestingly, we find remarkably robust results across a simple uniform Bayesian prior, a prior based on expert opinion, and a prior that models loss aversion (minimizing the likelihood of accepting the hypothesis one tries to reject). Our two case studies suggest that for both SO_2 and CO_2 emissions the income effect is driving emissions upward, whereas plausible estimates of the time effect have a clear U-shaped trend for SO_2-emissions and only slightly so for CO_2-emissions. Together, these effects seem to provide overwhelming evidence for an inverted-U for SO_2-emissions, but not for CO_2-emissions. Accordingly, our results not only nicely corroborate theoretical models that explicitly distinguish between scale, composition and technique effects (for example, Brock and Taylor [2005]), but also re-establish the search for inverted-U relationships on solid ground.

The remainder of the paper is organized as follows. Section II explains the identification problem in panel based reduced-form estimation in more detail. Section III illustrates the model assumption sensitivity in the empirical literature of inverted-U relationships for both our samples, i.e., for both CO_2 and SO_2 emissions. Next, section IV shows our results based on imposing the very weak condition of similar time effects between pairs of cross-sections. In this section we also quantify the dependence of the empirical inference on one's prior for both CO_2 and SO_2emissions. Finally, section V concludes.

II A new identification and estimation procedure

The typical reduced-form approach towards testing for a particular shape, such as an inverted U, starts from a panel data-set. Assume that as (panel) data one observes

(y_{rt}, x_{rt}), with $r \in \mathcal{R}$, where $\mathcal{R}$ denotes a set of cross-sections (in our case regions), and $t \in \mathcal{T}$, with typically $\mathcal{T} = \{1, 2, ..., T\}$. Let $\mathcal{X}$ stand for the set of possible values of x_{rt}. The typical inverted-U search is interested in econometric models of the type

$$y_{rt} = f(x_{rt}, r) + \lambda(r, t) + \epsilon_{rt}. \tag{1}$$

The goal is to find out which part of the variation in the variable y_{rt} (such as income inequality, emissions, or innovation) can be attributed to changes in an independent variable x_{rt} (such as economic growth or competition) via the function $f : \mathcal{X} \times \mathcal{T} \to \mathbb{R}$ (the systematic part), which part can be attributed to a deterministic time effect via the function $\lambda : \mathcal{R} \times \mathcal{T} \to \mathbb{R}$, and which part is idiosyncratic, captured by the region- and time-specific remainder or error term ϵ_{rt}. Given appropriate distributional assumptions the aim is to estimate the functions f and λ, with the function f the parameter of interest.

The fundamental problem one faces in trying to estimate such a model is that for each t one only has one observation (y_{rt}, x_{rt}), with $r \in \mathcal{R}$. This creates lack of identification or underidentification. For instance, for each f one might choose λ satisfying $\lambda(r, t) = y_{rt} - f(x_{rt}, r)$. This results in an exact fit $y_{rt} = f(x_{rt}, r) + \lambda(r, t)$ corresponding to a zero idiosyncratic remainder term $\epsilon_{rt} = 0$. Because the available data do not permit distinctions between different (f, λ)-combinations, the lack of identification is subsistent.

The standard solution to avoid underidentification is to restrict the possible functions λ and/or f. Typically, the choices for λ and f are restricted to some classes Λ and Φ of functions, respectively, such as time- or region-specific polynomials up to some order. In this way (f, λ) becomes identifiable. The typical *parametric* approach postulates the function f as

$$f(x, r) = g(x, \beta) + \sum_{r'} \alpha_{r'} dr_{r'}, \tag{2a}$$

with $\beta = (\beta_0, \beta_1, \beta_2, \beta_3)'$ such that

$$g(x, \beta) = \beta_0 + \beta_1 x + \beta_2 x^2 + \beta_3 x^3 \tag{2b}$$

and with dr_r being a dummy for cross-section r, and postulates the function λ as

$$\lambda(r, t) = \sum_{t'} \lambda_{t'} dt_{t'} \tag{2c}$$

with dt_t a dummy for year t. Thus, by assumption, homogeneity is imposed with respect to both the independent variable and the time effect: both functions f and

λ are assumed to be homogeneous over cross-sections, with the only exception being the region-specific constant terms of the function f. Obviously, these are very strong *ex ante* assumptions.

Such a model has been estimated, for instance, for many emission-income combinations, using standard panel data techniques, since Grossman and Krueger [1995] in the EKC literature. After imposing appropriate additional distributional assumptions[7] the typical inverted-U pattern is expected to follow from the gradient $\partial g(x, \beta)/\partial x$ first being positive and then, after the turning point (if present), becoming negative. Note that this approach assumes that every region reacts similarly to shifts in the causal variable, according to the same third-order polynomial, even if the cross-sectional units are allowed to differ in their intercepts. A similar approach is followed in the recent analysis of Aghion et al. [2005], who postulate an exponential specification of equation (2a). Clearly, these restrictions are much stronger than would be needed to identify f and λ in (2).

The typical *semi-parametric* framework allows a more flexible specification in the case of (2b). Instead of imposing prespecified polynomial patterns, several semi-parametric models have been applied to identify the effect of the independent variable, such as the spline method applied by Schmalensee et al. [1998] and again Aghion et al. [2005]. Even more general semi-parametric alternatives leave $g(.)$ completely unspecified, although homogeneity across cross-sectional units is usually imposed. Such a model has been estimated by Millimet et al. [2003], following the estimation techniques proposed by Robinson [1988] or Stock [1989]. They apply the semi-parametric partially linear regression (PLR) model to analyze inverted emission-income patterns for a panel of SO_2 and NO_x emissions in the USA and also report that this non-parametric estimator is clearly preferred over its parametric alternative for the panels they study.

Although g is made fully flexible in the semi-parametric framework, potential misspecification (due to too restrictive functional forms or overidentification) remains a problem due to the homogeneity assumption that this fully flexible function g is the same for all cross-sectional units. Indeed, doubts with respect to the (parametric) homogeneous specification (2b) have already been raised in the EKC literature by allowing for heterogeneous slope parameters (see section III.2). Instead

[7] In addition to (2a)-(2c) over cross-sectional units and time, we need an appropriate distributional assumption in terms of the idiosyncratic error terms ϵ_{rt}, as well as assumptions concerning the possible correlations over individuals and time.

of via (2b), more flexibility can be obtained by specifying cross-section specific βs:

$$f(x,r) = g(x,\beta_r) + \sum_r \alpha_r dr_r. \tag{3}$$

This specification allows one to test whether or not the homogeneity assumption is too restrictive. If tested explicitly, the null hypothesis of homogeneity is indeed often rejected, in particular within the parametric framework. However, rejection of the null hypothesis $\beta_r = \beta$ does not necessarily imply non-homogeneity, but might also indicate parametric model misspecification.[8]

To allow for heterogeneity in the time effect, a typical choice would be to model $\lambda(r,t)$ by means of a region-specific linear time trend, as Millimet et al. [2003] actually do, or to allow for region-specific higher-order terms, such as $\lambda(r,t) = \lambda_{r,1} \times t + \lambda_{r,2} \times t^2 ...$, *etc.* Such a specification fits in the PLR framework of Robinson [1988] and Stock [1989]. However, by allowing too much heterogeneous flexibility, for instance by including higher order terms in the time effect, $\lambda(r,t)$ will capture all time variation. This leaves no variation for $f(x,r)$, and this link function essentially becomes underidentified.

These developments in the EKC literature can be used to illustrate the serious dilemma one faces when using panel data to model and estimate a particular reduced-form relation. The regression-based estimation techniques typically employed try to fit the conditional expectation $E(y_{rt}|x_{rt} = x, r, t)$ as well as possible. Suppose $E(y_{rt}|x_{rt} = x, r, t) = f_0(x,r) + \lambda_0(r,t)$, where a subindex 0 indicates the "true" values of the functions f and λ. Then a regression-based method will try to select (f, λ), with $(f,\lambda) \in \Phi \times \Lambda$, such that $f(x,r)+\lambda(r,t)$ is close to $f_0(x,r)+\lambda_0(r,t)$. If one makes Λ too restrictive, however, the estimated λ might be far away from λ_0 which, in turn, might imply that the estimated f is quite distinct from f_0. If for example $f_0 = 0$, the estimated f will be such that $f(x,r)$ is close to $\lambda_0(r,t) - \lambda(r,t)$. This might correspond to an estimated f being quite different from zero when the estimated λ is far away from λ_0. Choosing Λ to be too flexible does not work either, since one would be back in the situation of underidentification. Accordingly, the standard approach faces a serious dilemma: only when Λ is large enough, might one expect some $\lambda \in \Lambda$ to be able to fit λ_0, and the estimated f to fit the "true" f_0, while at the same time one has to make Λ restrictive enough to avoid underidentification with possibly *no* $\lambda \in \Lambda$ being able to fit the "true" λ_0 and, as a consequence, the

[8]This can easily be illustrated by considering the case of two countries whose x-values do not overlap (for example, Luxemburg and Turkey). In the case of rejection of $\beta_{Luxemburg} = \beta_{Turkey}$, homogeneity might still be present.

estimated f being far away from the "true" f_0.

Our way out of the dilemma is an approach that allows full flexibility in the link function f and only imposes restrictions on the function λ, but without restricting its flexibility, based on a "most reasonable" decomposition. We start by interpreting equation (1) as a decomposition of y_{rt} into three effects a systematic part, captured by $f(x_{rt}, r)$, a deterministic time trend, captured by $\lambda(r,t)$, and a remainder term ϵ_{rt} that captures the region- and time-specific idiosyncratic effects. A "most reasonable" decomposition should satisfy two requirements that – we believe – any specific restriction should satisfy anyway. First of all, λ should not be region-specific, i.e., for a "reasonable" decomposition we require that λ is such that for each $r \in \mathcal{R}$ there exists at least one $s \in \mathcal{R}$, with $s \neq r$, such that for all $t \in \mathcal{T}$ we have $\lambda(r,t) = \lambda(s,t)$. Note that if λ does not satisfy this requirement, λ cannot really be distinguished from possible idiosyncratic effects. Second, given the first requirement, a "reasonable" decomposition should avoid restricting λ too much. This requires λ to be as flexible as possible because any additional structure imposed on λ (on top of the first requirement) will immediately affect the possible shape of f in the decomposition. As has been explained before, measurement of the systematic effect would otherwise be influenced in an "unreasonable" way.

Using the assumption $\lambda(r,t) = \lambda(s,t)$ for all $t \in \mathcal{T}$ for a given pair (r,s) we can identify and estimate $f(x,r)$ (and $f(x,s)$) by taking differences according to

$$y_{rt} - y_{st} = f(x_{rt}, r) - f(x_{st}, s) + (\epsilon_{rt} - \epsilon_{st}), \quad t = 1, 2, ..., T, \tag{4}$$

together with assuming $E(\epsilon_{rt} - \epsilon_{st} | x_{rt},\ x_{st}) = 0$. This approach allows full flexibility in f and λ, while the assumption $E(\epsilon_{rt} - \epsilon_{st} | x_{rt},\ x_{st}) = 0$ guarantees that it is reasonable to classify the effects captured by ϵ_{rt} as idiosyncratic. The unknown regression functions $f(x,r)$ and $f(x,s)$ of equation (4) are identified and can be estimated by imposing, for example, Linton and Nielsen's [1995] method and imposing their regularity conditions and (additional) distributional assumptions.[9] Note that this procedure is the ultimate reduced-form estimation of the inverted-U curve, because identifying the inverted-U relation between independent and dependent variables no longer depends on the effects of the time variables. Assuming that two regions have the same time effect does not impose *a priori* a specific structure on this time effect: it still allows *any* structure, as long as this structure applies to both regions under consideration. So, the only remaining choice is to select the

[9] Note that this specification also implicitly accounts for potential endogeneity if the time trend captures technological change which – in turn – depends on (the level of) emissions and income.

appropriate combination of cross-sectional units (r, s) according to the assumption $\lambda(r, t) = \lambda(s, t)$.

However, we cannot make this choice on the basis of the data alone. To make this clear, notice that the time effects $\lambda(r, t)$ and $\lambda(s, t)$ might be retrieved from

$$\begin{aligned} y_{rt} - f(x_{rt}, r) &= \lambda(r, t) + error, \\ y_{st} - f(x_{st}, s) &= \lambda(s, t) + error, \end{aligned} \tag{5}$$

using the estimated functions f on the left-hand sides. However, allowing full flexibility for each t, we only have one observation to retrieve $\lambda(r, t)$ and $\lambda(s, t)$, namely $y_{rt} - \widehat{f}(x_{rt}, r)$ and $y_{st} - \widehat{f}(x_{st}, s)$, respectively, and we only have two observations to retrieve $\lambda(t) = \lambda(r, t) = \lambda(s, t)$. Although this allows estimation of the time effects,[10] it does not allow a *consistent* estimation of fully flexible time trends, since this would require many cross-sectional observations, which, however, are unavailable. In other words, $\lambda(t)$, $\lambda(r, t)$, and $\lambda(s, t)$ are not identified and, as a consequence, we are unable to test a hypothesis such as $H_0 : \lambda(t) = \lambda(r, t) = \lambda(s, t)$.

Given that any pair of cross-sectional units (r, s) can be used, our approach leaves $N(N-1)/2$ possible relationships for a sample of N cross-sections. We are facing model ambiguity, due to a lack of identification (compare Manski [2000]). To deal with this ambiguity, we proceed by employing priors over the cross-sectional units. Such priors can be used to express one's views about which countries are more or less likely to have common time trends. Such views are clearly subjective. However, note that any specification of the time effect, such as fixed and homogeneous across cross-sections also reveals someone's prior, of course. Our approach simply makes *explicit* from the very beginning that the empirical "evidence" on the presence of a possible inverted-U relationship can no longer be inferred "automatically", but always depends upon one's prior. In our empirical application, we shall examine all possible pairs and base our inference on the combination of these possible pairs. We use three different priors to investigate the sensitivity to the prior choice.

III Model sensitivity illustrated

In this and the next section we present our empirical analysis considering two widely studied emission-income relationships, namely SO_2 and CO_2 emissions. In this section we investigate sensitivity to different model assumptions arising from the impo-

[10] A simple estimator for $\lambda(t)$ consists of taking the average of $y_{rt} - \widehat{f}(x_{rt}, r)$ and $y_{st} - \widehat{f}(x_{st}, s)$.

sition of different identifying restrictions needed to identify the underlying underidentified model given by equation (1). In the next section, we present our alternative approach. The current section does not aim to break new grounds. Instead, it provides benchmark estimations for our new approach in addition to illuminating the role of various modeling assumptions behind the current uncertainty as to whether inverted-U relations exist for both types of emissions.

III.1 Data

In our applications we are specifically interested in quantification of equation (1) with $y = \log(E/N)$ and $x = \log(Y/N)$, with E either SO_2 or CO_2 emissions, Y the GDP level and N the population size, and with the controls r and t referring to country r and year t, respectively. Note that the control r is usually thought to reflect 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.

We concentrate exclusively on two balanced panels of OECD countries between 1960 and 2000.[11] Specifically, the data for SO_2 emissions are in metric tons of sulfur based on estimated sulfur content and sulfur retention or removal from waste streams including emissions of sulfur from burning hard coal, brown coal and petroleum, and sulfur emissions from mining and smelting activities. Data for CO_2 emissions are in millions of metric tons of carbon and they are calculated from energy consumption. To calculate CO_2emissions, 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. Data on Y and N were taken from OECD [2000]. All figures are expressed in 1990 dollars, using purchasing power parities. The OECD has reconstructed data on Y for Germany (including the former GDR) for the years between 1970 and 1989. We further extrapolated GDP figures backwards to 1960 assuming that changes in GDP per capita for East Germany were similar to those for West Germany.

[INSERT TABLE 1]

[11] See the appendix for a complete description of our compiled data-set.

Table 1 shows some descriptive statistics of the raw data. Our overall data-set contains 984 observations for all variables for each panel on SO_2 and CO_2 emissions, and for each country we have 41 observations available. Our variables y and x are in log-s. But when presenting our estimated curves, we use the original values (E/N and Y/N). In addition, we also normalize all curves such that the average levels equal the sample average since in the semi-parametric specifications the level of the curves is not identified.

III.2 Benchmark estimations

We now turn to the sensitivity to employed modeling assumptions corresponding to models such as (2) or (3). For ease of comparison, Figures 1.a and 1.b summarize our main findings for the most important reduced-form econometric specifications applied in the literature for SO_2 and CO_2, respectively. The three curves in each figure represent estimated f-functions for the parametric cubic specification, based on the earliest estimations of an inverted U, including Grossman and Krueger [1995] and Holtz-Eakin and Selden [1995], for the (linear) spline method, applied by Schmalensee et al. [1998], and for the standard semi-parametric PLR estimation (including a 95% confidence band) as used in Millimet et al. [2003].[12] Vertical lines (together with the upper and lower limits of the corresponding 95% confidence intervals) are added at the predicted peak of the parametric EKC. Note that all estimation techniques are based on homogeneous cross-section and time effects as given in (2a) and (2c).

[INSERT FIGURE 1.a and 1.b]

Our estimations for SO_2 in the cases of the parametric and spline approaches are more or less in line with the existing literature. For instance, Selden and Song [1994] were the first to provide evidence for the existence of this relation, and their findings have been basically confirmed, for instance, recently by Stern and Common [2001] for 73 countries as well as by our OECD limited balanced panel data-set. Whereas the early parametric estimations for CO_2 emissions could only report a turning point (TP) far out of sample (for example, Holtz-Eakin and Selden [1995]), our parametric estimations using OECD restricted data as well as additional data for the 1990s yield a clear estimated within-sample TP at \$14,355. This is at 43%

[12] See the appendix for details.

of the maximum panel observation.[13] The results for the spline method more or less follow the results reported by Schmalensee et al. [1998] and also yield a within-sample TP, though now at 64% of the maximum value and significant at $p<0.01$.[14] When using the flexible semi-parametric PLR method for the SO_2 case, we find that at lower levels of income the estimated pattern follows the patterns found by the parametric and spline method quite closely, but it also shows a large, inconclusive boundary for higher-income observations (mainly USA and Luxemburg data). For the CO_2-case, the estimated curve using the PLR technique more or less follows the EKC pattern produced by the (parametric) cubic specification, but only for income levels up to $18,000 or 54% of the maximum income level.

To investigate the consequence of the homogeneity assumption, we simply re-estimate the curves without the Luxemburg data. Figure 2 contains the results. If the homogeneity assumption makes sense, eliminating a single country should not change the results dramatically.[15] However, looking at the PLR estimates in the case of SO_2 without the data for Luxemburg still produces a peak, but now also a trough, with emissions rising again after some income level (though within a large uncertainty bound). In the case of CO_2 we even no longer find an inverted U, but basically confirm Azomahou et al. [2006]. They concluded 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 would not have a TP at all.

[13] Indeed, the different result for the parametric specification of Holtz-Eakin and Selden [1995] is explained partly by the additional data points we included (the TP for the same years considered by them is located at 81% of the maximum of the panel). Even more important, however, is that we now restrict our analysis to OECD data, which start from higher initial income levels. This largely affects parametric specifications but has much less effect on splines because these follow the data more closely.

[14] 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.

[15] We focus on the PLR and spline-based specifications, since, applying the same specification test as in Millimet et al. [2003], i.e., 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 both in the case of CO_2 and in the case of SO_2. 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.

Also, with the spline method the CO_2 case no longer produces such a TP if we exclude Luxemburg. [16] We conclude that imposing the homogeneity assumption might result in outcomes rather sensitive to the inclusion or exclusion of particular countries.[17] This simple finding already confirms the confusion that characterizes the current literature on EKC, which has even fueled dissatisfaction with reduced-form EKC estimation in general.

[INSERT FIGURE 2.a and 2.b]

As explained in section II also the specification of the time effect might seriously influence the reduced-form estimations. This issue has so far generated much less attention in the literature, with some exceptions such as Grossman and Krueger [1995] who have pointed out the potential importance of the time variable in driving emissions down. To see whether the use of non-linear country-specific time trends may affect the results, we also consider an extension of the approach of Millimet et al. [2003] by modeling the time trend via a (country-specific) third-order polynomial. By way of illustration, Figure 3 shows the results for both Luxemburg and the USA for both samples and for both parametric and non-parametric models.[18] In the parametric cases both the income link function and the time effect are modeled

[16] In the case of homogeneity, one major event – the closing-down of a large steel firm in the 1980s in Luxemburg – seems to drive our ultimate judgment on whether or not an EKC for SO_2 and CO_2 exists. Steel production was responsible for over 50% of industrial production in 1980 but was down to 3% in 2000.

[17] Specification tests reject the imposition of homogeneity on the cross-sections. For instance, we generate 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. This results in a Wald test statistic that is asymptotically χ^2_{69}-distributed under the null hypothesis. The values of the Wald statistic for the SO_2 and CO_2case are 1,254 and 1,219, respectively (see also List and Gallet [1999], Martinez-Zarzoso and Bengochea-Morancho [2004] and Dijkgraaf and Vollebergh [2005]). We also find clear indications that the spline models do not allow enough heterogeneity if country-specific trends are included. With the same income levels for the different segments applied at the country level, the homogeneity assumption is rejected for the preferred models in all cases. For instance, the Wald test on heterogeneous coefficients of the income variables for the 8-spline model is asymptotically χ^2_{126}-distributed under the null hypothesis. The test statistic's value is 1,428 (we found similar results for 12-, 10- and the (non-preferred) 6-spline models; results available upon request). Also, Millimet et al. [2003] report sensitivity of their semi-parametric panel data results for the homogeneity assumption, particularly for the case of SO_2 emissions.

[18] We provide country specific graphs for all countries in our supplement.

as third-order polynomials, estimated simultaneously, resulting in the pronounced graphs for the income curves. In the case of the PLR approach, however, one first corrects for the time effect. Since a third-order polynomial time effect already captures most of the variation, this results in rather flat curves for the income effects. As a consequence, the results of the parametric and PLR approaches turn out to be quite different, with the exception the CO_2 case for the USA. Clearly, the imposed model structure determines the outcomes. These findings for the two countries in the upper tail of the income distribution are quite representative of the whole sample. The estimations for all countries illustrate the importance of the imposed structure, including the specification of the time effect. Comparing the results for countries with overlapping income levels, or for a single country with the homogeneous case, also yields notable differences in many cases. Both the existence and the location of the TP differ, and also the polynomial-based parametric and PLR estimates sometimes point to very different development patterns for a considerable number of countries over time for both samples.

[INSERT FIGURE 3.a.1, 3.a.2, 3.b.1 and 3.b.2]

These results show that reduced-form estimations of an inverted-U relation for both our emission data-sets with income are very sensitive to the model assumptions imposed. We find overwhelming support for the observation that inference of reduced-form relationships with panel data crucially depends on the subjective model choice, which is necessary since the underlying model (1) lacks identification. Particular, the sensitivity to the way the time component is modeled might be substantial. This is unsatisfactory, as it thwarts robust inference as to whether a TP exists or not. Therefore, we now turn to our approach that, apart from a very weak identifying condition, allows full flexibility, and thus, given the identifying restriction, allows proper inference on the existence of inverted U-shaped link functions.

IV The pairwise estimation approach

In this section we present the results from our new identification and estimation procedure, and show that inference based on different priors generates remarkably consistent results. Our pairwise (non-parametric) estimation approach allows as much heterogeneity as possible, but still exploits the advantages of joint parameter estimation. The pairwise procedure starts from the idea that countries might develop (more or less) similarly over time – for instance, because they are exposed to common (technology, regulatory or price) shocks. By taking differences between "co-developing" countries, we can identify their (country-specific) "pure" income link function. As explained in section II, we estimate our pairwise model by applying (4) and using the Linton and Nielsen [1995] (LN) method. 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.[19] Finally, we take it that our data obtained after differencing do not suffer from unit root problems.[20]

Obviously, choosing the "right" combination of countries is crucial to identification of the income effect in this pairwise procedure. Results are likely to be sensitive to combinations of countries for which one assumes that the time trend is similar. This assumption, however, is untestable and therefore causes model ambiguity (compare Manski [2000] and Brock et al. [2003]).[21] In other words, exact identification comes at a price, because as many identifications as potential pairs of countries $(N-1)$ are possible, i.e., in our case 23 identifications for each of 24 countries. The (weak) assumption of similar time trends for a given pair of countries can only be justified by an appeal to intuition or prior information [Heckman, 2000, p. 64].

[19] The asymptotic variance of the estimator of $f(x,r)$ changes from the expression in Linton and Nielsen [1995], which is given by $\sigma^2 \int p_s^2(y_{st})/p_{r,s}(y_{rt},y_{st})dy_{st}$, to the new expression

$$\int E((\varepsilon_{rt}-\varepsilon_{st})^2|y_{rt},y_{st})p_s^2(y_{st})/p_{r,s}(y_{rt},y_{st})dy_{st}$$

with $p_s(y_{st})$ the density of y_{st} and $p_{r,s}(y_{rt},y_{st})$ the density of (y_{rt},y_{st}). The sample analog follows straightforwardly and is similar to Linton and Nielsen [1995].

[20] Recently, several papers have raised doubts about the stationarity of the sample data commonly used for testing inverted U-shapes for SO_2 and for CO_2 (for example, Stern and Common [2001]), although the findings of Lanne and Liski [2003] suggest that it is quite unlikely that we are missing a structural break in the CO_2-series for the limited period spanned by our data. Whether unit roots are present or not does not have any consequence, however, for the identification problem which is our main concern in this paper. Furthermore, the presence of unit roots in the original data does not necessarily carry over to the data we use in our pairwise procedure. We found ambiguous results using the KPSS test for unit roots in heterogeneous panels for randomly chosen combinations of pairs [Kwiatkowski et al., 1992]. Indeed, results strongly depend on the modeling assumptions of the test itself, which, as is well known, strongly affect the size and power of this test.

[21] Note the important difference with the extra restrictions imposed within the standard literature as explained in section II (in particular on the time effects included). These restrictions can be tested; the results have been reported in the previous section.

Unfortunately, prior information on equal time trends to select pairs of countries is not as obvious as one might wish. Take as an example two closely linked countries such as Belgium and the Netherlands. These countries are geographically close, form a customs union throughout our sample period, and closely cooperate on many policy issues. Nonetheless, their energy systems – which are to a large extent responsible for the level of both SO_2 and CO_2 emissions – show notably different development over time. Non-fossil-fuel energy use has grown from 0% to 22% of TPES in Belgium but only to a small 2% in the Netherlands in 2000 [OECD, 2000]. Energy use per capita, however, has grown much faster in the Netherlands than in Belgium in the same period, namely by 160% and 120%, respectively.

To deal with the model ambiguity, we discuss three priors in detail.[22] The first, somewhat ad hoc, approach is a simple uniform prior (Bayes) that gives each likely candidate an equal probability and then looks at the average of all 23 pairs (referred to as BAYES). The second approach attaches *a priori* probabilities on some subset of country pairs based on expert opinion on the likelihood of similar time effects. We label this prior EXPERT. To derive this prior we use time-related developments in energy use of country pairs and categorize countries using both the level of non-fossil-fuel use and its developments over time, i.e., between 1960 and 2000.[23]

Even if the priors BAYES and EXPERT suggest that no inverted U exists, one might still be able to infer an inverted-U shape for a country, if one is prepared to choose a particular (set of) country pair(s) based on *some* (possibly *extreme*) prior. To judge such priors that yield an inverted-U shape, we quantify the dependence of any inference based on such a prior using an index $\omega(r,t)$ that minimizes the likelihood of accepting the hypothesis we try to reject ("cross-section r has an inverted U for the pure income effect"). The index is computed for a given country r and a given year t in the following way. First of all, for each of the 23 pairs we count the number of country pairs that generate an inverted-U pattern. Next, we compute the index as a factor that attaches a weight to the number of pairs that generate inverted-U patterns as well as to the strength of this pattern by taking its gradient into account. The factor $\omega(r,t)$ is then computed as the minimal weight that we need to attach to the pairs generating an inverted-U shape compared with those without such a shape, which are weighted by $\widetilde{\omega}(r,t)$. To be precise, to compute this

[22] Another likely candidate suggested by Brock et al. [2003] would be a goodness-of-fit measure for the different possible pairs. However, because our non-parametric estimation procedure leads to very high goodness-of-fit statistics, the cutting power of this measure is rather weak.

[23] See the appendix for an explanation of the country pairs considered under prior EXPERT.

factor, we minimize for each country and year the following LOSS program:

$$\min \omega(r,t)\,,\ \text{subject to}\ \omega(r,t)\sum_{s\neq t} D(s,t) + \widetilde{\omega}(r,t)\sum_{s\neq t}(1-D(s,t)) = 23,\ \text{and}$$

$$\omega(r,t)\sum_{s\neq t} D(s,t)(-Grad(s,t)) \geq \widetilde{\omega}(r,t))\sum_{s\neq t}(1-D(s,t))\,Grad(s,t)$$

where $D(s,t)$ is a dummy variable that is equal to 1 if an inverted U is observed in case of country s in year t, and equal to 0 if this is not the case, and $Grad(s,t)$ measures the gradient of country s for the emission level in year t compared with the year 2000, which is negative when $D(s,t)$ is 1 and positive otherwise. So, with $\omega(r,t) < 1$, an inverted U is likely to exist, because one does not have to attach much additional weight to the pairs that do show an inverted U. However, with $\omega(r,t) >> 1$ an inverted U is very unlikely for this country given that so much weight has to be given to pairs that confirm this pattern. If there is some country r for which all pairs have an inverted-U shape we set $\omega(r,t) = 0$, and if there is no pair (r,s) with an inverted-U shape we set $\omega(r,t) = \infty$.

[INSERT FIGURE 4.a and 4.b]

We present the results for the priors BAYES and EXPERT in Figures 4.a and 4.b, and for the index LOSS in Table 2 for both the SO_2 and CO_2sample. The figures represent the (computed) average pure income and time effects for all relevant country pairs.[24] The results clearly show that the pure income effect is positive and more or less linear. In other words, the scale effects positively influence per capita emission levels for both samples. Also, the difference between the priors is small to very small. This unambiguous result finds further support from using the index LOSS. Table 2 shows the results for this prior for each of the different countries and for two particular years, i.e. 1991 and 1997. The countries are ranked from lowest to highest $\omega(r,t)$, using this index for the SO_2 case in 1997. The level of the factor $\omega(r,t)$ in both the SO_2 and CO_2 samples is usually (far) above 1 and there is generally little difference between the two years, indicating that the result of a positive pure income effect is very robust. The factor is only below 1 for Sweden and Iceland in the CO_2 case. These countries are also precisely the ones for which the other priors generate an inverted U. For our SO_2 sample all factors are above 1 and

[24]By averaging we deal with the problem that particularly country-specific time effects might be estimated quite inaccurately. However, in the supplement we also present a complete country-specific picture.

on average higher than for the CO_2 sample. For the SO_2 and CO_2 samples country pairs that do yield an inverted U have to be counted as respectively 3.89 and 3.33 times stronger on average in 1991 than those country pairs that do not yield such an inverted-U pure income effect. We conclude that it is very unlikely that the pure income effect is negative.

[INSERT TABLE 2]

Overall the results for our three priors are remarkably consistent. Exact identification of the reduced-form hypothesis does not provide evidence of an inverted U for the income effect in many countries. Our estimations confirm the importance of the time effect but not the income effect in causing a downward trend in emissions. Looking at Figure 4.a again we find that the (average) time-related effects show a clear inverted-U pattern with per-capita SO_2 emissions. Their peak comes around 1965 with a steady decline since. In other words, the combined composition and technique effect is clearly negative and produces lower overall (per-capita) emission levels. Time effects on per-capita CO_2 emissions (Figure 4.b) also tend to peak, though during an almost decade-long trajectory, and then more or less stabilize from the beginning of the '80s. Thus composition and technique effects seem to have much less impact for CO_2 than for SO_2emissions. Given the clear upward trend in the income effect, it is hardly surprising that there has been an almost linear rise in overall CO_2 emissions per capita since the trough at the beginning of the 1980s. For SO_2emissions the overall effect is clearly downward given the rather steep decline in the time effect. These findings also substantiate common sense observations for both types of emissions. The level of (per capita) SO_2emissions initially benefited mainly from fuel substitution away from coal, and later on from the rather intensive regulatory effort to bring these emissions down through abatement technologies, which was also coordinated internationally by a substantial number of countries within our panel (see for example, Popp [2002]). The picture is entirely different for CO_2emissions. In particular the benefit from fuel substitution and to a lesser extent compositional changes is much smaller for these emissions, and international standards for CO_2 emissions are still quite lax and often almost non-binding despite coordinated efforts such as the Kyoto protocol.

V Conclusion

This paper shows that reduced-form panel-based estimations of hypothesized inverted-U relationships should be treated with care. We demonstrate for two widely studied panels, namely SO_2 and CO_2 emissions for OECD countries, that the current lack of robustness of inverted-U estimations of emission-income relationships is due to underidentification. In particular, results are strongly dependent on the imposed identifying restrictions with respect to the independent variable (income) and the control variable (time). Different identifying assumptions result in different model specifications, inducing different inferences. Fortunately, our alternative inference procedure makes clear that some merit still exists in reduced-form estimations of inverted-U shapes, such as emission-income relationships.

Our pairwise estimation procedure, based on a very weak identifying assumption, combined with different priors, generates clear and convincing patterns for the two mechanisms that are widely perceived as being theoretically important in explaining long-run developments. Specifically, our empirical analysis justifies the inference that (on average) the income effect is not responsible for an inverted U. Instead, on average it is time that explains the overall downward trend in country-specific emission-income relationships, if such a trend exists at all. These results nicely corroborate theoretical models that explicitly distinguish between scale, composition and technique effects (for example, Stokey [1998], Andreoni and Levinson [2001] and Brock and Taylor [2005]). Our pure income effect is consistent with the scale effect that the theory expects to be positive: economies operating at a larger scale generally use more inputs (emissions). One would only expect a declining overall effect from a shift in sectors and technological change strong enough to offset this scale effect. Such effects are typically time related, and our time effect estimates are again plausible. Time effects are negative enough to more than offset the positive scale effect in the case of the strongly regulated SO_2-emissions, but not so for CO_2 emissions which tend to go more or less unregulated.

The robust findings for our case studies suggest that our pairwise estimation procedure, in combination with the sensitivity analysis of the priors involved, provides a promising direction for future work for comparable panel-based reduced-form estimations suffering from similar identification problems.

A. Appendix

A.1 Data description

We have taken our SO_2 data from http://www.rpi.edu/~sternd/datasite.html and they are described in more detail by Stern [2005]. Stern took his data for OECD countries from the UNECE/EMEP emission database WebDab, which has been constructed with the purpose of facilitating the access to the emission data reported to the Convention on Long-Range Transboundary Air Pollution (CLRTAP) on Main Pollutants among other compounds. The database contains officially reported emission data for the emission years 1980 to 2003. Data for the 70's are obtained from OECD sources and for earlier periods from a database from ASL and Associates. Stern [2005] and Stern and Common [2001] have also checked their results for SO_2 emissions vis-a-vis earlier findings in the literature and they report almost no sensitivity of their findings for the data-set they use.

Our data on CO_2 emissions are calculated from energy consumption measured in million tons of oil equivalent (TOE) 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. Our procedure for calculating CO_2 emissions from OECD energy consumption data is similar to the approach followed by the Carbon Dioxide Information Analysis Center of Oak Ridge National Laboratory (ORNL), whose data are usually employed in empirical research on CO_2 emissions, such as Holtz-Eakin and Selden [1995] and Schmalensee et al. [1998]. To check the sensitivity of our CO_2 data-set, we also tested our results using this data-set for a similar sample period, i.e., excluding data between 1990 and 1997.[25] In all cases our basic findings are similar.

Figures A.1.a and A.1.b show the scatter plots for both our SO_2.and CO_2 data-sets. To illustrate the potential role of country heterogeneity, in particular in the upper tail of the distribution, we have highlighted the data for the two countries at

[25] For this sensitivity analysis to be fully comparable we have also used income data taken from the Penn World Table until 1992 for the same (OECD) sample. This also accounts for potential problems with data on Y for Germany, as these data are restricted to West Germany only. These results are available upon request.

the highest income levels, namely the USA and Luxemburg.[26]

[INSERT FIGURE A.1.a and A.1.b]

A.2 Additional details for Figures 1.a and 1.b

We present results only for the best-performing models. In the SO_2 case we find that the cubic form is rejected when we allow for time fixed effects, but the cubic model is preferred with country-specific trends. In the CO_2 case 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.[27] Table A.1 summarizes our main findings for the (pooled) parametric (log-linear) specification for both emissions. The response coefficients for income in all specifications are significantly different from zero at the $p<0.01$ level even when estimated jointly.

[INSERT TABLE A.1]

In the case of the flexible piecewise (linear) spline framework, such as in 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. Our findings for the spline method are included in Figures 1.a and 1.b in the main text. We only present splines that are significant. Vertical lines are added at the predicted peak of the parametric EKC and its upper and lower limits of the 95% confidence interval.

A.3 Prior EXPERT

The prior EXPERT attaches *a priori* probabilities on some subset of country pairs on the likelihood of homogeneous time effects as judged by some rationalized expert judgment. We take it that expert opinion is shaped by time-related developments in energy use of country pairs. Accordingly, the prior categorizes countries using both the level of non-fossil fuel use in 1960 and 2000 and its development over time,

[26] Note that the high per capita emissions in Luxemburg are mainly due to the fact that the share of steel production in GDP was over 50% in the first two decades of our sample period.

[27] Response coefficients for the quadratic model, as well as for models without country-specific fixed effects and time fixed effects, are available upon request.

i.e., between 1960 and 1997. Table A.2.a summarizes major developments in and levels of energy use and its composition for fossil and non-fossil energy use, for all countries in our sample using the OECD Energy Balances [OECD, 2000]. The first four columns show the level and overall growth in non-fossil fuel use between 1960 and 1997 (measured as a percentage of overall TPES). For instance, the United Kingdom only took 1% of its total primary energy use from non-fossil fuels in 1960, whereas this percentage is as high as 11% in 1997. Therefore, both the level in 1997 and the growth rate in this period have been high. The next four columns provide insight into the level and growth in overall energy use since 1960. Again take the UK as an example. The level of primary energy use per capita has grown here from 3 in 1960 to only 4 in 1997 which is only a modest rise of 26%.

As to the overall ranking of the countries in groups, we followed a lexicographic rule. First of all, a country gets an assessment of "good" if the level of non-fossil fuel energy use exceeds 10% in 1997 and the growth rate is above 50%, and of "bad" otherwise. Next, we categorize countries into "good", "neutral" and "bad" according to whether the growth of overall energy use is below 100%, between 100 and 200% or above 200%, respectively. Accordingly, we create 6 groups of "homogeneous" countries, putting most weight on the first indicator which captures the level of non-fossil-fuel energy use in 1997. For instance, the first group has a high level of non-fossil-fuel use in 1997 and a growth in energy use below 100% between 1960 and 1997. Accordingly, we find that the United Kingdom and Canada are the only members of this group. Next, we apply our pairwise estimation procedure to both countries using the other country as its reference country, which is clarrified in Table A.2.b. The five other groups consist of respectively 7, 2, 3, 7 and 3 countries, which is clarified in the last column of Table A.2.a. As a consequence, if a group contains 7 countries, we include for each of the countries in this group country pairs taking the other 6 countries as their reference country. Finally, we have averaged these results for each country.

[INSERT TABLE A.2.a and A.2.b]

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Tables and Figures

Table I.: Descriptive statistics[a]

Variable	Unit	Mean	SD	Minimum	Maximum
Income	mln 1990 $	483,479	972,380	1,218	7,500,777
Carbon	tons	103,858	251,789	323	1,593,490
Sulfur	tons	1,071	2,315	1.51	14,421
Population	mln	33	50	0.2	275
Per-capita income	1990 $	13,172	4,992	2,771	33,635
Per-capita carbon	kg	2,606	1,801	167	12,333
Per-capita sulfur	kg	29	24	1.25	154

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

Table 2: Turning-point sensitivity for index LOSS for SO_2 and CO_2

	SO_2		CO_2	
	1991	1997	1991	1997
JPN	1.07	1.07	2.70	3.03
SWI	1.23	1.22	3.67	3.66
DNK	1.51	1.59	2.79	3.13
NOR	1.77	1.64	2.29	2.00
CAN	1.60	1.66	1.92	2.03
UKD	1.88	1.67	1.71	1.62
NLD	2.04	1.98	2.15	1.96
AUT	1.85	2.04	2.00	1.91
BEL	2.07	2.08	1.80	1.87
SWE	2.39	2.43	0.62	0.60
LUX	2.38	2.45	1.74	1.66
NZL	2.63	2.75	7.46	5.64
IRE	3.57	2.78	6.46	3.71
USA	3.58	3.11	3.30	3.49
GER	3.13	3.18	1.30	1.31
FRA	3.17	3.19	1.28	1.28
ITA	2.93	3.37	4.14	4.17
SPA	3.42	3.40	4.94	3.52
TUR	3.11	4.08	9.76	7.27
GRE	4.27	4.35	8.34	6.18
FIN	6.91	6.76	1.63	1.46
ICE	7.05	7.13	0.68	0.68
AUS	7.20	20.17	3.92	4.73
POR	22.65	22.89	∞	∞
Average	3.89	4.46	3.33	2.91
Stdev	4.36	5.48	2.50	1.78

Table A.1: Main test results for parametric estimations based on homogeneity[a]

	SO_2 per capita		CO_2 per capita	
	A[b]	B	C	D
Independent variables				
GDP	28.01***	-192.02***	-31.12***	-30.88***
	(1.12)	(17.31)	(-7.58)	(-6.12)
GDP^2	-1.50***	21.91***	4.22***	3.80***
	(0.06)	(1.89)	(-0.83)	(-0.67)
GDP^3		-0.82***	-0.18***	-0.15***
		(0.07)	(-0.03)	(-0.02)
Fixed effects, countries	Yes	Yes	Yes	Yes
Fixed effects, years	Yes		Yes	
Country-specific trend		Yes		Yes
Homogeneity tests				
Wald (GDP variables)	2,949***c	1,254***c	817***c	1,219***c
Wald (country-specific trends)		429***d		357***d
Wald (all variables)		4,514***e		5,389***e

a) Standard errors in parentheses.

b) Cubic form not significant.

c) Wald test with H0: $b_{1r}=b_{1r+1}$ and $b_{2r}=b_{2r+1}$ and $b_{3r}=b_{3r+1}$.

d) Wald test with H0: $\lambda_r=\lambda_{r+1}$.

e) Wald test with H0: $b_{1r}=b_{1r+1}$ and $b_{2r}=b_{2r+1}$ and $b_{3r}=b_{3r+1}$ and $\lambda_r= \lambda_{r+1}$.

*** Significant at 99% level.

Table A.2.a: Data used for expert opinion

	Non-fossil fuel use				TPES				Rank
	Level[1]		Growth[2]	Assess-	Level[3]		Growth[2]	Assess-	
	1960	1997	'60-'97	ment	1960	1997	'60-'97	ment	
UKD	1	11	2,049	good	3.1	3.9	26	good	1
CAN	12	22	82	good	4.3	7.9	82	good	1
SWE	13	47	258	good	2.7	5.9	114	neutral	2
GER	1	13	1,732	good	2.0	4.2	116	neutral	2
BEL	0	22	33,482	good	2.5	5.6	120	neutral	2
FRA	4	44	881	good	1.7	4.2	143	neutral	2
SWI	23	37	57	good	1.4	3.7	160	neutral	2
ICE	27	64	134	good	3.2	8.6	172	neutral	2
FIN	5	20	324	good	2.2	6.4	192	neutral	2
JPN	6	18	195	good	0.9	4.1	370	bad	3
SPA	8	16	96	good	0.5	2.7	417	bad	3
LUX	0	0	290	bad	10.5	8.0	-24	good	4
USA	1	10	691	bad	5.7	8.1	43	good	4
AUS	1	2	38	bad	3.0	5.5	83	good	4
DNK	0	1	3,709	bad	2.0	4.0	103	neut.	5
AUT	9	11	25	bad	1.6	3.4	122	neutral	5
NZL	20	22	9	bad	1.7	4.4	156	neutral	5
IRE	2	0	-77	bad	1.3	3.4	156	neutral	5
NLD	0	1	na	bad	1.8	4.8	161	neutral	5
NOR	38	39	1	bad	1.9	5.5	183	neutral	5
TUR	1	5	543	bad	0.4	1.1	190	neutral	5
ITA	14	4	-73	bad	0.8	2.8	260	bad	6
POR	9	6	-35	bad	0.3	2.1	489	bad	6
GRE	2	2	15	bad	0.3	2.4	703	bad	6

1. In % of TPES. 2. In % of 1960 level. 3. Per capita.

Table A.2.b: Pairwise combinations for expert opinion

No	Country	Paired with: 1^{st}	2^{nd}	3^{rd}	4^{th}	5^{th}	6^{th}
4	AUS	LUX	USA				
5	AUT	DNK	IRE	NLD	NOR	NZL	TUR
2	BEL	FIN	FRA	GER	ICE	SWE	SWI
1	CAN	UKD					
5	DNK	AUT	IRE	NLD	NOR	NZL	TUR
2	FIN	BEL	FRA	GER	ICE	SWE	SWI
2	FRA	BEL	FIN	GER	ICE	SWE	SWI
2	GER	BEL	FIN	FRA	ICE	SWE	SWI
6	GRE	ITA	POR				
2	ICE	BEL	FIN	FRA	GER	SWE	SWI
5	IRE	AUT	DNK	NLD	NOR	NZL	TUR
6	ITA	GRE	POR				
3	JPN	SPA					
4	LUX	AUS	USA				
5	NLD	AUT	DNK	IRE	NOR	NZL	TUR
5	NOR	AUT	DNK	IRE	NLD	NZL	TUR
5	NZL	AUT	DNK	IRE	NLD	NOR	TUR
6	POR	GRE	ITA				
3	SPA	JPN					
2	SWE	BEL	FIN	FRA	GER	ICE	SWI
2	SWI	BEL	FIN	FRA	GER	ICE	SWE
5	TUR	AUT	DNK	IRE	NLD	NOR	NZL
1	UKD	CAN					
4	USA	AUS	LUX				

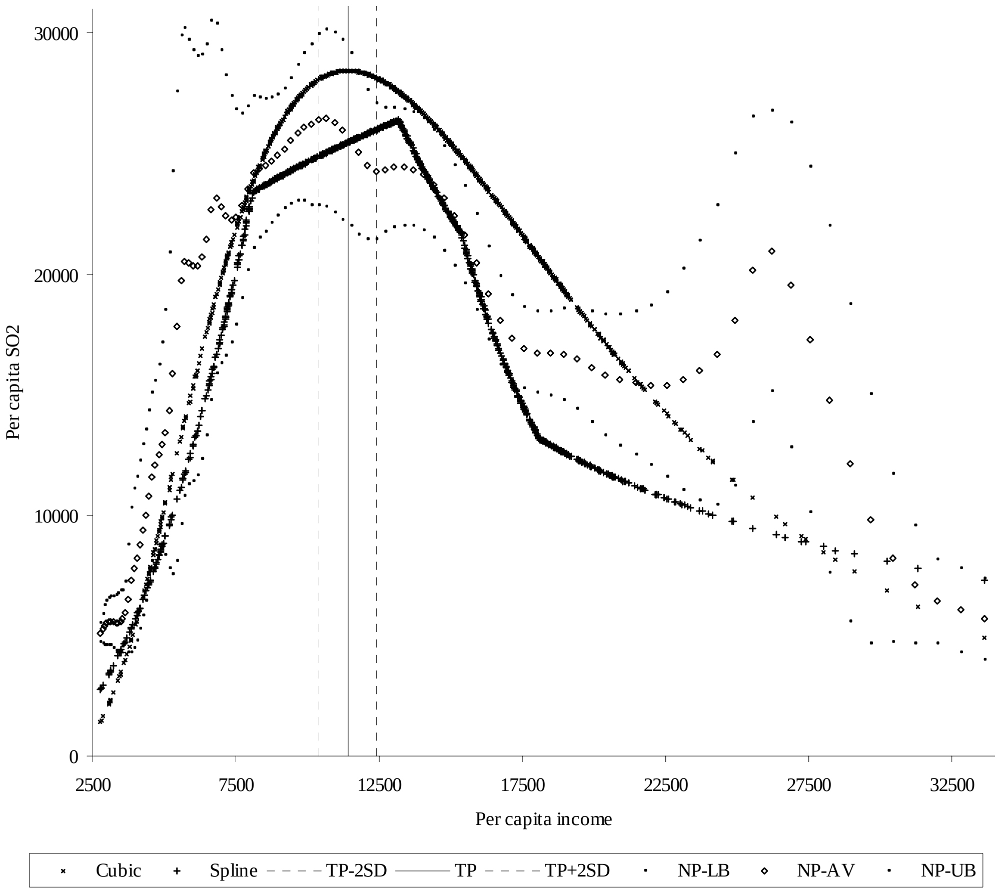

Figure 1.a. Estimation results for 24 OECD countries based on homogeneous country and time fixed effects for SO_2

Explanatonary legend:

- Cubic: parametric cubic specification
- Spline: 24 piecewise linear (significant splines only)
- TP±2SD: turning point ±2 standard deviations
- NP-LB/AV/UB: non-parametric PLR lower, average and upper bound

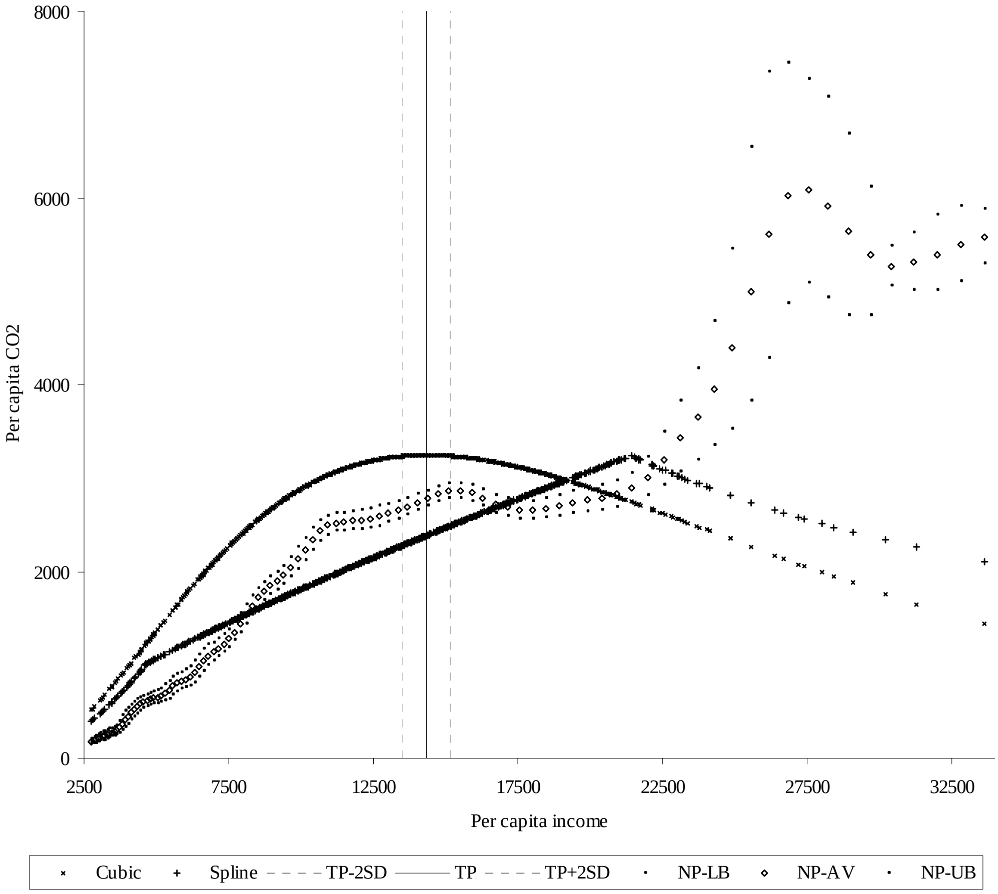

Figure 1.b. Estimation results for 24 OECD countries based on homogeneous country and time fixed effects for CO_2

Explanatonary legend:

- Cubic: parametric cubic specification
- Spline: 24 piecewise linear (significant splines only)
- TP$\pm$2SD: turning point ± 2 standard deviations
- NP-LB/AV/UB: non-parametric PLR lower, average and upper bound

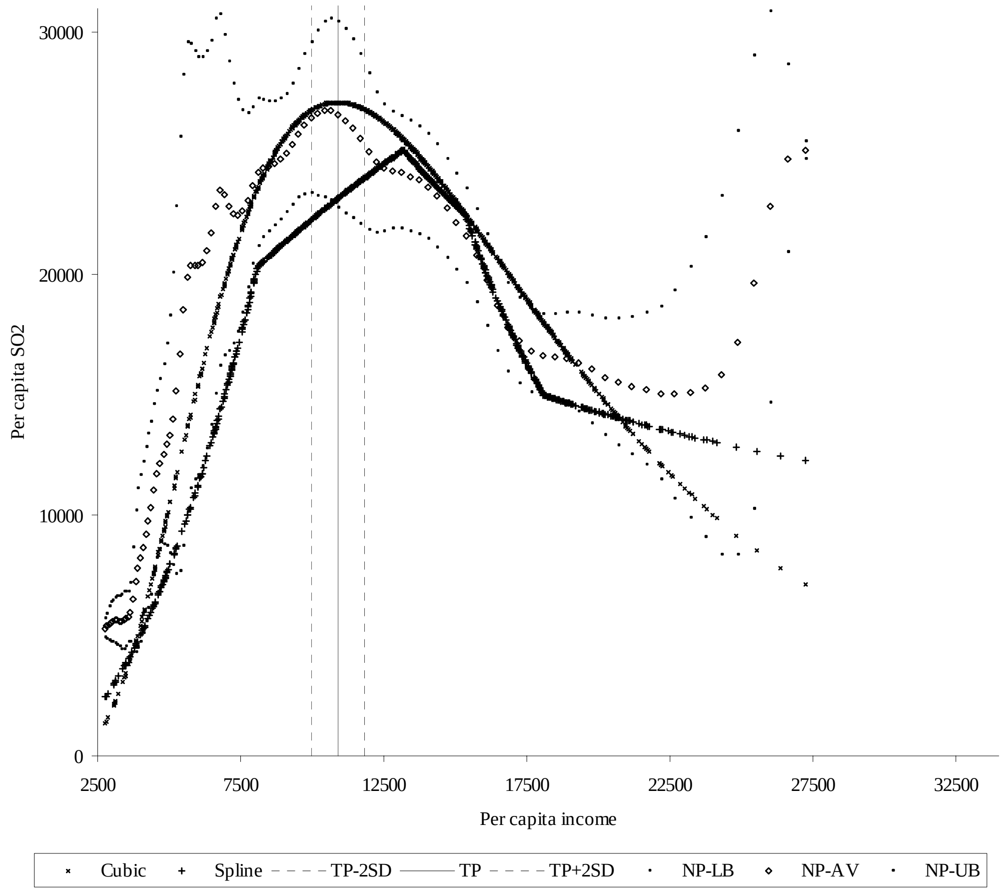

Figure 2.a. Estimation results for 23 OECD countries (excluding Luxemburg) based on homogeneous country and time fixed effects for SO_2

Explanatonary legend:

- Cubic: parametric cubic specification
- Spline: 24 piecewise linear (significant splines only)
- TP$\pm$2SD: turning point ± 2 standard deviations
- NP-LB/AV/UB: non-parametric PLR lower, average and upper bound

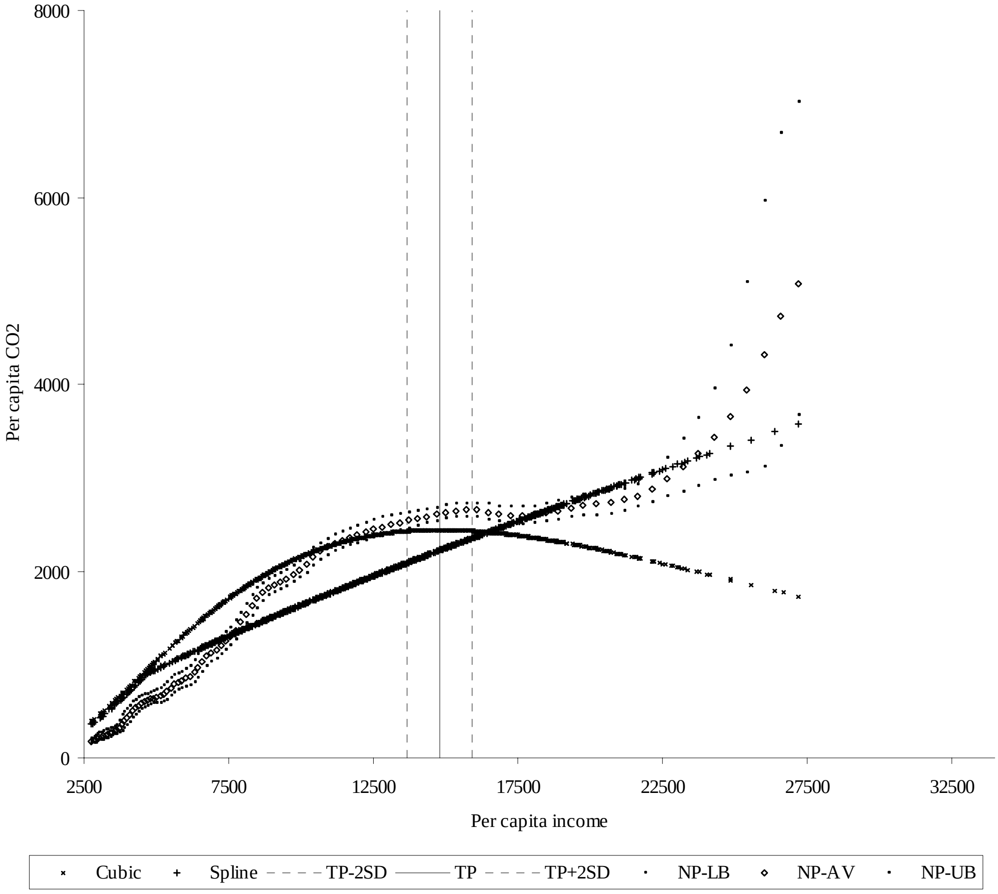

Figure 2.b. Estimation results for 23 OECD countries (excluding Luxemburg) based on homogeneous country and time fixed effects for CO_2

Explanatonary legend:
- Cubic: parametric cubic specification
- Spline: 24 piecewise linear (significant splines only)
- TP$\pm$2SD: turning point ± 2 standard deviations
- NP-LB/AV/UB: non-parametric PLR lower, average and upper bound

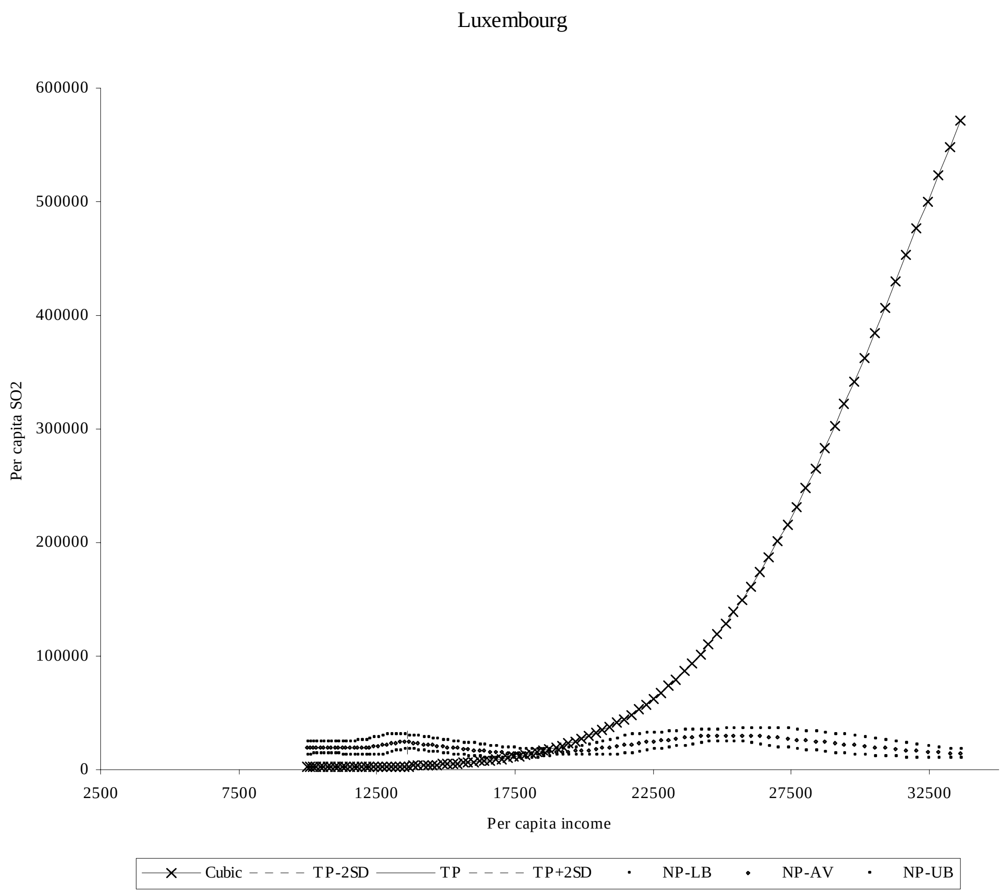

Figure 3.a.1. Results for third- order polynomial time effect assumption for Luxemburg: SO_2

Explanatonary legend:

- Cubic: parametric cubic specification
- TP±2SD: turning point ±2 standard deviations
- NP-LB/AV/UB: non-parametric PLR lower, average and upper bound

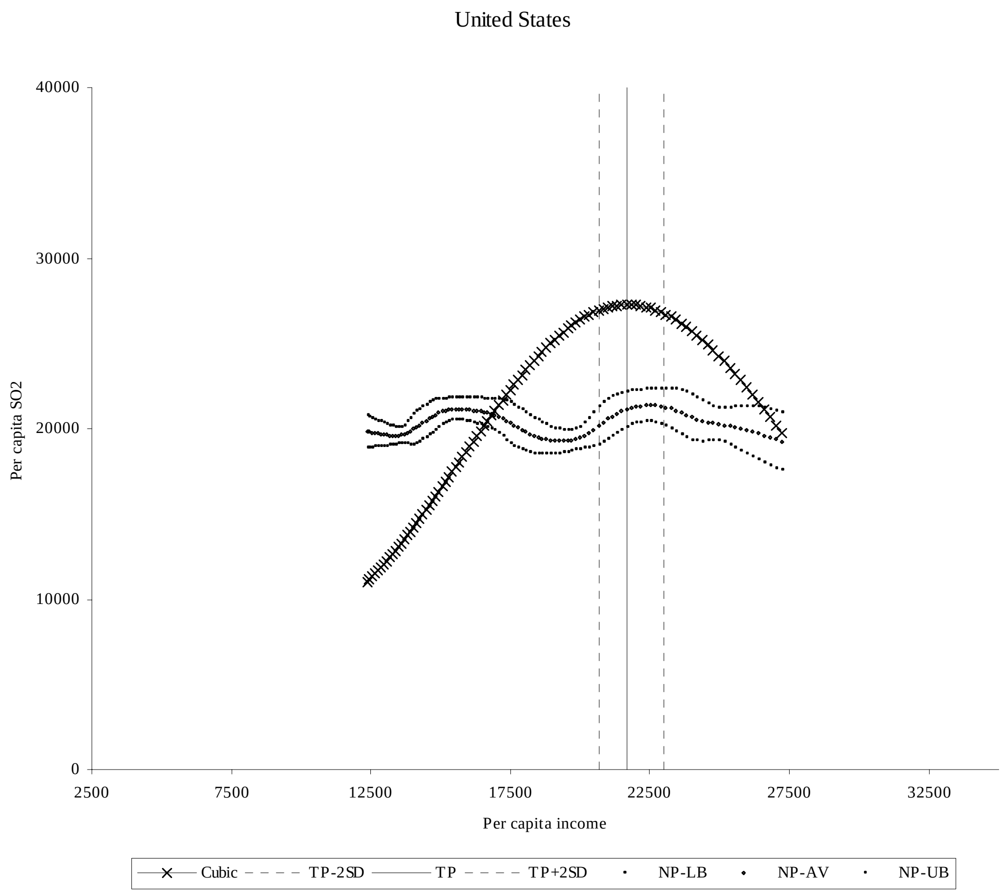

Figure 3.a.2. Results for third- order polynomial time effect assumption for the USA: SO_2

Explanatonary legend:

- Cubic: parametric cubic specification
- TP$\pm$2SD: turning point $\pm$2 standard deviations
- NP-LB/AV/UB: non-parametric PLR lower, average and upper bound

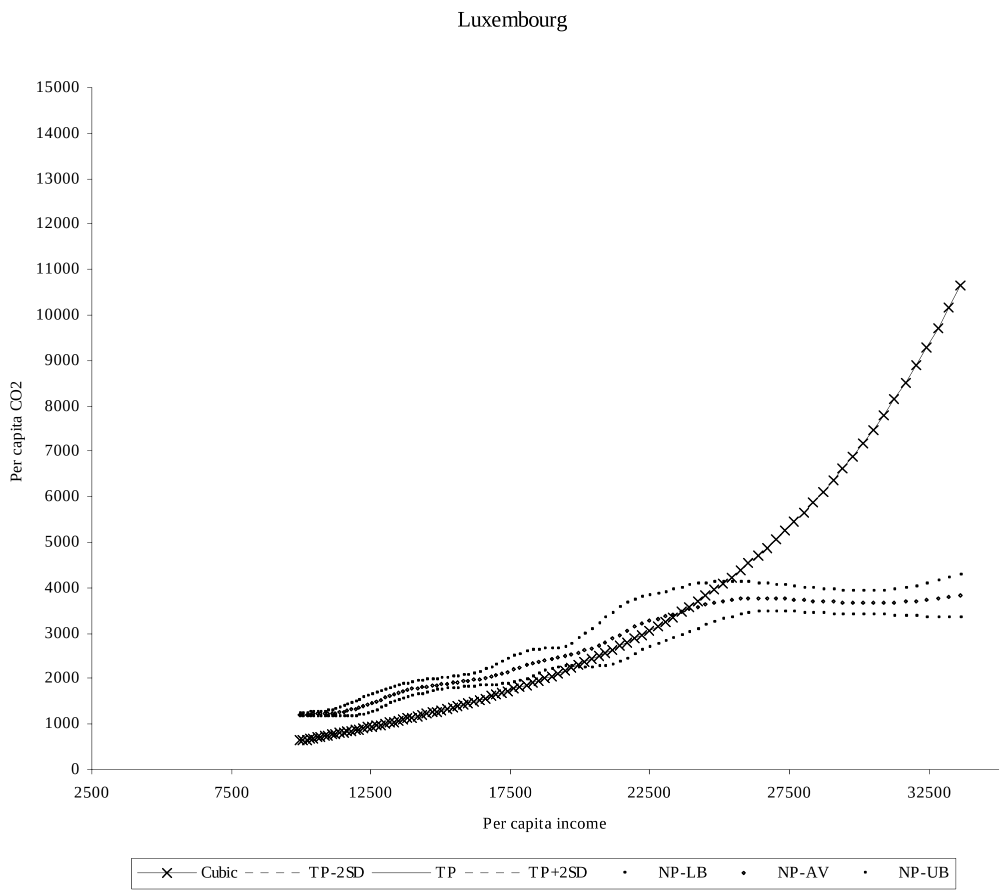

Figure 3.b.1. Results for third- order polynomial time effect assumption for Luxemburg: CO_2

Explanatonary legend:
- Cubic: parametric cubic specification
- TP±2SD: turning point ±2 standard deviations
- NP-LB/AV/UB: non-parametric PLR lower, average and upper bound

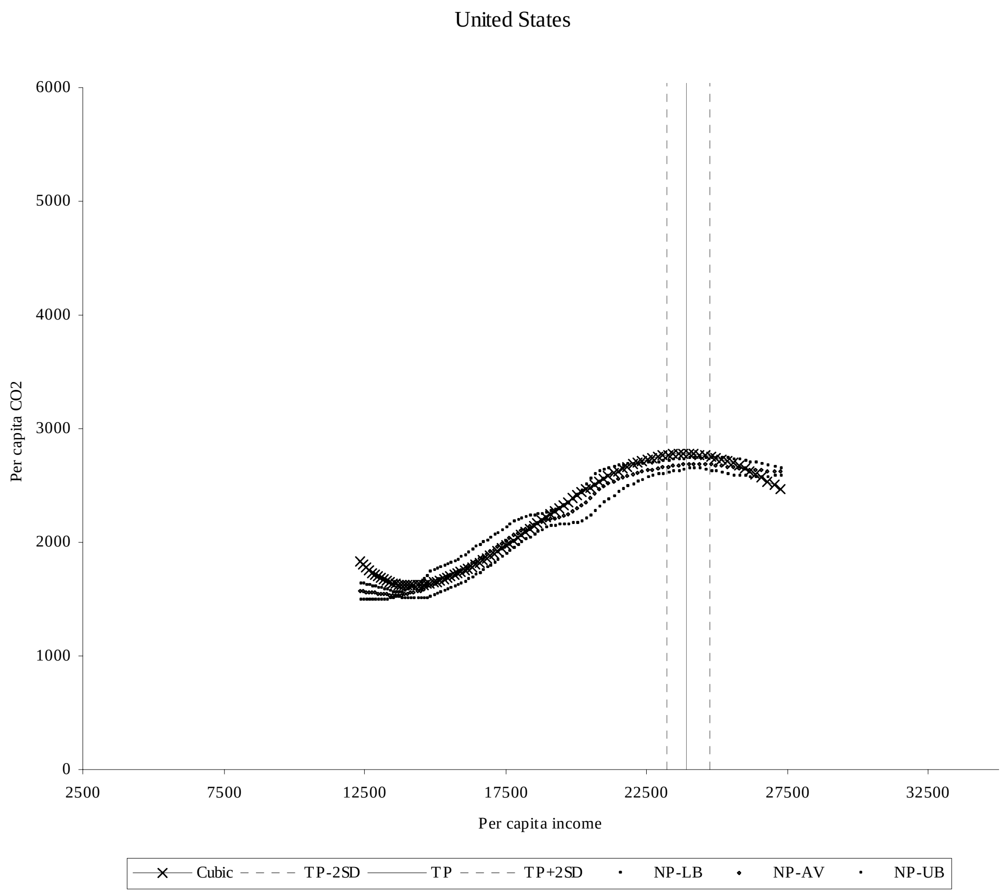

Figure 3.b.2. Results for third- order polynomial time effect assumption for the USA: CO_2

Explanatonary legend:

- Cubic: parametric cubic specification
- TP±2SD: turning point ±2 standard deviations
- NP-LB/AV/UB: non-parametric PLR lower, average and upper bound

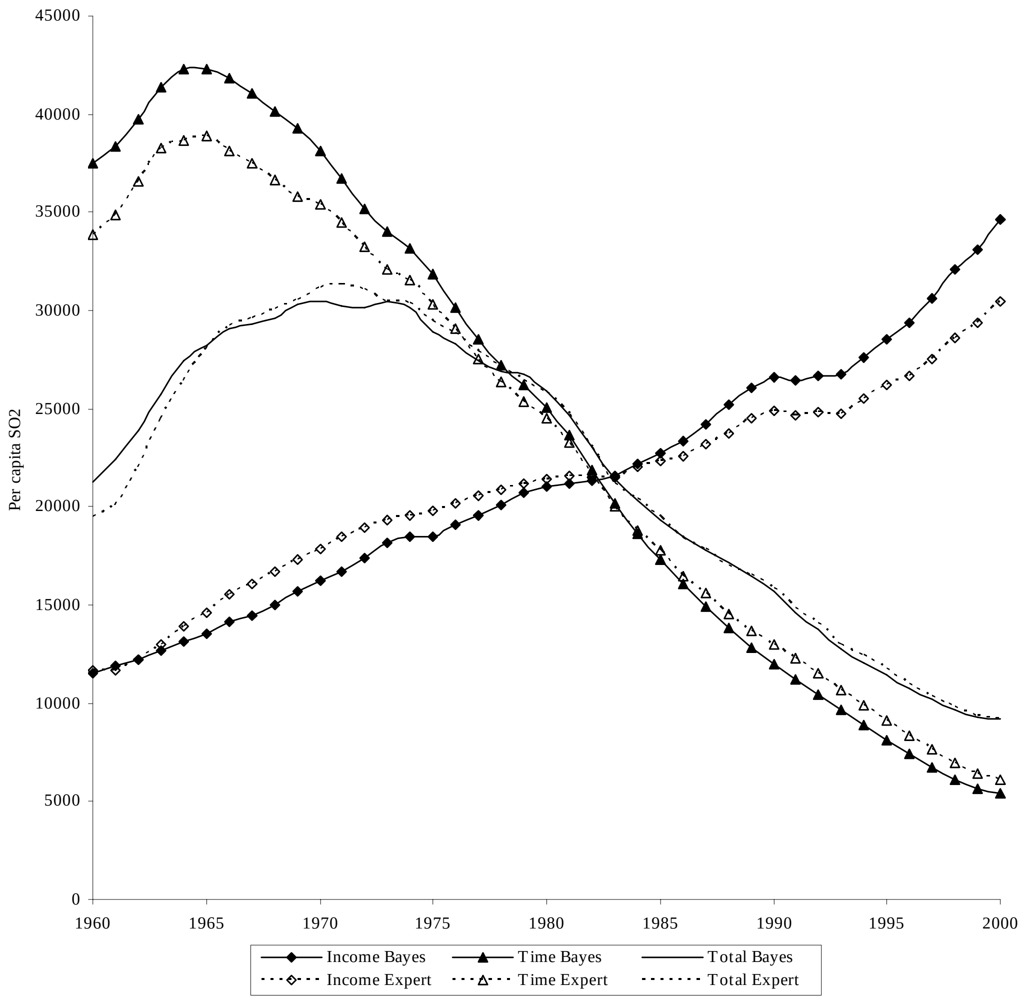

Figure 4.a. Time- and income- related plots for whole sample using prior BAYES and EXPERT for SO_2

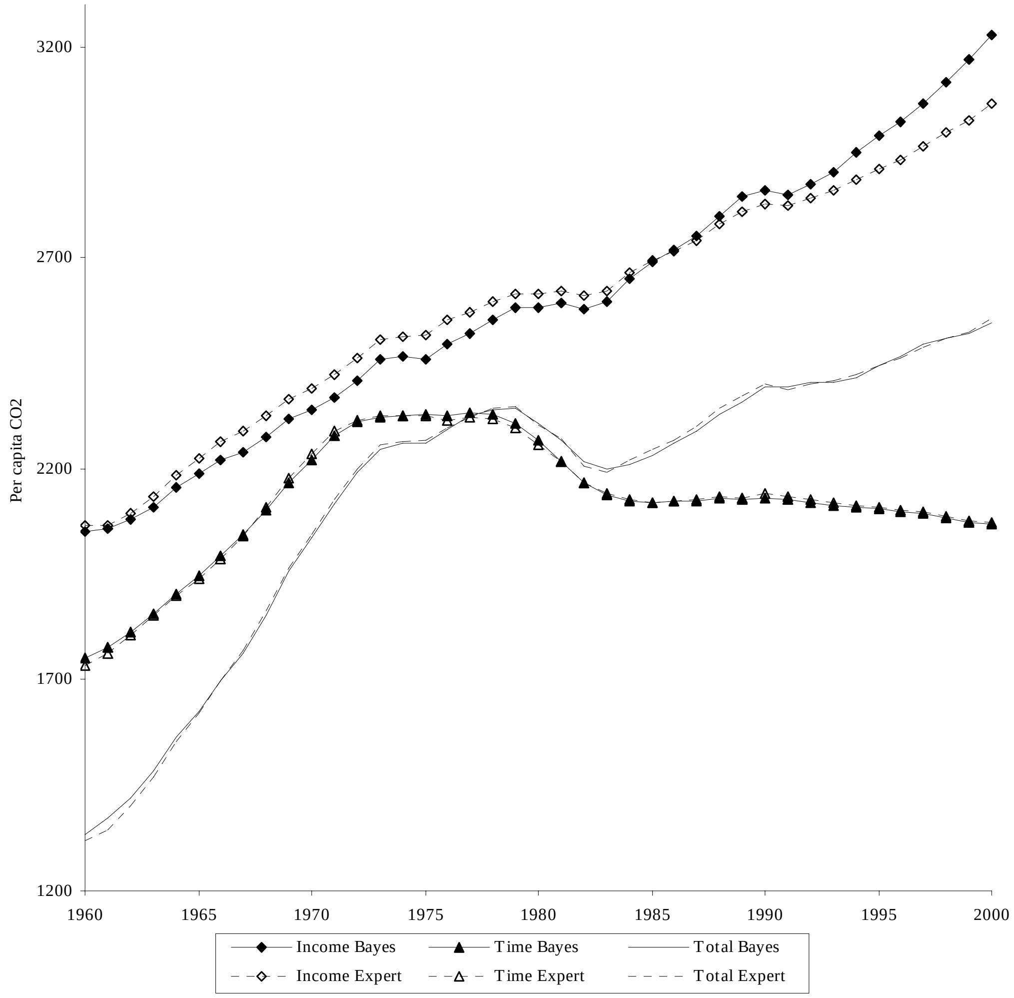

Figure 4.b. Time- and income- related plots for whole sample using prior BAYES and EXPERT for CO_2

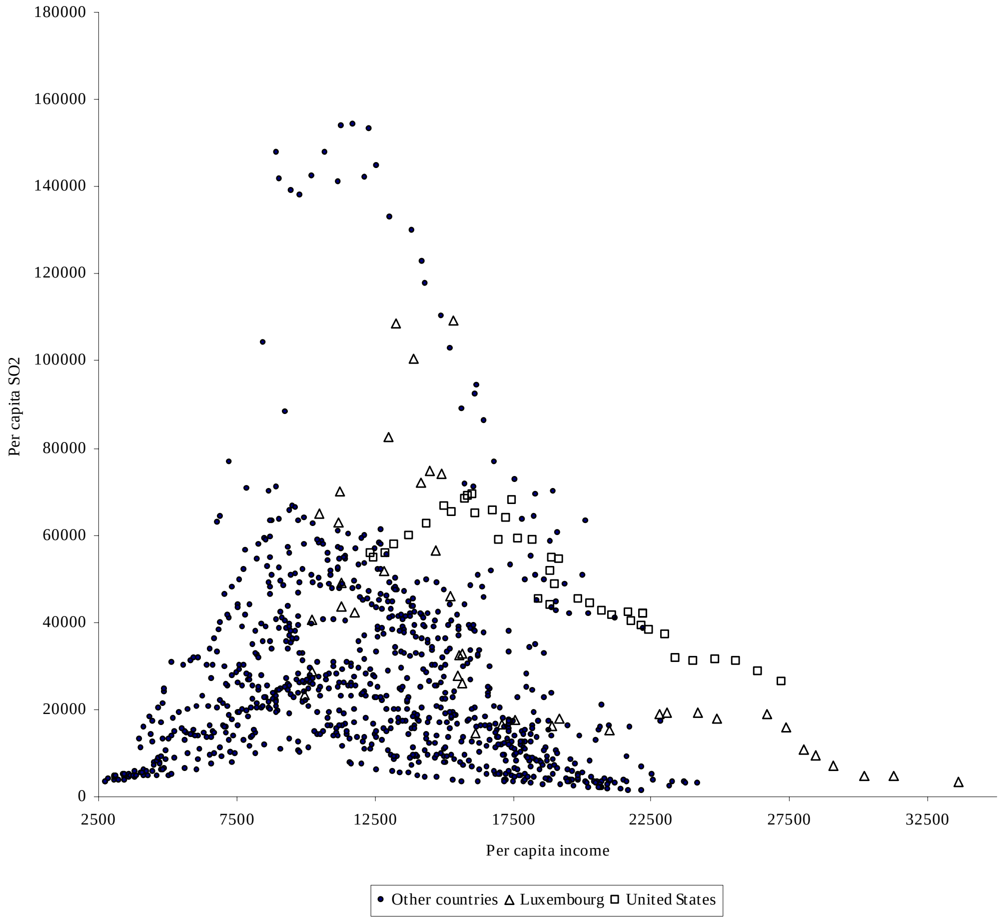

Figure A.1.a. Data plot for SO_2

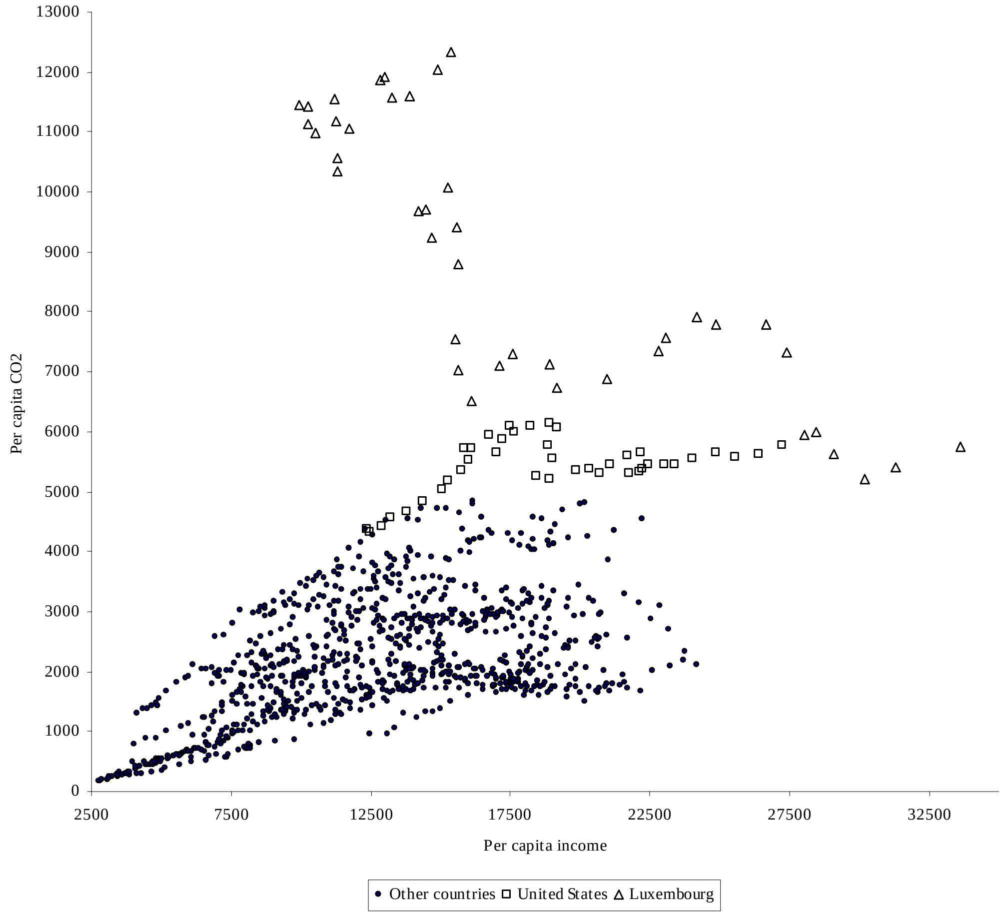

Figure A.1.b. Data plot for CO_2

Supplement: Country-specific results

S.1 Traditional approach

Estimated plots – similar to those presented in Figures 3.a and 3.b – are presented for each country separately in Figure S.1.

[INSERT FIGURE S.1]

First of all, the graphs clearly indicate heterogeneity. Comparing countries with overlapping income levels or comparing a single country with the homogeneous case yields notable differences in many cases. For instance, the TP estimates across countries for the parametric specification differ remarkably, if they exist at all. Interestingly, these findings confirm the heterogeneity predicted by some recent theoretical models (see Brock and Taylor [2005]). According to such models, emission-income 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 growth rates. Brock and Taylor [2005] even claim that empirical assessments should typically have difficulties in finding the inverted U if they do not allow for heterogeneity across countries in "when" (time) and "where" (income level) the peak occurs and for differences in the growth rate of emissions. With this much more flexible reduced-form specification, we indeed confirm notable differences across countries, but also, as we like to stress, patterns that are far from a convincing picture of an inverted U.

Secondly, the difference between estimation methods is sometimes much less pronounced and even disappears for several countries at different income levels. In the case of CO_2 emissions, for example, parametric pattern of countries such as Turkey, Australia and the USA fits almost entirely within the PLR bounds. In some other cases, however, such as Greece, Italy and Luxemburg, 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 judgments more difficult as to whether a TP exists or not.

Thirdly, the TP estimates for the countries differ remarkably, if they exist at all. In the SO_2 case we find no TP at all for 8 countries and of those that do produce a TP 4 have a TP that is (far) out of their own sample. It is notable that in the case of CO_2 emissions as many as 17 of the 24 countries have a TP within the pooled sample and most TPs are even 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 country, the PLR method quite often does not indicate a TP at all. 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!) as an important exception.

S.2 Pairwise approach

Figure S.2.a shows the country specific results for the SO_2 sample, Figure S.2.b for the CO_2 sample. We present the average results per country, where we average over the 23 pairs formed with the other countries.

[INSERT FIGURE S.2.a AND S.2.b]

In the case of the BAYES prior, we find that for the SO_2 sample there is a clear tendency for the income effect to be positive or at least stable for almost all countries. The general picture that emerges from the CO_2 sample is roughly similar, with perhaps Canada being the main exception again. For some countries, such as Australia, Finland, Germany and Portugal, the income effect is really strong. Average time effects are clearly negative for most countries in the SO_2 sample and they even often reflect an inverted U-shaped pattern. In the CO_2 case these effects are much less strong and even provide an upward trend for several countries such as Norway and New Zealand. The results from the prior EXPERT are more sensitive as fewer observations underly the derivation of the country-specific income effects. For instance, the UK only has Canada as the alternative country to form a pair with, and vice versa, and the same holds for Spain and Belgium. For these countries, differences with the BAYES prior can indeed be large.

Tables S.1.a and S.1.b present $\omega(r,t)$ for both samples for all countries and for five years. The level of factor $\omega(r,t)$ in both tables is usually (far) above 1, and there is typically little difference between the years, indicating that the result of a positive pure income effect is very robust. The factor is only below 1 for Sweden and Iceland in the CO_2 case. These countries are also precisely the ones for which the other priors generate an inverted U. For our SO_2 sample all factors are above 1, and on average higher than for the CO_2 sample. On average, country pairs that do yield an inverted U have to be counted as 3.89 and 3.33 times stronger in 1991 than those country pairs that do not yield such an inverted-U pure income effect for both samples respectively.

[INSERT TABLES S.1.a AND S.1.b]

Supplement: Tables and Figures

Table S.1.a: Turning-point sensitivity for index LOSS for SO_2

	1991	1993	1995	1997	1999
JPN	1.07	1.07	1.07	1.07	1.07
SWI	1.23	1.21	1.21	1.22	1.25
DNK	1.51	1.52	1.56	1.59	1.61
NOR	1.77	1.69	1.62	1.64	1.65
CAN	1.60	1.61	1.64	1.66	1.71
UKD	1.88	1.88	1.76	1.67	1.69
NLD	2.04	2.06	2.10	1.98	2.02
AUT	1.85	1.85	2.02	2.04	1.90
BEL	2.07	2.07	2.07	2.08	2.08
SWE	2.39	2.12	2.40	2.43	2.47
LUX	2.38	2.42	2.44	2.45	2.23
NZL	2.63	2.67	2.73	2.75	2.51
IRE	3.57	3.50	3.05	2.78	2.56
USA	3.58	3.58	3.58	3.11	2.75
GER	3.13	3.12	3.15	3.18	3.21
FRA	3.17	3.17	3.18	3.19	2.81
ITA	2.93	2.92	3.36	3.37	3.39
SPA	3.42	3.43	3.41	3.40	2.97
TUR	3.11	3.34	3.28	4.08	3.98
GRE	4.27	4.23	4.28	4.35	4.41
FIN	6.91	10.17	6.85	6.76	6.78
ICE	7.05	6.99	7.04	7.13	7.20
AUS	7.20	10.52	19.98	20.17	20.31
POR	22.65	22.68	22.79	22.89	22.96
Average	3.89	4.16	4.44	4.46	4.40
Stdev	4.36	4.66	5.44	5.48	5.54
Correlation		0.98	0.93	1.00	1.00

Table S.1.b: Turning-point sensitivity for index LOSS for CO_2

	1991	1993	1995	1997	1999
SWE	0.62	0.63	0.61	0.60	0.56
ICE	0.68	0.64	0.68	0.68	0.68
FRA	1.28	1.29	1.28	1.28	1.28
GER	1.30	1.30	1.30	1.31	1.32
FIN	1.63	1.73	1.55	1.46	1.44
UKD	1.71	1.71	1.67	1.62	1.45
LUX	1.74	1.84	1.66	1.66	1.66
BEL	1.80	1.79	1.83	1.87	1.92
AUT	2.00	2.00	1.95	1.91	1.86
NLD	2.15	2.15	2.13	1.96	1.92
NOR	2.29	2.26	2.05	2.00	1.86
CAN	1.92	1.93	1.98	2.03	2.16
JPN	2.70	2.70	2.70	3.03	3.03
DNK	2.79	2.79	2.78	3.13	3.14
USA	3.30	3.33	3.39	3.49	3.60
SPA	4.94	5.04	4.55	3.52	3.24
SWI	3.67	3.65	3.20	3.66	3.69
IRE	6.46	4.95	3.84	3.71	3.71
ITA	4.14	4.96	4.16	4.17	4.19
AUS	3.92	4.69	4.69	4.73	4.03
NZL	7.46	5.69	5.65	5.64	5.61
GRE	8.34	8.29	8.36	6.18	6.06
TUR	9.76	10.00	9.84	7.27	10.35
POR	∞	∞	∞	∞	∞
Average	3.33	3.28	3.12	2.91	2.99
Stdev	2.50	2.38	2.31	1.78	2.17
Correlation		0.98	0.99	0.97	0.96

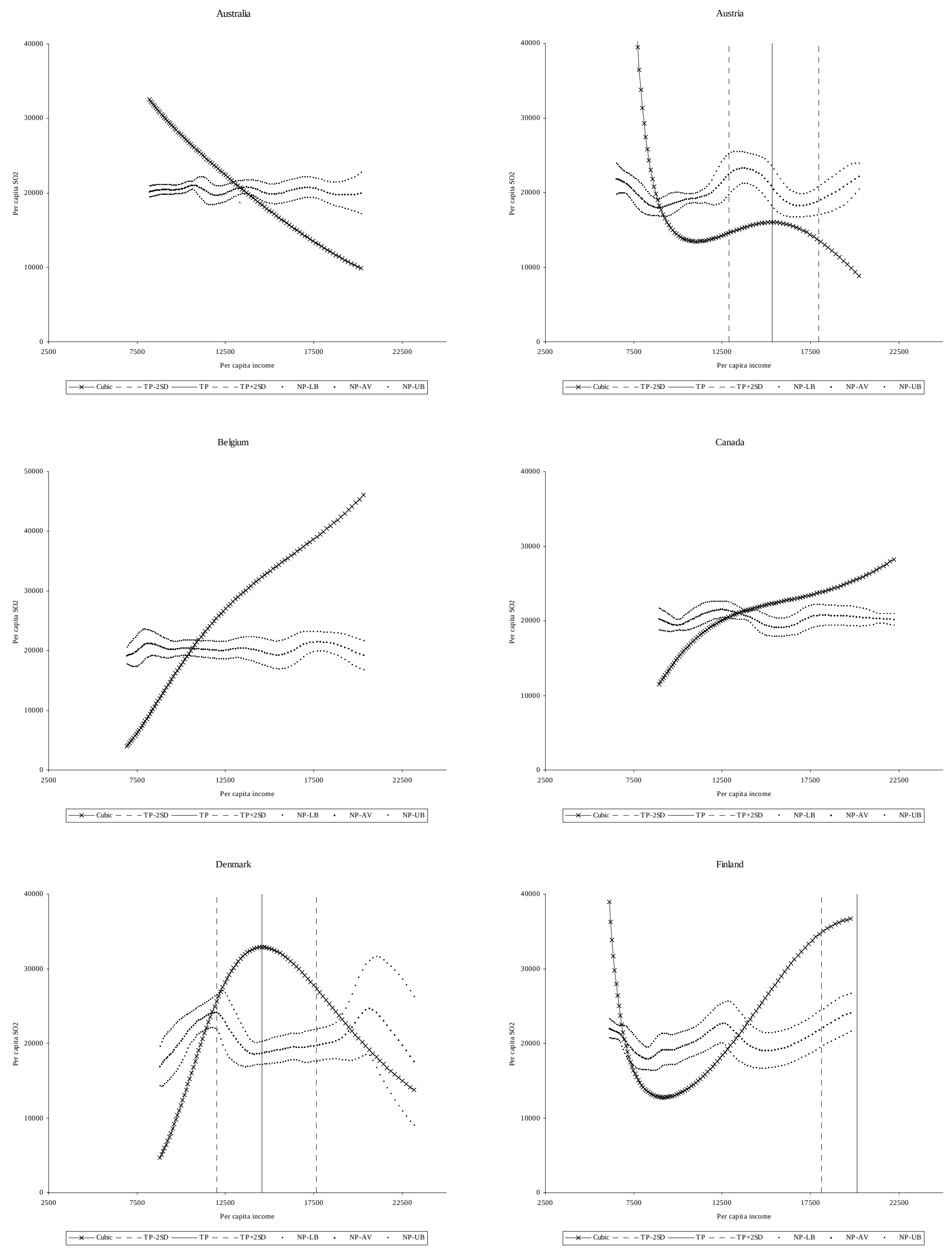

Figure S.1.a. Estimation results for 24 OECD countries based on heterogeneous country and time fixed effects for SO_2

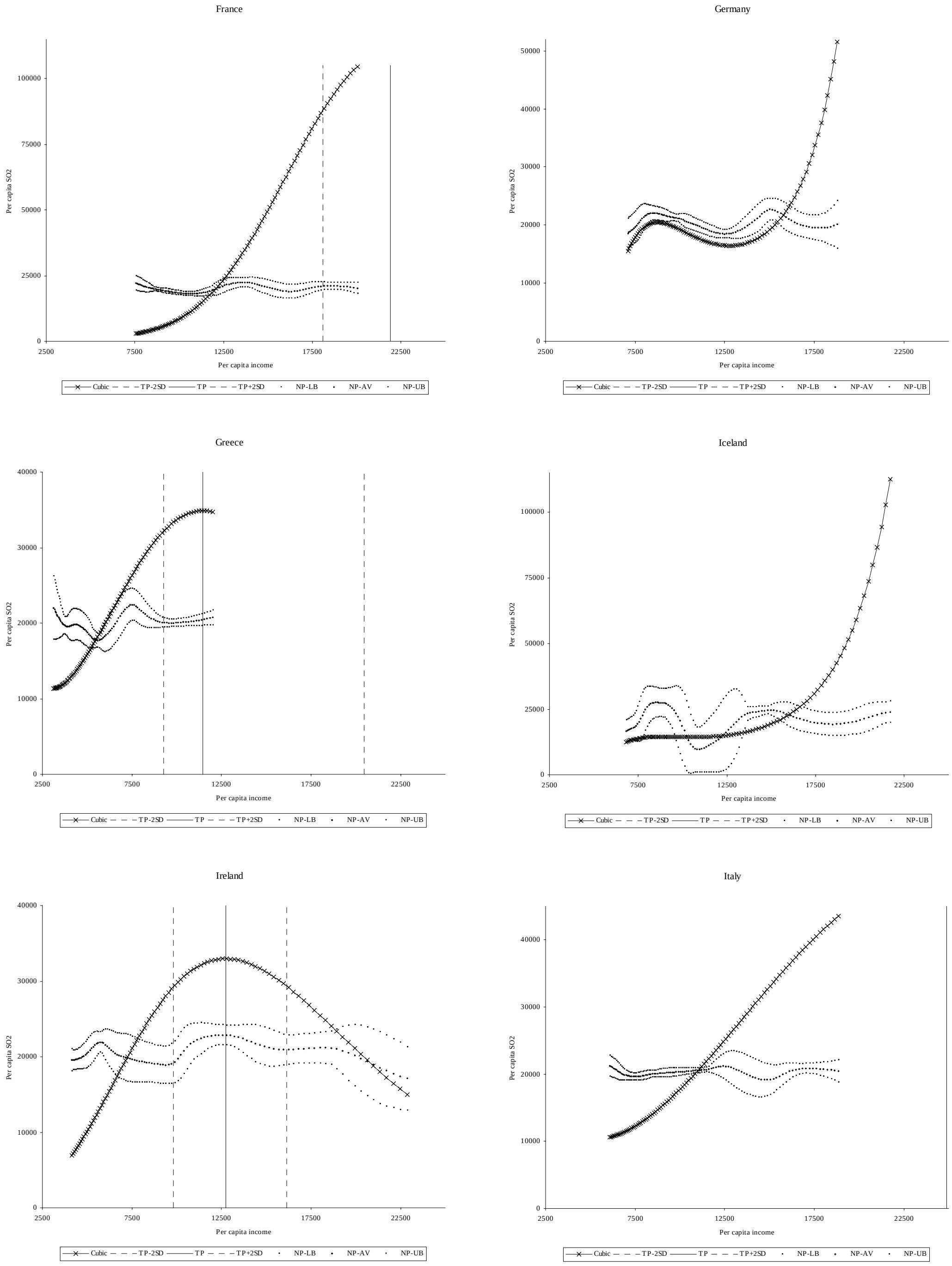

Figure S.1.a (cont.) Estimation results for 24 OECD countries based on heterogeneous country and time fixed effects for SO_2

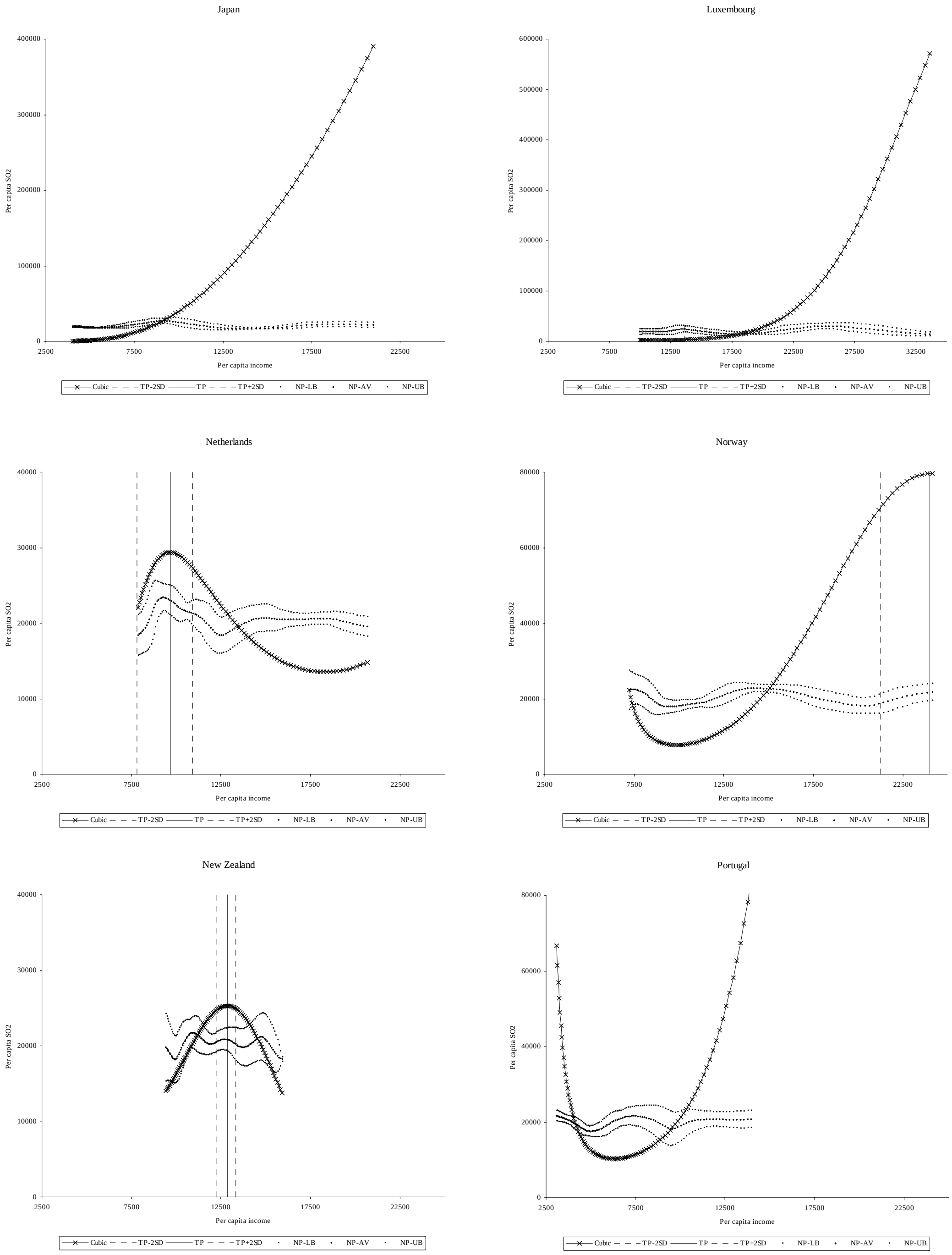

Figure S.1.a (cont.) Estimation results for 24 OECD countries based on heterogeneous country and time fixed effects for SO_2

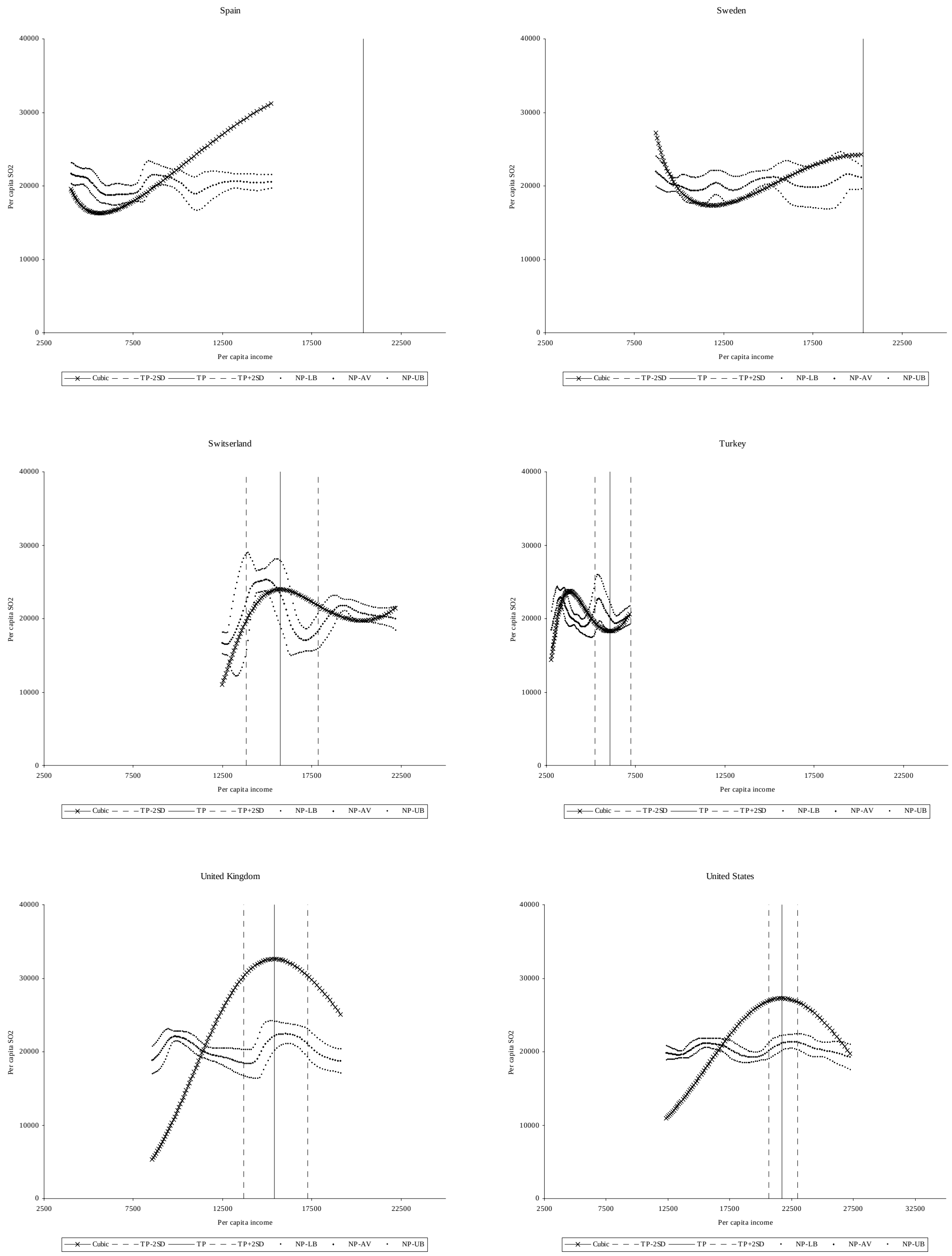

Figure S.1.a (cont.) Estimation results for 24 OECD countries based on heterogeneous country and time fixed effects for SO_2

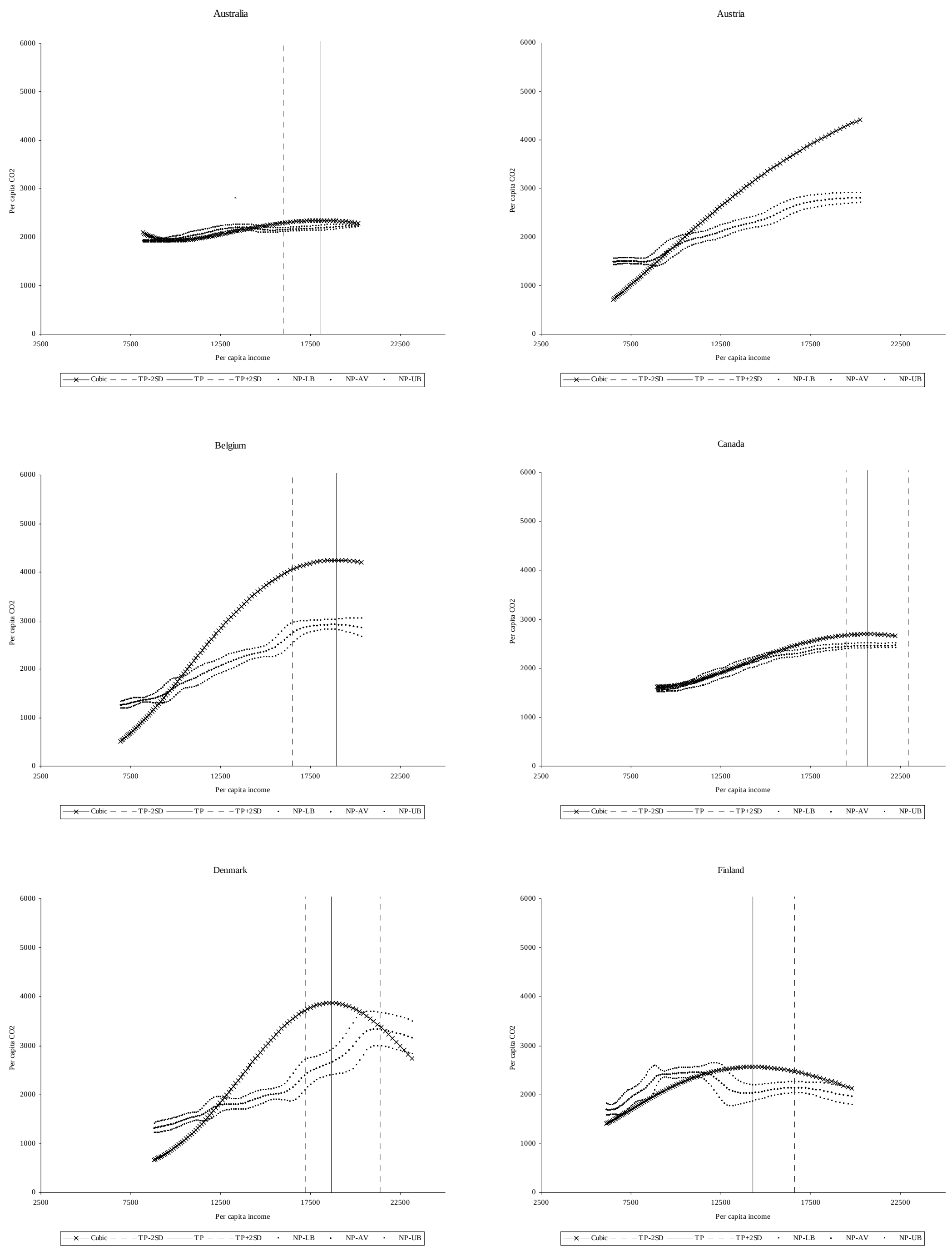

Figure S.1.b Estimation results for 24 OECD countries based on heterogeneous country and time fixed effects for CO_2

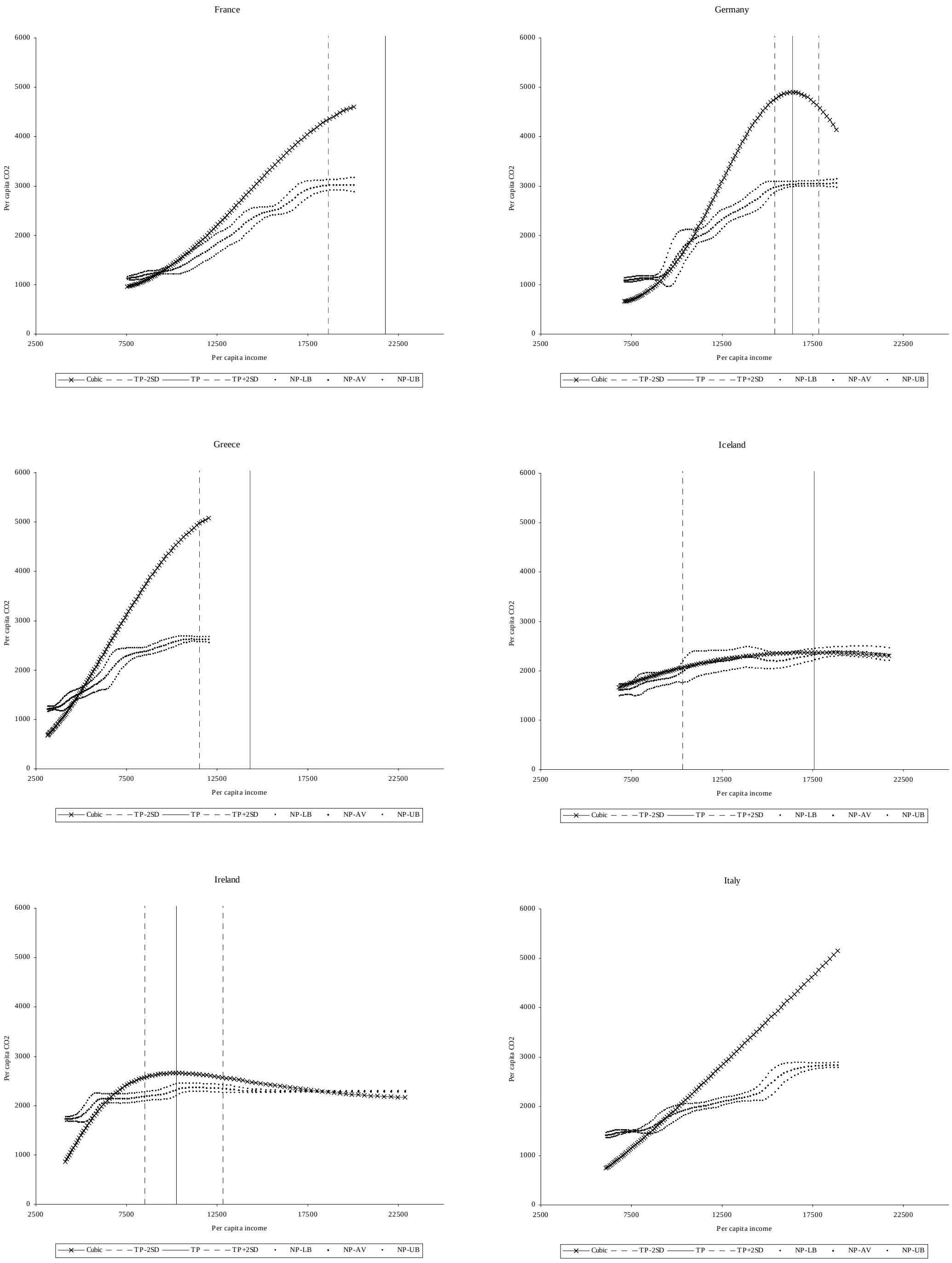

Figure S.1.b (cont.) Estimation results for 24 OECD countries based on heterogeneous country and time fixed effects for CO_2

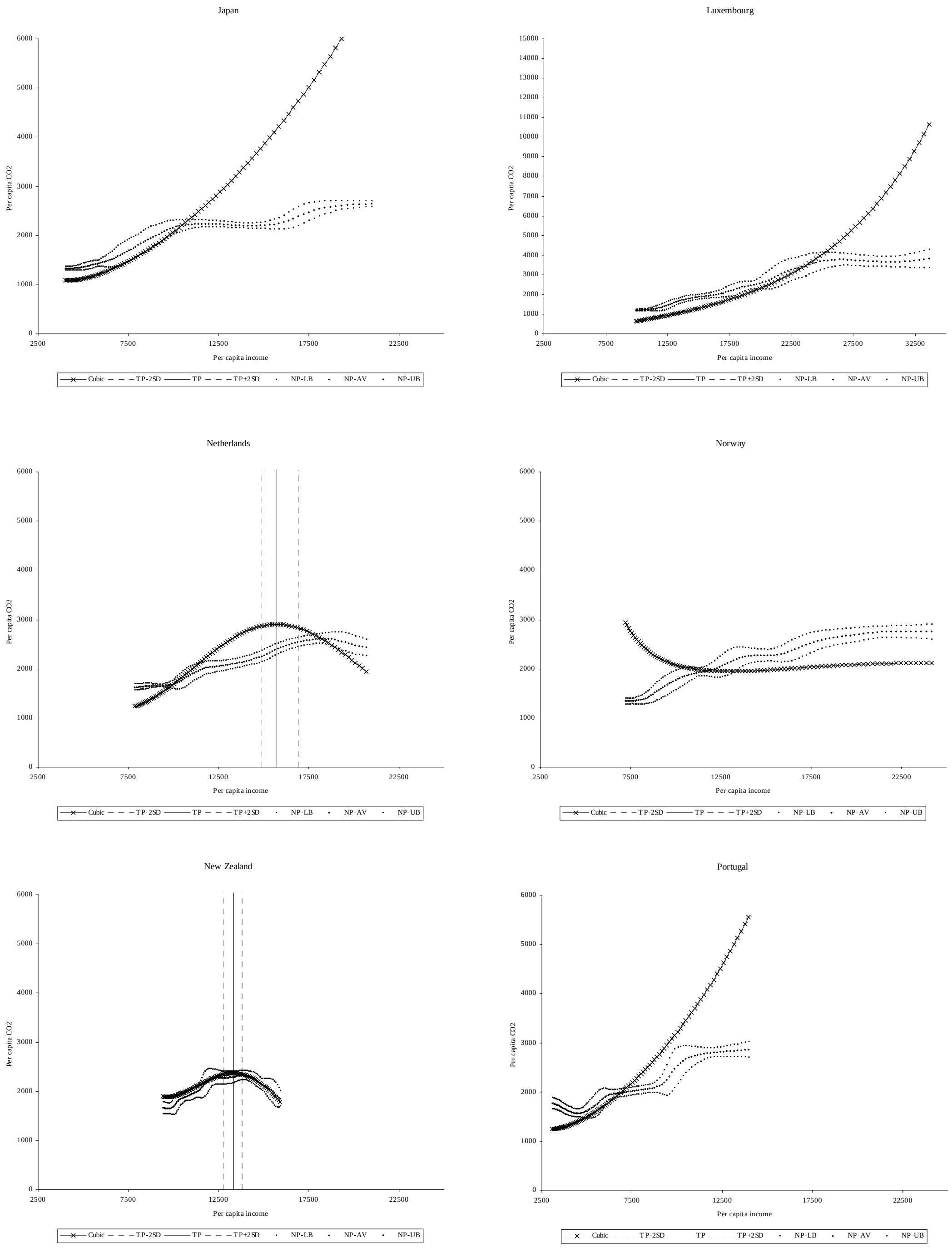

Figure S.1.b (cont.) Estimation results for 24 OECD countries based on heterogeneous country and time fixed effects for CO_2

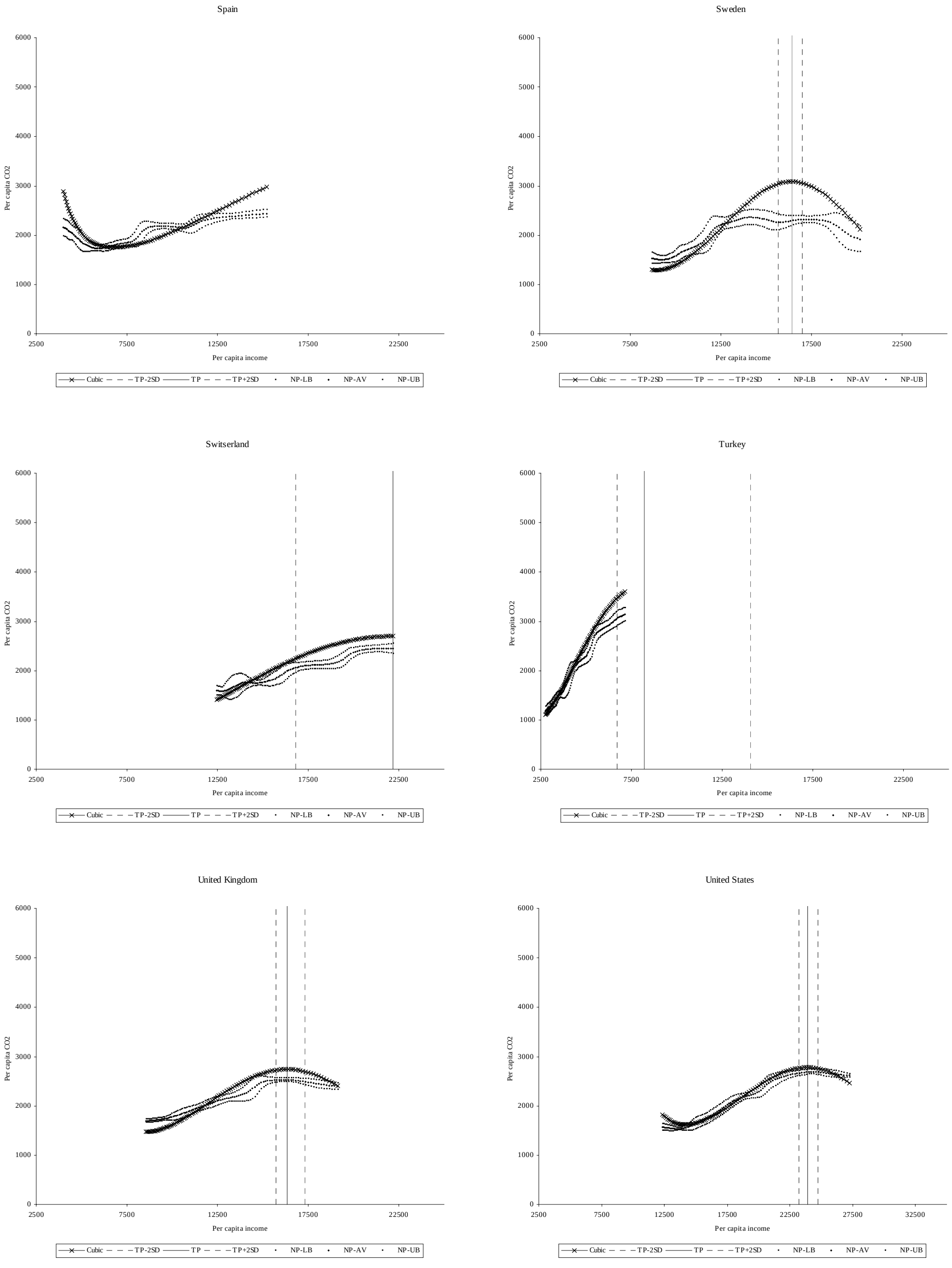

Figure S.1.b (cont.) Estimation results for 24 OECD countries based on heterogeneous country and time fixed effects for CO_2

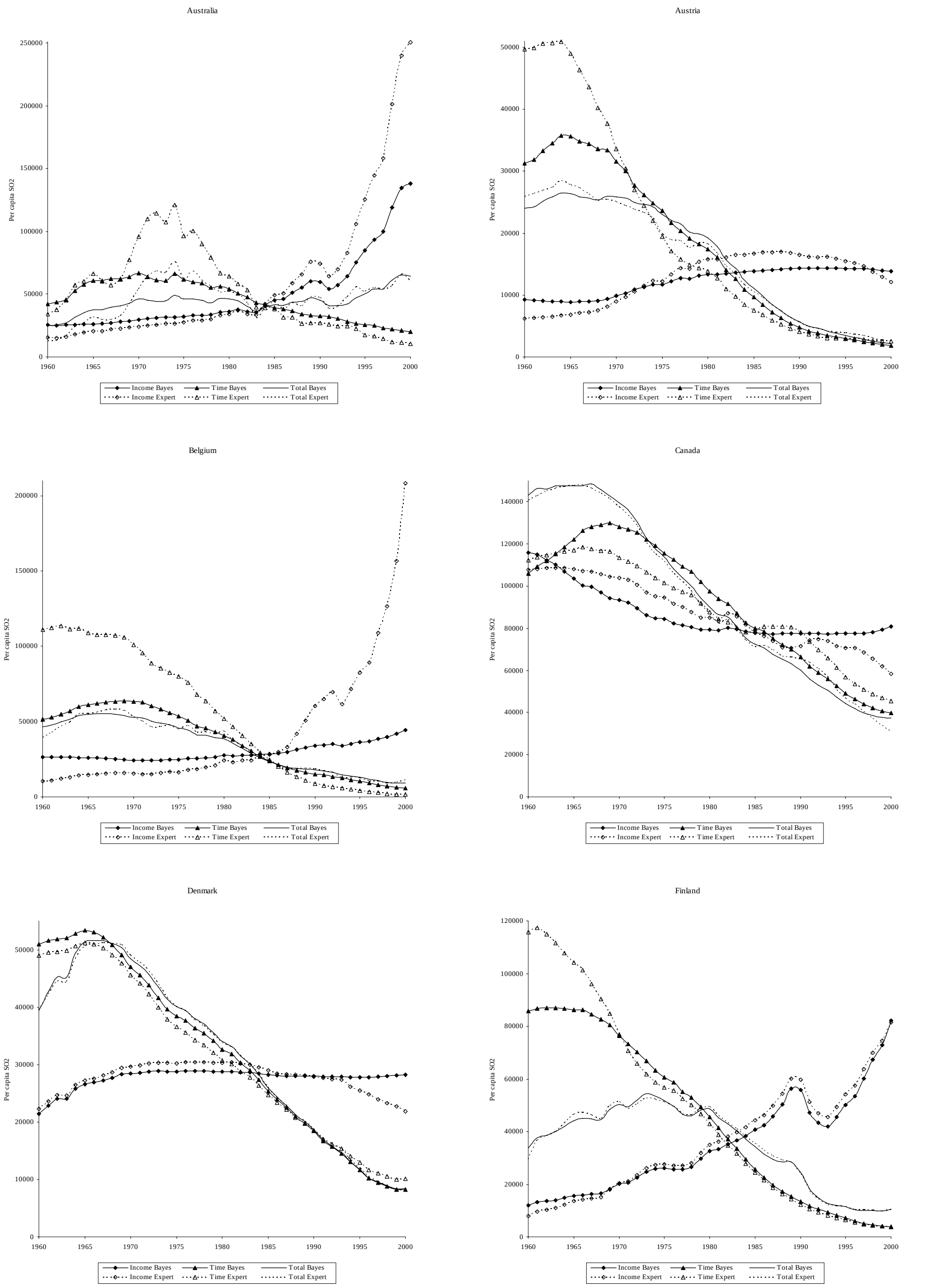

Figure S.2.a. Estimation results for 24 OECD countries based on BAYES and EXPERT prior for SO_2

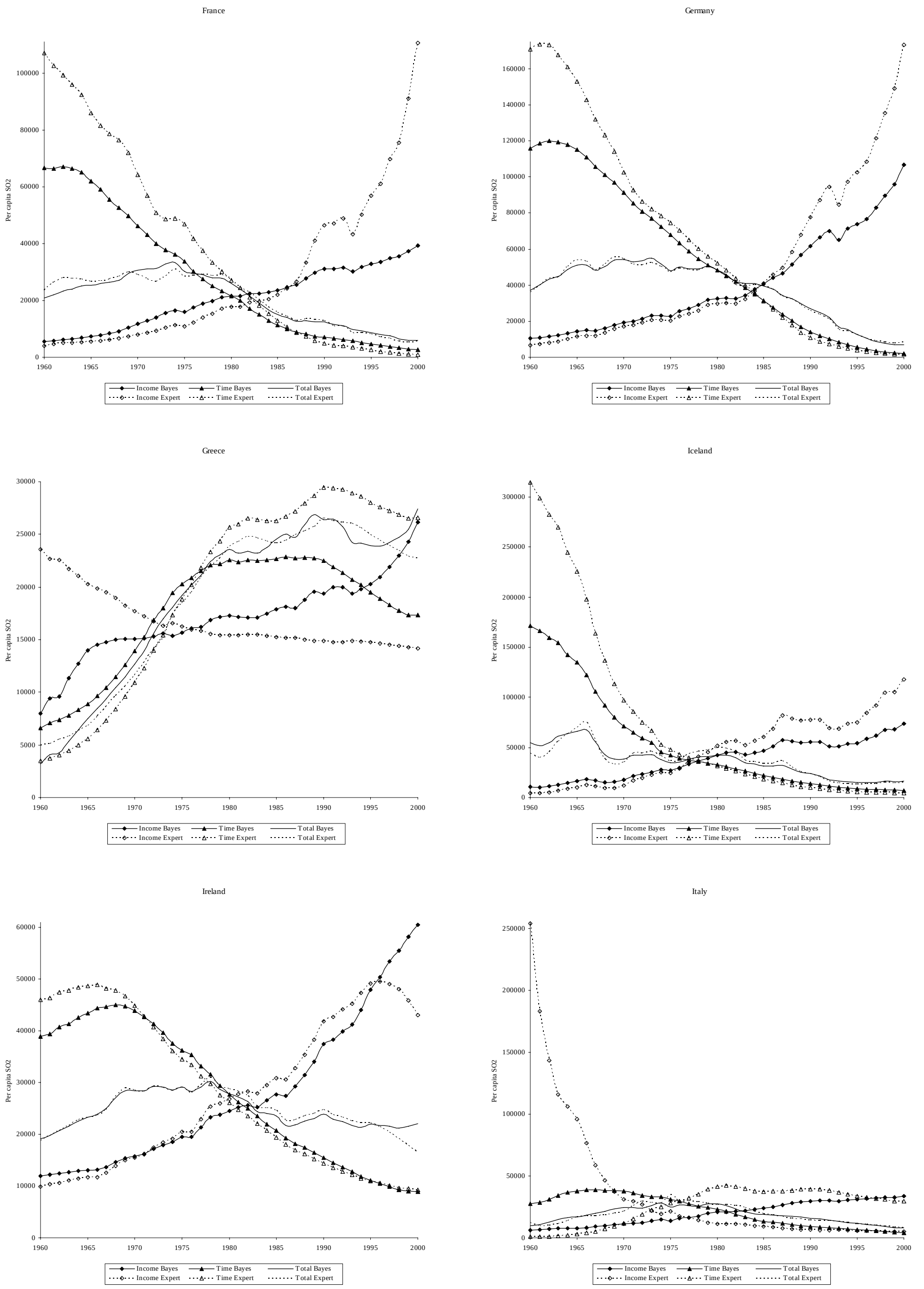

Figure S.2.a (cont.) Estimation results for 24 OECD countries based on BAYES and EXPERT prior for SO_2

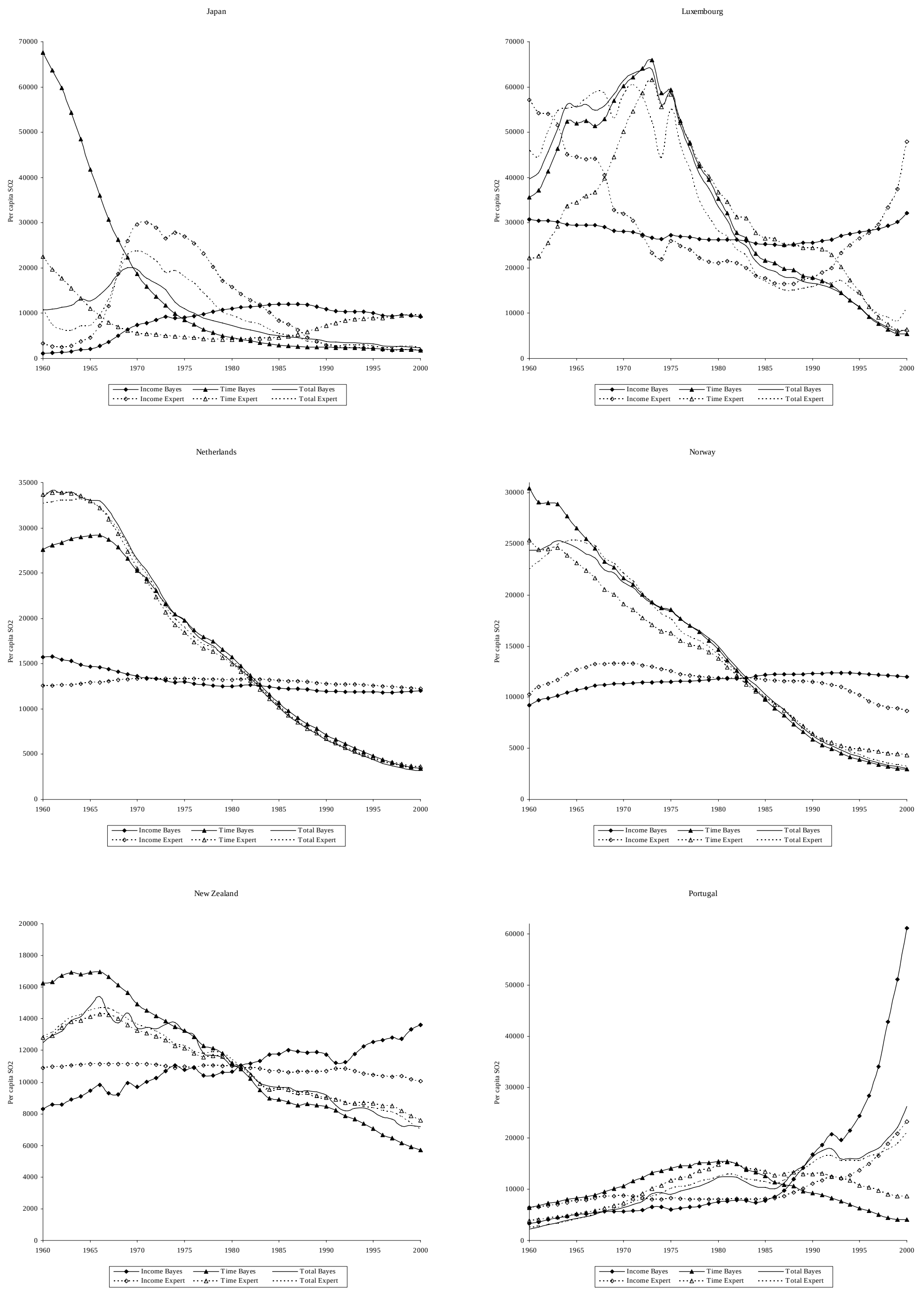

Figure S.2.a (cont.) Estimation results for 24 OECD countries based on BAYES and EXPERT prior for SO_2

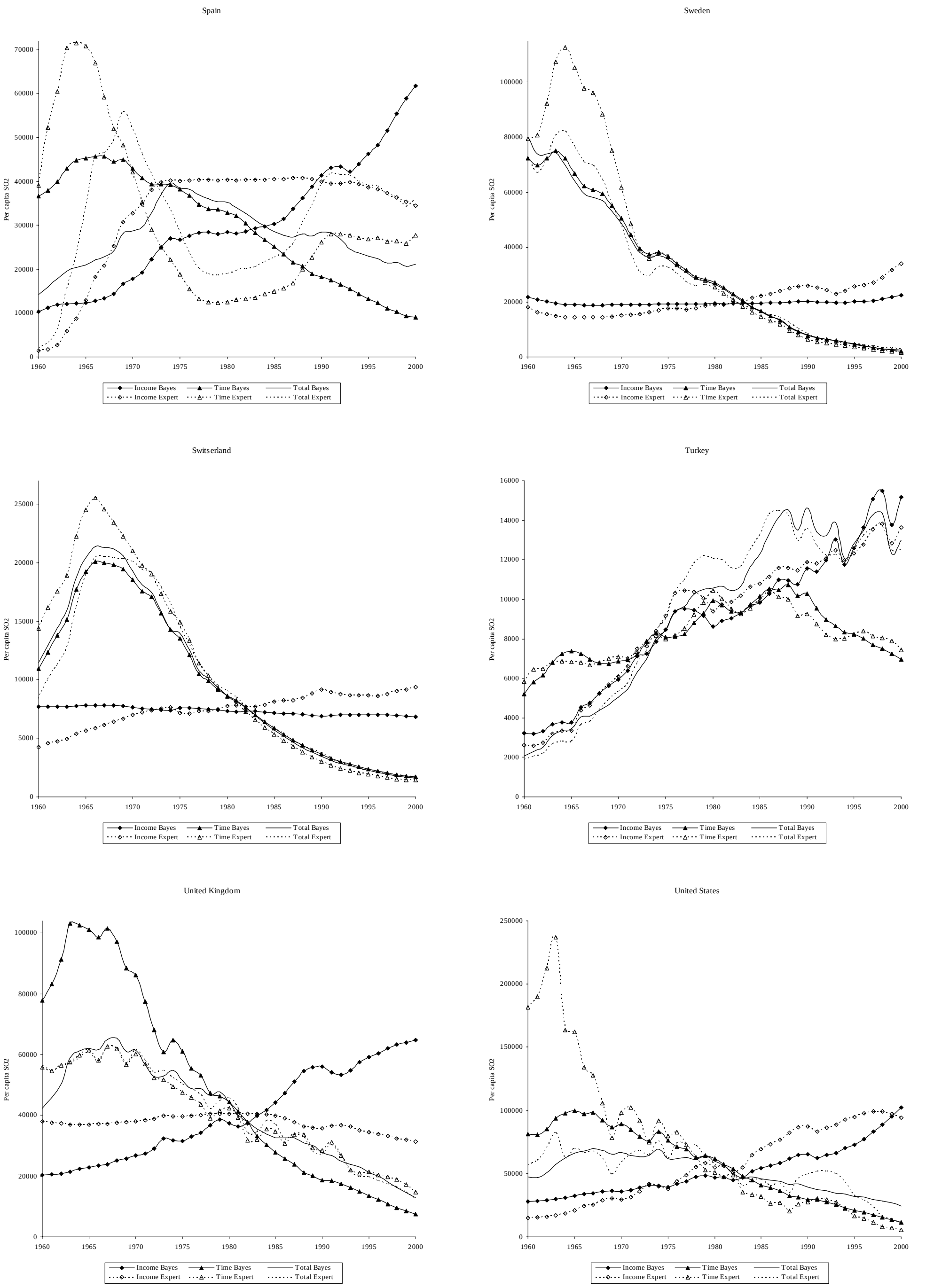

Figure S.2.a (cont.) Estimation results for 24 OECD countries based on BAYES and EXPERT prior for SO_2

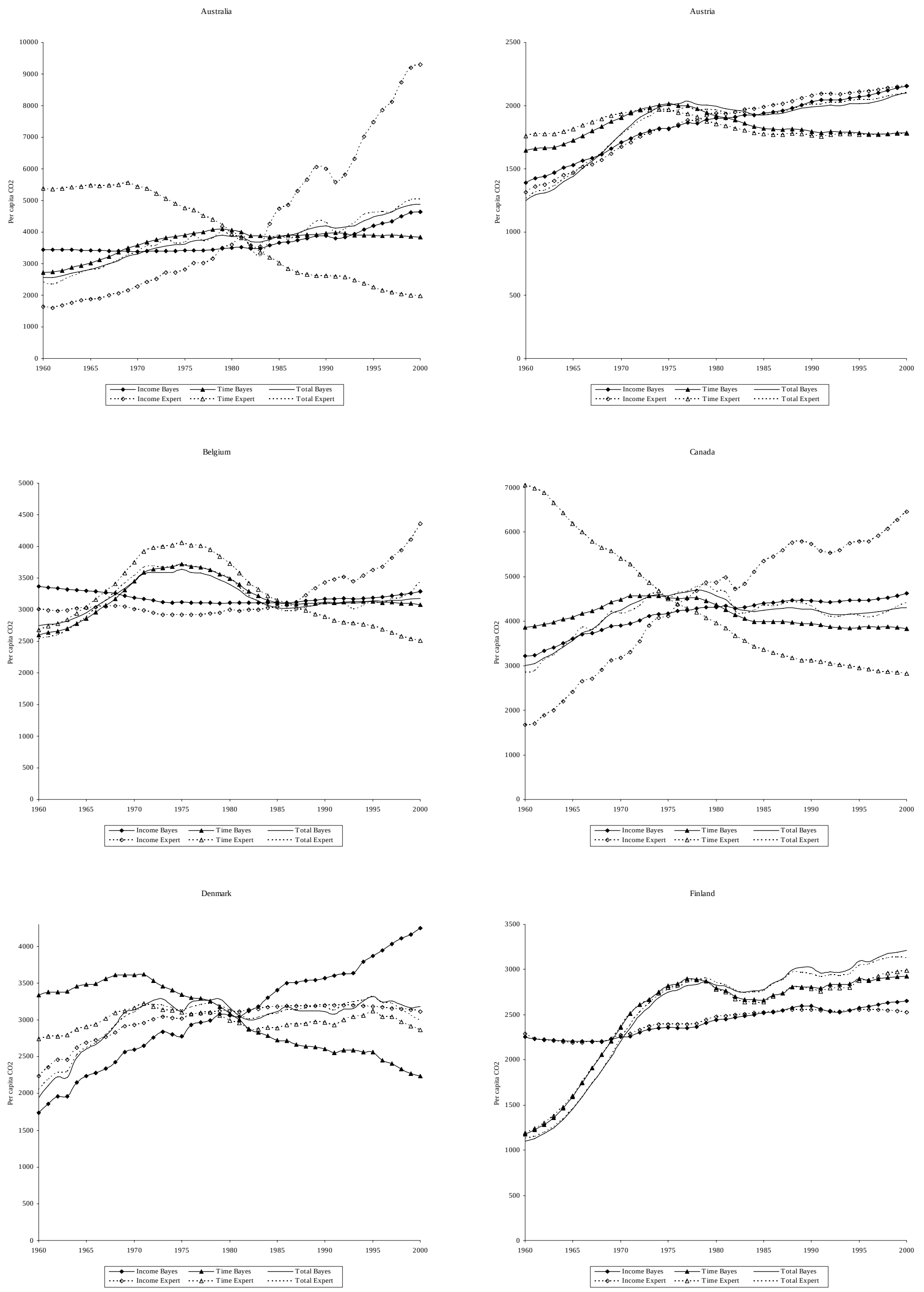

Figure S.2.b Estimation results for 24 OECD countries based on BAYES and EXPERT prior for CO_2

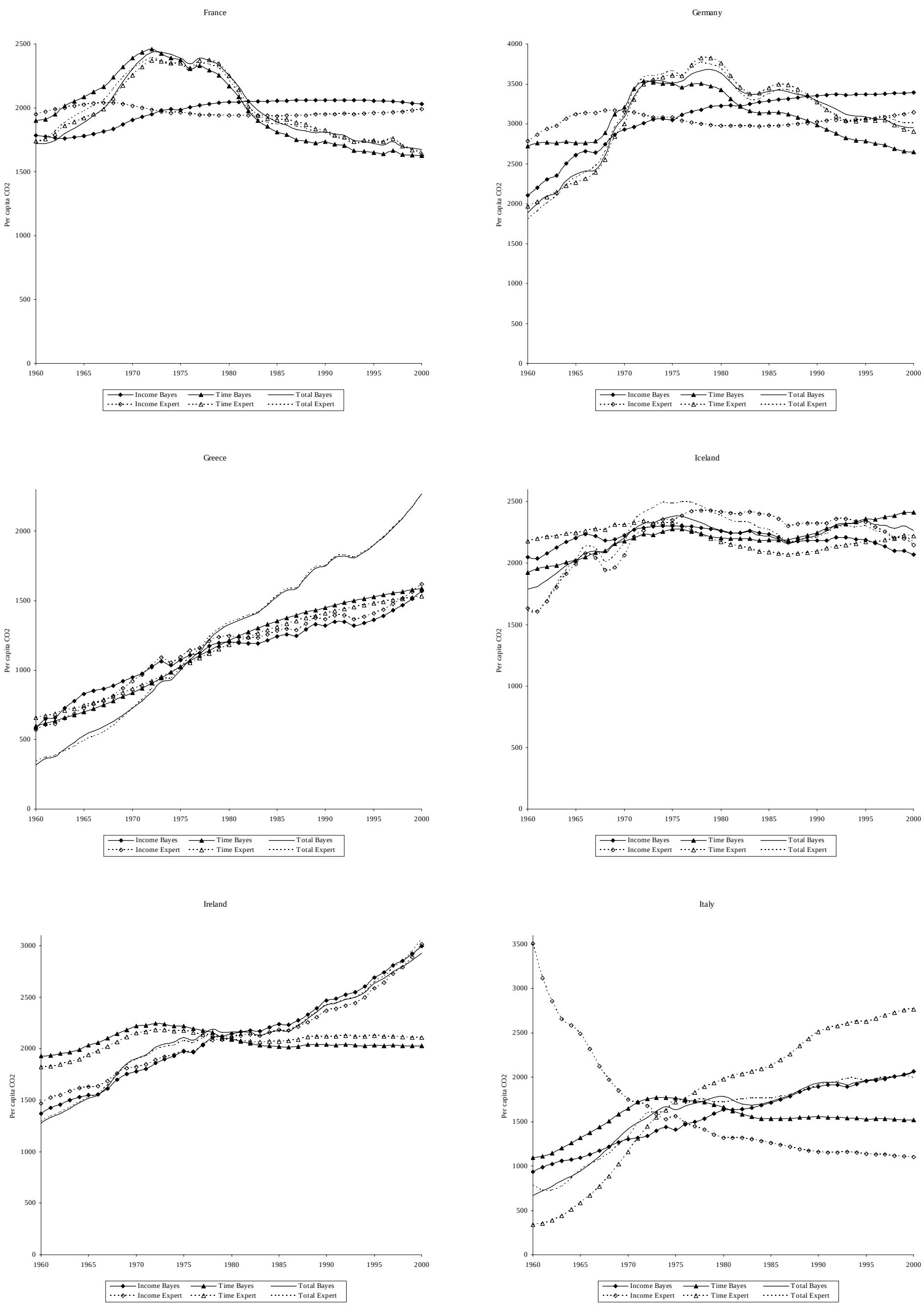

Figure S.2.b (cont.) Estimation results for 24 OECD countries based on BAYES and EXPERT prior for CO_2

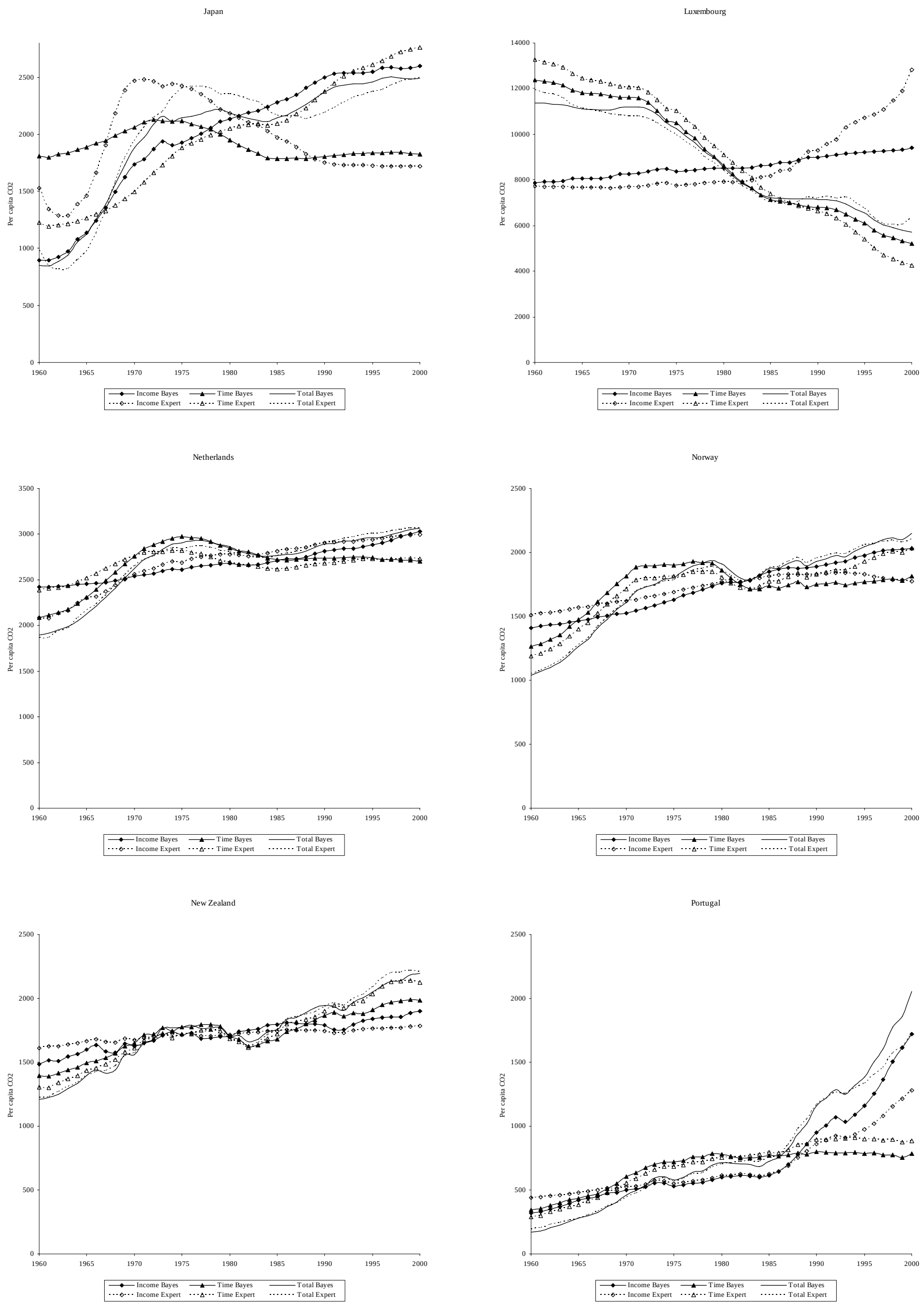

Figure S.2.b (cont.) Estimation results for 24 OECD countries based on BAYES and EXPERT prior for CO_2

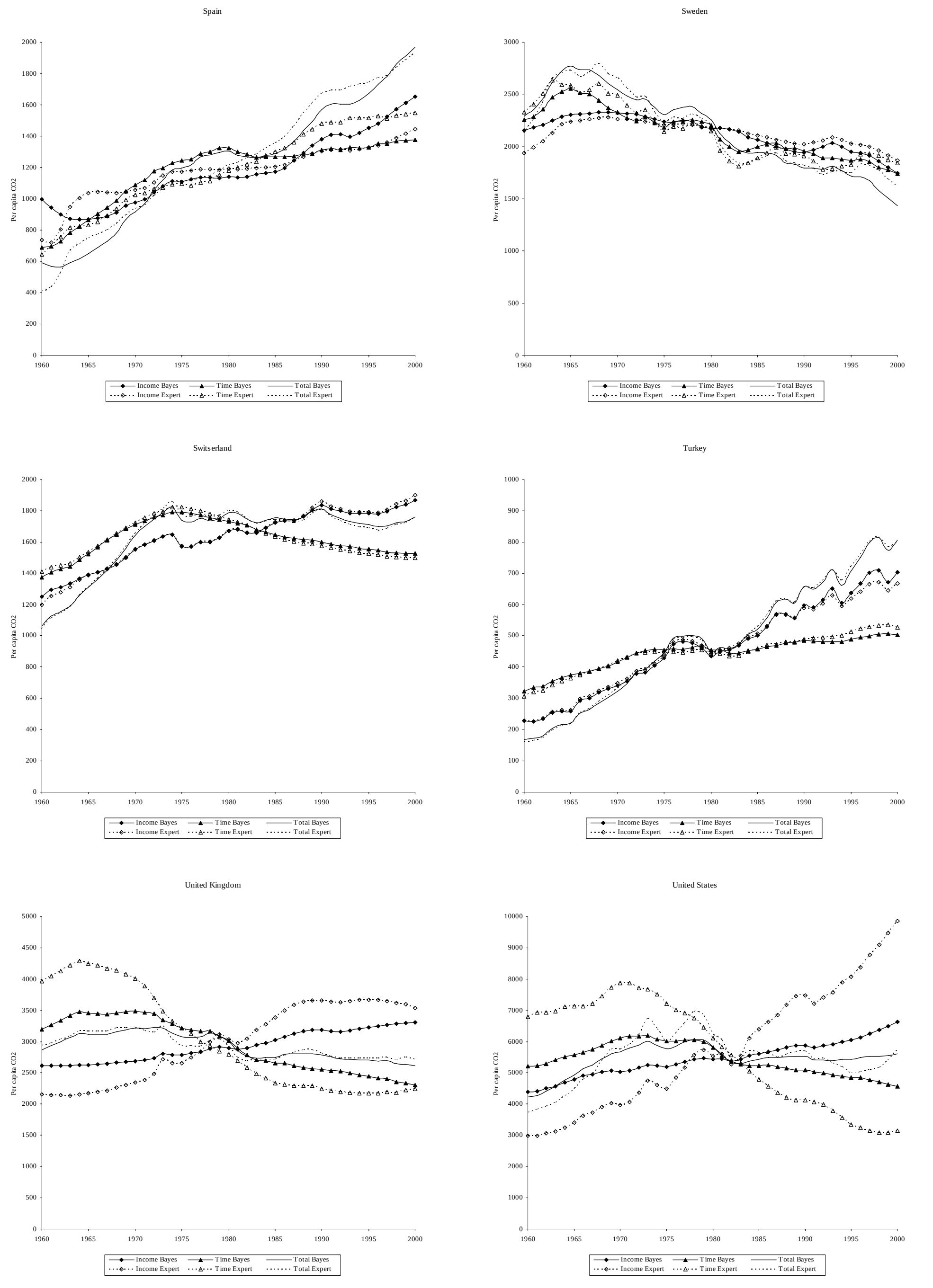

Figure S.2.b (cont.) Estimation results for 24 OECD countries based on BAYES and EXPERT prior for CO_2