UNIVERSITÀ DEGLI STUDI DI FERRARA
DIPARTIMENTO DI ECONOMIA E MANAGEMENT
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A Nonlinear Analysis of CO2-Income Relation for Advanced Countries

Massimiliano Mazzanti – Antonio Musolesi

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Massimiliano Mazzanti* Antonio Musolesi**

Abstract

We study long run carbon emissions – income relationships for advanced countries grouped in policy relevant groups – North America and Oceania, South Europe, North Europe. By relying on recent advances on Generalized Additive Models and adopting interaction models, we handle simultaneously three main econometric issues, named here as *functional form bias, heterogeneity bias* and *omitted time related factors bias*, which have been proved to be relevant but have been addressed separately in previous papers. We consider a model which includes both country-specific nonparametric time effects and country-specific nonparametric income effects. We find that country-specific time related factors weight more than income in driving the northern EU Environmental Kuznets Curves, that cross country heterogeneity is high and that only two countries - Finland and Sweden - show bell shapes for both income and time relationships to CO2. Overall, the countries differ more on their carbon-time relation than on the carbon-income relation which is in almost all cases monotonic positive. The former may represent idiosyncratic innovation, energy and policy features of the countries under study.

Keywords: *Semi parametric models, GAM, interaction models, environmental Kuznets curve*
JEL classification: *C14, C23, Q53*

* Dipartimento di Economia e Management, Università di Ferrara; corresponding author: massimiliano.mazzanti@unife.it
** INRA Grenoble

1 Introduction

Many and diversified stylised facts have been proposed on the relationship between pollution and economic development. An extensive overview of the main theoretical issues can be found in Borghesi (2001), who discusses the famous Kuznets growth framework, which touches upon inequality, in relation to its extensions to sustainable development issues.[1] Recently Brock and Taylor (2010) explain how the environmental Kuznets curves (EKC) framework[2] is coherent with a reformulated green Solow model. Moreover, the relationships between environmental performance, growth and innovation patterns has received increased attention in the policy agenda of advanced economies, (OECD, 2002, 2010, 2011), and in particular within the European Union (EU), within the general debate around climate change adaptation and mitigation action's that has followed the Stern Review (Dietz, 2011).

This paper specifically analyses the CO2 emission-income relation, which offers the most robust long-run time series data and gives the opportunity to enter the hot current topic of climate change. The relevance of carbon is also depending on the fact that even advanced economies have not substantially reduced CO2 emissions (Musolesi et al., 2010; Mazzanti and Musolesi, 2013). More precisely, we investigate which (groups of) advanced countries have succeeded to reducing CO2 emissions while growing, thus effectively achieving a negative elasticity of greenhouse gas emissions with respect to income. We use the same groups 'classification adopted by Mazzanti and Musolesi (2013) who focused on advanced countries, by subdividing them into the Umbrella group[3], Southern and Northern Europe, which witness quite different economic and institutional features. The analysis of regional and country heterogeneity is key from both methodological perspectives and policy settings as well.

Notwithstanding the adopted groups 'classification may provide relevant policy oriented results, the main contribution we intend to deliver with this paper is of methodological flavour. In particular, we try to handle simultaneously three main econometric issues, named here as *functional form bias*, *heterogeneity bias* and *omitted time related factors bias*.

Looking at the recent related literature, it seems to be especially worth emphasising the role of time related factors and try to answer to the following questions: how does time related factors affect (eventually heterogeneously) the CO2 long run dynamics? How does their inclusion in the model affect the estimation of income effects?

Indeed, the early EKC literature has focused on very constrained specifications, such as parametric formulations (typically polynomial functions) imposing common slopes across countries and do not accounting for the (possibly heterogeneous) effect of time related factors. A strand of the empirical literature has emphasised the importance to relax the parametric formulation and adopt non parametric methods (Azomahou et al.2006; Azomahou and Mishra, 2008). This may help, for instance, to avoid finding the false inference that the CO2-income relation is not monotonic if the true relation has a threshold. Another strand has, instead, focused on the heterogeneity bias associated with the estimation of models with common slopes. As pointed out by Hsiao (2003), if the true relation is characterised by heterogeneous intercepts and slopes, estimating a model with individual intercepts but common slopes could produce the false inference that the estimated relation is curvilinear. Empirically, this situation is more likely when the range of the explanatory variables varies across cross-sections. This situation generally corresponds to the estimation of EKC for groups of countries because: i) per capita GDP presents high

[1] A recent survey of theoretical oriented papers with an eye to dynamic issues is Kijima et al. (2010).

[2] See e.g. Andreoni and Levinson, 2001; Millimet et al., 2003; Grossman and Krueger, 1994.

[3] The Umbrella group refers to a loose coalition of non EU developed countries formed after Kyoto that has sustained a mild approach to climate policy, in primis North America and Australia. See Barrett (2003) for further insights.

variation across countries, ii) the different groups of countries cannot be characterised by a common slope and, consequently, there is a high risk of estimating a false curvilinear relation when using homogeneous estimators. Only very recently, both strand recognised the relevance of taking into account unobserved time effects, which may eventually explain a large part of the evolution of CO2. This has been supported for instance by Melenberg et al. (2009) using a nonparametric setting and by Musolesi and Mazzanti (2013) who adopted, among other estimators, the Common Correlated Effect (CCE) approach developed by Pesaran (2006) in a parametric framework. A major limitation of the former is that it allows neither the effect of income nor that of time to vary across cross-sections, while the latter do not allow for non parametric effects.

It is also worth noting that the adopted classification, which is aimed at providing original insights for policy, is strictly integrated with the methodological development. We in fact suggest that the analysis of cross country heterogeneity and separated time-income effects is further enhanced in value if we focus on relevant country aggregation, from policy and economic perspectives. It seems indeed interesting to investigate whether countries that belong to groups sharing structural similarities may eventually present different income effects and additionally tend to 'specialize' with respect to time related unobservable factors such as innovation and technological progress, energy and also policy which in turn may heterogeneously affect CO2 emissions.

In order to achieve our goal, i.e. disentangling (possibly heterogeneous across countries) income and time related effects in the study of greenhouse gas dynamics, we adopt the Generalized Additive Model methodology (GAM) initially introduced by Hastie and Tibshirani (1990) and more recently developed both on theoretical and computational directions. Estimation relies on the decomposition of the smooth functions on spline basis; then a penalty term is added in the log-likelihood (Wood, 2003, 2006). In particular, the estimation algorithm is based on the approach proposed by Wood (2004) providing an optimally stable smoothness selection method which presents some advantages compared with previous approaches, such as the modified backfitting (Hastie and Tibshirani, 1990) or the Smoothing Spline ANOVA (e.g. Gu and Wahba, 1993). Smoothing parameter estimation and reliable confidence interval calculation is difficult to obtain with the modified backfitting, whereas Smoothing Spline ANOVA provide well founded smoothing parameter selection methods and confidence intervals with good coverage probabilities but at high computational costs. To avoid these problems, Wood (2000) among others suggests representing GAM using penalised regression splines, but leaves a number of practical problems, concerning convergence and numerical stability, unresolved. Wood (2004) developed it further by providing an optimally stable smoothness selection method whereas Wood (2008) provides a computationally efficient method for direct generalized additive model smoothness selection. A very appealing feature of the method proposed by Wood (2004) compared with other approaches is that it has been shown to perform very well even in the case of almost co-incident covariates. Indeed, income and time may present a relatively high degree of collinearity. These recent improvements in GAM theory and computation can be implemented by using the Wood's (2012) *mgcv* R package where the default underlying fitting methods are given in Wood (2011 and 2004).

A first interesting feature of such an approach, compared for instance with Melenberg et al. (2009), is that it allows the estimation of the nonparametric time effect rather than considering it as nuisance term. This is very important from an economic and policy oriented analysis because it allows not only obtaining a proper income effect but also allows investigating nonparametrically how the time related factors may drive the CO2 long-run evolution. Moreover, the adoption of *interaction models* (see e.g. Ruppert et al., 2003) allow us to consider a specification allowing for both country-specific nonparametric time effects and country-specific nonparametric income effects. This is possible in practice given the large time series dimension of our data set. This permits a maximum level of country-specific heterogeneity.

The remainder of paper is structured as follows. Section 2 presents the country groups, the data and some descriptive statistics. Section 3 debates around the econometric specification, estimation and identification issues. Section 4 comments on the main results and finally section 5 concludes.

2 Country groups and data

2.1 Country groups

We do exploit CO2 data as environmental indicator, as it was discussed above. Groups are:

(a) The *'Umbrella group'*: Australia, Canada, Japan, New Zealand, Norway, U.S.A. this is a set of 'anti Kyoto' countries, or rather countries more willing to adopt flexible instruments (such as joint implementation, clean development mechanisms) rather than stringent and specific national policies (carbon taxes, emission trading) in order to achieve climate change related international and national goals. We remark that if on the one hand Australia has recently introduced some carbon pricing element into the economy, the whole North America is far from achieving a consensus on what carbon pricing, if any, would be implemented.

(b) The *'European Union (EU) North'*: Belgium, Denmark, Finland, France, Germany, Netherlands, Sweden, U.K. Those are the relatively more climate change policies supportive countries.

(c) The *'EU south'*: Austria, Greece, Ireland, Italy, Portugal, Spain. Those are the countries that were still relatively over 'development oriented paths', and less in favour of stringent climate policies and targets.

Environmental policy, eco-innovation and energy issues are key pillars which are behind such categorisation.

2.2 Data

Data on emissions are from the database on global, regional, and national fossil fuel CO2 emissions prepared for the US Department of Energy's Carbon Dioxide Information Analysis Centre (CDIAC). For our study, we use the subset of emissions data that matches the available time series on GDP per capita. Data on GDP per capita in 1990 International 'Geary-Khamis' dollars are from the database managed by the OECD.

For our study we use the subset of emission data that matches the available time series on GDP per capita on the basis of joint availability, series continuity, and country definitions. This resulted in a sample which covers a long period (1960-2001). Table 1 below summarises the main variables used and the descriptive statistics.

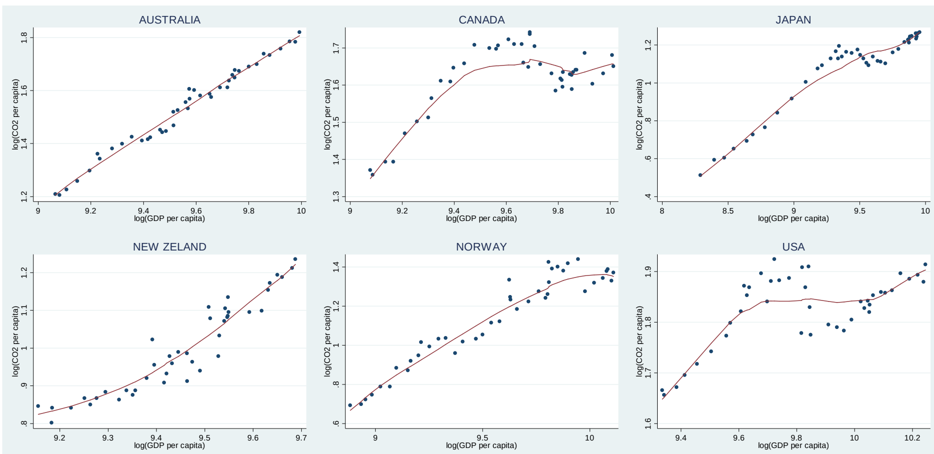
The Umbrella group presents the highest average level of both CO2 per capita (expressed in terms of tonnes per capita) and GDP per capita (3.14 and 15,143, respectively) while southern European countries are characterised by the lowest average levels of such variables (1.48 and 10,215). The northern European countries have a similar average level of GDP per capita (14,203) compared to the Umbrella group but are characterised by lower levels of emissions (2.61).

Table 1: Descriptive statistics

	Mean	S.D.	Min	Max
Umbrella group				
CO2 per capita	3.144921	1.393584	0.67	5.85
GDP per capita (GDPpc)	15,143.21	4,763.547	3,986.417	28,129.23
EU North				
CO2 per capita	2.60875	0.5630643	0.91	3.88
GDP per capita (GDPpc)	14,203.73	3,759.392	6,230.359	23,160
EU South				
CO2 per capita	1.488294	0.6085014	0.25	3.05
GDP per capita (GDPpc)	10,215.44	4,265.277	2,955.836	23,201.45

T= 1960-2001; CO2 per capita in t/pc; GDP per capita in 1990 International ‘Geary-Khamis’ dollars

Figure 1: UMBRELLA countries (scatter: real values. Line: robust locally weighted scatterplot smoothing)



Figures 1–3 depict the relationship between CO_2 and income for the three samples. We provide real data, and the curve fitted (non-parametrically) by robust locally weighted scatter plot smoothing (lowness). The relationship CO2-GDP is quite homogeneous within each group: it is clearly monotonic (eventually non linear) for the Umbrella group and for EU-South but shows an inverted U shape for EU-North countries.

3 Econometric specification, identification and estimation

3.1 Econometric specification: various mispecification biases

Let us suppose that the researcher observes panel data (y_{it}, x_{it}), where y is the logarithm of CO_2 emissions per capita, x is the logarithm of per capita GDP; $i \in \Gamma$, and Γ is the set of cross-section units $\Gamma = \{1, 2, ..., N\}$ and $t \in \Lambda{=}\{1, 2, ..., T\}$ indicates time series observations. A very general specification is obtained adopting a fully non separable model such as

Figure 2: EU-SOUTH countries (scatter: real values. Line: robust locally weighted scatterplot smoothing)

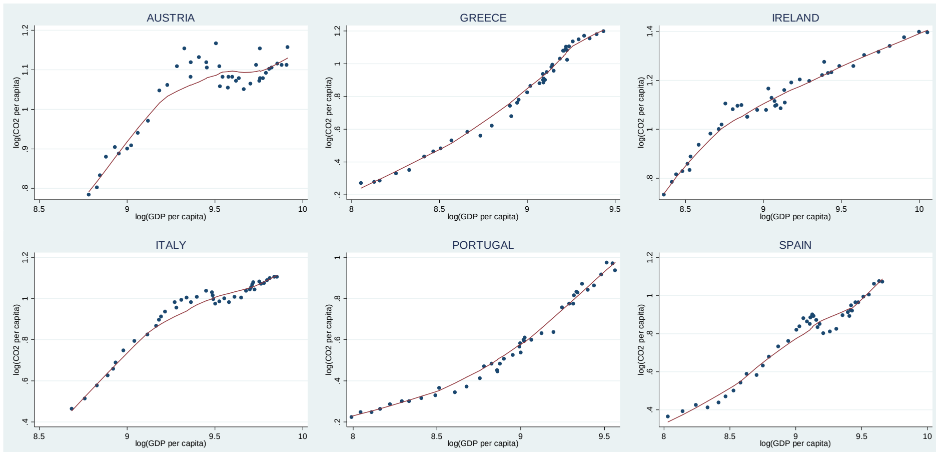
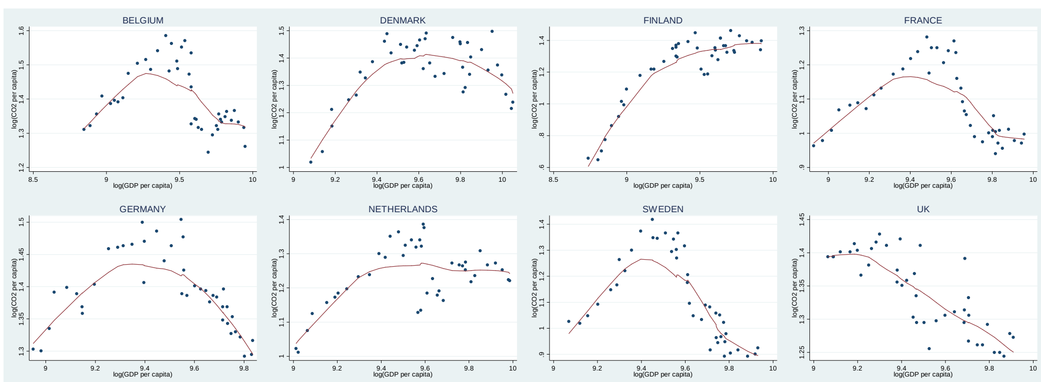


Figure 3: EU-NORTH countries (scatter: real values. Line: robust locally weighted scatterplot smoothing)



$$y_{it} = f\left(x_{it}, c_i, t, \varepsilon_{it}\right)$$

where f is real unknown function, c_i are individual effects capturing time invariant heterogeneity, t capture the effect of time related omitted factors, and ε_{it} is the the idiosyncratic term.

To to date, there is an increasing amount of theoretical literature on non parametric panel data estimators (Henderson et al. 2008; Su and Ullah, 2010), aiming to provide very general econometric set-ups such as the non-parametric panel data model, i.e. a model of the kind $y_{it} = f(x_{it}^1, ..., x_{it}^k) + c_i + \varepsilon_{it}$, the partially or fully non-separable models, i.e. $y_{it} = f(x_{it}^1, ..., x_{it}^k, c_i) + \varepsilon_{it}$ and $y_{it} = f(x_{it}^1, ..., x_{it}^k, c_i, \varepsilon_{it})$. An approach which has been proposed to estimate models in cases where explanatory variables do not enter additively, differently from individual effects and the error term, is recurring to a local linear approximation of the model and them using the profile least square method (Su and Ullah, 2006, 2010). This allows estimating the model without using a transformation to eliminate the fixed effects. Another and widely adopted approach has been taking first differences to eliminate the individual effects. Then, the differenced equation can be estimated, after a local linear approximation, for exemple by using local linear least squares (Li and Stengos, 1996) or by iterative kernel estimator (Henderson et al, 2008).

Despite their appeal, fully or partially non-separable models present theoretical and computational difficulties and have received little attention in empirical works, compared to additive ones. Moreover, the identification conditions arising in such models can be difficult to hold (see Hoderlein and White, 2012 and Evdokimov, 2010).[4]

These considerations allow us focusing on additive models (Stone, 1985, Hastie and Tibshirani 1990). They indeed avoid the curse of dimensionality since each of the individual additive terms is estimated using a univariate smoother. They are also easily interpretable, while fully non-separable models present problems of interpretability, and they do not present big identification problems. Finally, and very importantly, GAMs fit perfectly with the purpose of this paper to disentangle (possibly heterogeneous) income and time effects. Therefore, we more specifically assume that the income effect, the effect of (time invariant) unobserved heterogeneity, the effect of time and the idiosyncratic effect are separable:

$$y_{it} = c_i + f_i\left(x_{it}\right) + g_i\left(t\right) + \varepsilon_{it} \tag{1}$$

where f_i captures the effect of income on CO_2 emissions while the effect of time is measured through the function g_i. Both effects are eventually heterogeneous across countries. In the following we focus attention in the estimation of such an equation. Moreover, even if it is not the specific focus of this paper, GAMs may also allow, using a bivariate smoother, removing the hypothesis that income and time have a separable effect on pollution and estimate a model of the kind $y_{it} = c_i + f_i\left(x_{it}, t\right) + \varepsilon_{it}$.

It is worth noting, however, that the early literature on income environment long run relationships has focused on very constrained specifications, as for instance setting $g_i\left(t\right) = 0$; $f_i\left(x_{it}\right) = p\left(x_{it}, \beta\right)$, where $p\left(x_{it}, \beta\right)$ is a polynomial function, and obtaining the additive fixed effects specification

$$y_{it} = c_i + p\left(x_{it}, \beta\right) + \varepsilon_{it}$$

Compared to (1), such a specification may suffer of different kinds of misspecification bias, and in particular:

- *functional form bias* if the true relation between CO2 and GDP cannot be approximated with a polynomial function $p\left(x_{it}, \beta\right)$. This has been largely recognised in the literature which stresses the need of non-constrained functional specifications (Azomahou et al.2006; Azomahou and Mishra, 2008; Azomahou et al. 2009);

- *heterogeneity bias* since it is possible that the effect of GDP on CO2 can be heterogeneous across countries. A more realistic assumption would allow for individual income effects, $f_i\left(x_{it}\right)$ (Musolesi et al., 2010; Mazzanti and Musolesi, 2013);

- *omitted time related factors bias* dues to the omission of a (eventually heterogeneous) relevant time effect. The literature has widely adopted the restriction $g_i\left(t\right) = 0$. This is motivated by the following reasons: it allows for a greater comparability with existing studies and, maybe more important, this kind of econometric specification is useful if the researcher is interested in capturing the global

[4] Hoderline and White (2012) focus on the identification of fully non separable models and in spite that their main result is that a generalised version of differencing identifies local average responses, they also find that such a result is confined to the subpopulation of "stayers" (Chamberlain, 1982), i.e. the population for which the explanatory variables do not change over time; a case which does not correspond to our empirical framework.

effects of GDP on CO_2 including the indirect effects linked to the omitted (or unobserved) variables, such as energy prices, technological change, environmental policies, etc, which are correlated with both GDP and time. However, if the goal is measuring the ceteris paribus impact of GDP on CO_2 emissions, imposing $g_i(t) = 0$ might be not appropriate because it leads to an omitted time related factors bias. At the best of our knowledge, to date, very few studies focused on such an issue. For instance, Mazzanti and Musolesi (2013) applied, among other panel data estimators, the CCE approach proposed by Pesaran (2006). Such a method allows for unobserved common factors affecting heterogeneously the dependent variable. However, such factors are viewed as nuisance variables while the main focus rests on the estimation of the heterogeneous (but parametric) effect of income on CO2. Nonparametric analyses have been provided by Melenberg et al. (2009) and by Ordás Criado et al. (2011). Both studies estimated eq. 1 without imposing a parametric formulation but imposing that $f_i(x_{it})$ is homogeneous across countries. A difference between these two works is that, while Melenberg et al. (2009) assumes that the unobserved time related factor $g_i(t)$ is common to specific groups of countries within the sample and considered the function $g_i(t)$ as a nuisance term, Ordás Criado et al. (2011) introduced a common time effect by means of time fixed effects.

The main modelisation difficulty is to simultaneously address the above mentioned econometric issues. Most of the previous cited (even recent) works address one (or two) specific issue. The main advantage of using the recent developments in GAM theory is that it allows tackling the three issues, *not constrained functional form*, *omitted time related factors* and *heterogeneity bias*, simultaneously.

3.2 Identification and estimation

A fully additive model as in eq. (1) can be dealt with GAMs. This does not require a local linear approximation and, also in this case, the individual fixed effects can be treated as nuisance terms to be eliminated with a transformation or as dummies variables, and have to be estimated. Both approaches present some relative drawbacks and benefits. In particular, the latter approach may be computational costly but does not suffer, differently from the former, from the possible (partial) lack of identification arising when adopting a transformation approach such as first differencing to eliminate the individual effects. Indeed, by differencing Equation (1) we get (see also Azomahou and Mishra, 2008; Azomahou *et al.* 2009, Su and Ullah, 2010):

$$(y_{it} - y_{it}) = f_i(x_{it}) - f_i(x_{it-1}) + g_i(t) - g_i(t-1) + (\varepsilon_{it} - \varepsilon_{it-1}),$$

and some components of the functions f anf g may not fully identified because as argued by Su and Ullah (2010), if, for exemple,

$$f(x_{it}) = a + m(x_{it}),$$

then differencing does not allow the identification of $f(x_{it})$, and eventually only $m(x_{it})$ can be identified. Secondly, such an approach doubles the non-parametric functions to be estimated. In our empirical framework this problem becomes extremely important because estimating eq. (1), after differencing and without imposing the constraint that $f_i(x_{it}) = f(x_{it})\ \forall i$ or that $g_i(t) = g(t)\ \forall i$, requires the estimation of $N * 4$ nonparametric functions. Thus, first differencing may be useful in practice when N is large compared to T, as usual in micro data, or to estimate a 'feedback effect' through the function $f(x_{it-1})$ as in Azomahou and Mishra (2008).

Given the structure of our panel data set (small N and large T), it is not computationally costly to estimate the model directly without eliminating the individual effects. We follow thus such an approach by including the individual intercepts in the parametric part of the level equation as in Mammen *et al.* (2009) and Ordás Criado *et al.* (2011).[5]

The estimation is carried out by exploiting recent advances on GAMs. It is done by maximizing a penalised likelihood by penalised iteratively reweighted least squares and in particular by adopting the approach by Wood (2004, 2011) available with the *mgcv* routine; Penalised Regression Splines are adopted as a basis to represent the smooth terms (Wood, 2003, 2006ab). The smoothing parameters values are selected by the GCV (Generalised Cross validation) criterion [6] and statistical inference is made by computing 'Bayesian p-values' (Wood, 2010). These appear to have better frequentist performance (in terms of power and distribution under the null) than the alternative strictly frequentist approximation (Wood, 2006a,b).

4 Estimation results

4.1 Alternative specifications

In the following, we provide alternative specifications for both $f_i(x_{it})$ and $g_i(t)$ starting from a rather constrained model and moving towards a more unconstrained one, until to the estimation of eq. (1). This is aimed to inform how different kinds of misspecification may affect the results. In particular, this section is structured as follows. We first estimate a specification imposing a common income effect and without accounting for any kind of time effect. This model has been largely adopted in previous works (Azomahou et al., 2006; Azomahou and Mishra, 2008; or Azomahou et al., 2009) and allows getting results on the global effect of income on CO2.

Next, we introduce in the model time related factors. This is the main focus of the paper. We first assume that both these time factors and the income affect homogeneously the CO2 evolution. This should allow both to get a "net" income effect and at looking inside the effect of time related factors which may drive the CO2 evolution. This specification, however, may suffer of a heterogeneity bias. Third, we thus relax the hypothesis of a homogeneous time effect and estimate a semiparametric model allowing for country-specific nonparametric time effects, $g_i(t)$. Such a kind of specification has been already proved to be very useful in a parametric framework. In a policy evaluation framework, Heckman and Hotz's (1989) proposed the so called random growth model allowing for individual specific trend, i.e. a model of the kind $y_{it} = c_i + \gamma_i t + \beta x_{it} + \varepsilon_{it}$. Wooldridge (2005) provides very useful methodological insights, while Papke (1994) and Friedberg (1998) are examples showing empirically how important can be to allow for individual specific trends. A motivation of such specification is that it allows (c_i, γ_i) to be arbitrarily correlated with x_{it}. This can certainly relevant when x_{it} is an indicator of program evaluation as in Heckman and Hotz (1989) but could also be a key issue in our framework since both CO2 emissions, since per capita GDP can be plausibly depend on individual-specific trends in addition to the level effect, c_i. More recently, Pesaran (2006) proposed, in a more macroeconometric oriented

[5] It is worth to note that it is also possible to introduce the individual effects as random elements (Augustin *et al.*,2009).

[6] Since the GCV may present a tendency to over fitting, we have increased the amount of smoothing by correcting the GCV score by a factor $\delta = 1.4$ which can correct the over fitting without compromising model fit (Kim and Gu, 2004).

framework, the CCE approach, which makes use of a factor model representation to allow that a finite number of unobservable (and/or observed) common factors have an heterogamous effect on the dependent variable. One main reason supporting a modelisation allowing for country-specific nonparametric time effects, $g_i(t)$ is that even for countries that belong to similar geographical/economic, the effect on CO2 of unobservable time related factors can be expected to be heterogeneous across countries. This because countries tend to 'specialize' with respect to unobservable time related factors such as to innovation, energy and also policy. Such a kind of modelisation may also be motivated in cases with common time effects, e.g. the case of a common policy, but with country-specific reactions. Moreover, there are not well established (theoretical or empirical) reasons to impose linearity. More specifically, innovation specialization is due to both market characteristics and willingness to create comparative advantages. Ennvironmental Policy 'specialization' largely depends on the belief on policy-induced innovation effects (Costantini and Mazzanti, 2012), on which some world areas might construct green technology competitive advantages. Energy issues depend both on policy frameworks and structural countries features. The analysis of specific country characteristics is scope for further research in various applied economics and econometrics fields.

Finally - fourth step - we fully exploit the time dimension of our data and estimate an "unconstrained" model with both heterogeneous time effects and heterogeneous income effects (for a detailed discussion of this latter issue see e.g. Musolesi et al. 2010 and Mazzanti and Musolesi, 2013). In summary, the four specifications presented in this paper can be therefore written as:

- Individual Fixed Effects specification (IFE). $g_i(t) = 0$ (no time effect), $f_i(x_{it}) = f(x_{it})\ \forall i$ (homogeneous income effect), so that $y_{it} = c_i + f(x_{it}) + \varepsilon_{it}$;
- Individual Fixed Effects and Common Trend (IFE_CT). $g_i(t) = g(t)\ \forall i$ (homogeneous time effect), $f_i(x_{it}) = f(x_{it})\ \forall i$ (homogeneous income effect), $y_{it} = c_i + f(x_{it}) + g(t) + \varepsilon_{it}$;[7]
- Individual Fixed Effects and Individual Trends (IFE_IT). We hold the constraint $f_i(x_{it}) = f(x_{it})$ $\forall i$ (homogeneous income effect), $y_{it} = c_i + f(x_{it}) + g_i(t) + \varepsilon_{it}$;
- Individual Fixed Effects, Individual Time and Individual GDP effect (IFE_IT_IG), $y_{it} = c_i + f_i(x_{it}) + g_i(t) + \varepsilon_{it}$.

As in Augustin et al. (2009) we use model selection criteria incorporating a trade-off between model fit and model complexity to compare such models.

4.2 Results

Concerning the first specification, $y_{it} = c_i + f(x_{it}) + \varepsilon_{it}$ (IFE), the estimation results for the nonparametric part of the model are shown in tables 2, 3 and 4 below where for each smooth term there are reported

[7]We also present in the appendix the findings related to the non additive specification $y_{it} = c_i + f(x_{it}, t) + \varepsilon_{it}$ and adopt a scale invariant tensor product smooth (Wood, 2006) to represent f. Invariance to the scale makes such smooths good to analyse quantities expressed in different units. This seems also a first step to relax the additivity hypothesis towards realms of partially or fully not separable models. We do believe this is scope for further research that can investigate various specifications, as examples $y_{it} = f(c_i, x_{it}, t) + \varepsilon_{it}$ or $y_{it} = f(c_i, x_{it}, t, \varepsilon_{it})$,which have been proposed very recently in the econometric literature by (among others) Evdokimov (2010) and Hoderleine and White (2012), respectively. This is an ancillary, we believe worth emphasising but not a core issue in our analysis, given that our main focus is disentangle between time and income effects and analyse their heterogeneity.

Table 2: Semi-parametric estimations - Umbrella countries

SMOOTH	"IFE" Edf(p)	"IFE_CT" Edf(p))	"IFE_IT" Edf(p)	"IFE_IT_IG" Edf(p)
LGDPPC	7.13 (2.00e-16)	4.69 (6.25e-06)	1 (2.00e-16)	
TIME		7.1 (-2e-16)		
TIME_AUSTRALIA			1 (-0.42)	6.62 (-0.011)
TIME_CANADA			7 (2.00e-16)	5.96 (2.00e-16)
TIME_JAPAN			5.97 (2.00e-16)	5.26 (2.00e-16)
TIME_NEWZELAND			8.14 (4.89e-13)	8.18 (1.98e-15)
TIME_NORWAY			8.7 (2.00e-16)	7.42 (8.20e-06)
TIME_USA			5.85 (2.00e-16)	6.1 (2.00e-16)
LGDPPC_AUSTRALIA				1 (-0.056)
LGDPPC_CANADA				1 (-0.156)
LGDPPC_JAPAN				1 (1.01e-12)
LGDPPC_NEWZELAND				1 (-0.012)
LGDPPC_NORWAY				5.67 (-0.018)
LGDPPC_USA				1 (1.32e-05)
AIC	-639.21	-672.85	-1102.64	-1148.41
BIC	-593.85	-606.53	-944.99	-946.5

Notes. L indicates log (LGDPPC=log(GDP per capita)). Edf indicates estimated degrees of freedom. (p) is the p-value. TIME_ "NAME OF THE COUNTRY" is a "factor-by-curve interaction" i.e. the interaction between the common trend and the country's indicator variable. LGDPPC_ "NAME OF THE COUNTRY" is a "factor-by-curve interaction" i.e. the interaction between log(GDP per capita) and the country's indicator variable. AIC: Akaike Information Criterion and BIC: Bayes Information Criterion. IFE (individual fixed effects), IFe-CT (individual fixed effects with common trend), IFe-IT (individual fixed effects with individual trend), IFe-IT-IG (individual fixed effects with individual trend and individual GDP effect).

the estimated degrees of freedom (edf) and the corresponding p-value whereas the resulting plots of the smooth terms (with their confidence intervals) are depicted in fig. 4.

The results clearly indicate that all groups of countries present nonlinear and quite complex CO_2-GDP relations (the edf being 7.13, 6.59 and 5.50 for the Umbrellas, EU-North and EU-South, respectively). Umbrella and EU-South as groups present a monotonic (but with a clear threshold) relation whereas for EU NORTH the CO_2-income relation is not monotonic (inverted U). This kind of modelisation broadly reproduces the descriptive country-specific plots depicted in fig. 1–3. This because $g_i(t) = 0$ implies

Table 3: Semi-parametric estimations - EU North

SMOOTH	“IFE” Edf(p)	“IFE_CT” Edf(p))	“IFE_IT” Edf(p)	“IFE_IT_IG” Edf(p)
LGDPPC	6.59	7.04	1.28	
	(2.00e-16)	(2.00e-16)	(3.60e-12)	
TIME		7.61		
		(2.73e-05)		
TIME_BELGIUM			6.42	6.81
			(2.00e-16)	(2.00e-16)
TIME_DENMARK			6.85	7.56
			(2.00e-16)	(5.37e-08)
TIME_FINLAND			8.51	9
			(2.00e-16)	(3.59e-09)
TIME_FRANCE			4.95	5.21
			(2.00e-16)	(2.00e-16)
TIME_GERMANY			2.87	2.38
			(2.00e-16)	(8.97e-11)
TIME_NETRHERLANDS			5.86	3.65
			(2.00e-16)	(3.88e-11)
TIME_SWEDEN			8.06	8.56
			(2.00e-16)	(2.10e-11)
TIME_UK			1	1
			(2.00e-16)	(5.30e-06)
LGDPPC_BELGIUM				1
				(8.40e-05)
LGDPPC_DENMARK				6.81
				(1.45e-06)
LGDPPC_FINLAND				4.62
				(2.27e-05)
LGDPPC_FRANCE				1
				(1.17e-05)
LGDPPC_GERMANY				1.28
				(6.38e-05)
LGDPPC_NETRHERLANDS				5.2
				(1.28e-06)
LLGDPPC_SWEDEN				2.74
				(-0.39)
LGDPPC_UK				1
				(3.23e-05)
AIC	-659.7	-776.07	-1240.65	-1331.64
BIC	-600.19	-685.81	-1031.54	-1038.39

Notes. L indicates log (LGDPPC=log(GDP per capita)). Edf indicates estimated degrees of freedom. (p) is the p-value. TIME_ “NAME OF THE COUNTRY” is a ”factor-by-curve interaction” i.e. the interaction between the common trend and the country’s indicator variable. LGDPPC_ “NAME OF THE COUNTRY” is a “factor-by-curve interaction” i.e. the interaction between log(GDP per capita) and the country’s indicator variable. AIC: Akaike Information Criterion and BIC: Bayes Information Criterion. IFE (individual fixed effects), IFe-CT (individual fixed effects with common trend), IFe-IT (individual fixed effects with individual trend), IFe-IT-IG (individual fixed effects with individual trend and individual GDP effect).

Table 4: Semi-parametric estimations - EU South

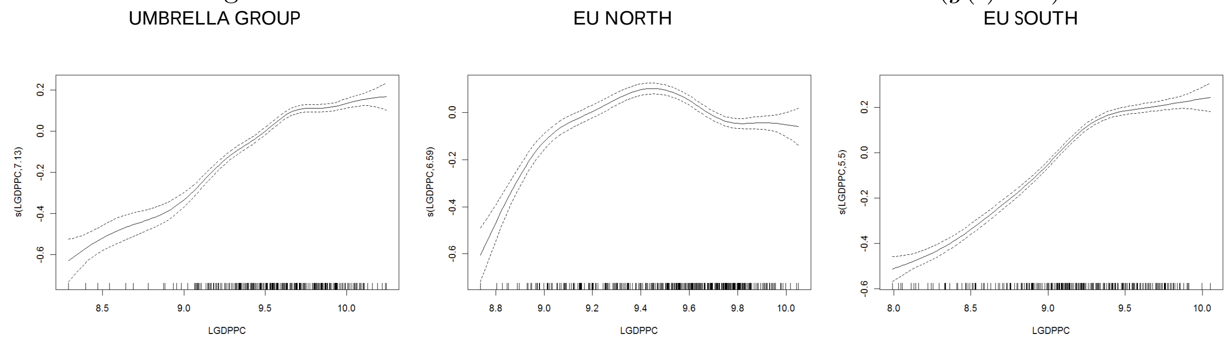
SMOOTH	"IFE" Edf(p)	"IFE_CT" Edf(p))	"IFE_IT" Edf(p)	"IFE_IT_IG" Edf(p)
LGDPPC	5.5	4.83	3.87	
	(2.00e-16)	(1.39e-12)	(2.00e-16)	
TIME		7.26		
		(2.00e-16)		
TIME_AUSTRIA			4.97	1
			(2.00e-16)	(-0.0013)
TIME_GREECE			4.78	4.61
			(2.00e-16)	(2.00e-16)
TIME_IRELAND			6.18	5.74
			(2.00e-16)	(2.00e-16)
TIME_ITALY			5.18	4.99
			(2.00e-16)	(2.00e-16)
TIME_PORTUGAL			1	1
			(3.48e-05)	(8.59e-05)
TIME_SPAIN			6.39	4.51
			(2.00e-16)	(8.08e-02)
LGDPPC_AUSTRIA				4.7
				(2.00e-16)
LGDPPC_GREECE				1
				(-0.001)
LGDPPC_IRELAND				1
				(-0.0012)
LGDPPC_ITALY				1
				(1.45e-05)
LGDPPC_PORTUGAL				3.28
				(1.08e-07)
LGDPPC_SPAIN				5.39
				(-0.0089)
AIC	-677.44	-745.67	-1192.58	-1201.58
BIC	-633.33	-678.31	-1053.63	-1041.8

Notes. L indicates log (LGDPPC=log(GDP per capita)). Edf indicates estimated degrees of freedom. (p) is the p-value. TIME_ "NAME OF THE COUNTRY" is a "factor-by-curve interaction" i.e. the interaction between the common trend and the country's indicator variable. LGDPPC_ "NAME OF THE COUNTRY" is a "factor-by-curve interaction" i.e. the interaction between log(GDP per capita) and the country's indicator variable. AIC: Akaike Information Criterion and BIC: Bayes Information Criterion. IFE (individual fixed effects), IFe-CT (individual fixed effects with common trend), IFe-IT (individual fixed effects with individual trend), IFe-IT-IG (individual fixed effects with individual trend and individual GDP effect).

focusing on the global effect of GDP on CO_2 and if the the effect of income does not vary greatly across cross-sections, then the estimation results from eq. (2) will mimic the country-specific CO_2-income plots. Moreover, it is worth noting that Mazzanti and Musolesi (2013) find evidence of inverted U relation when using homogeneous panel data estimators. This clearly shows the relevance of adopting nonparametric methods to avoid to find a false nonmonotonic relation.

We next allow unobserved common factors to enter the equation, $y_{it} = c_i + f(x_{it}) + g(t) + \varepsilon_{it}$ (IFE_CT). The outcomes with group's specific non parametric temporal trend now present a very different picture

Figure 4: GAM with individual fixed effects but no trend ($g(t) = 0$)



Notes. s(LGDPPC, edf) indicates the estimated smooth function (and its 95% confidence interval) of log (GDP per capita) and edf represents the estimated degrees of freedom.

(tables 2, 3 and 4, column "IFE_CT", Individual Fixed Effects and Common Trend, and fig. 5) and show the first of our main evidences. Indeed, the CO_2-GDP relation turns into a bell shaped curve for UMBRELLA and EU SOUTH groups, while is now monotonic for EU NORTH. The relation between emissions and the time factor is instead positive for UMBRELLA and EU SOUTH and significantly negative for EU NORTH. Even more relevant, these results show that the overall time evolution of per capita emissions is driven more by the unobserved common factors related to various time effects, rather than by economic development per se.

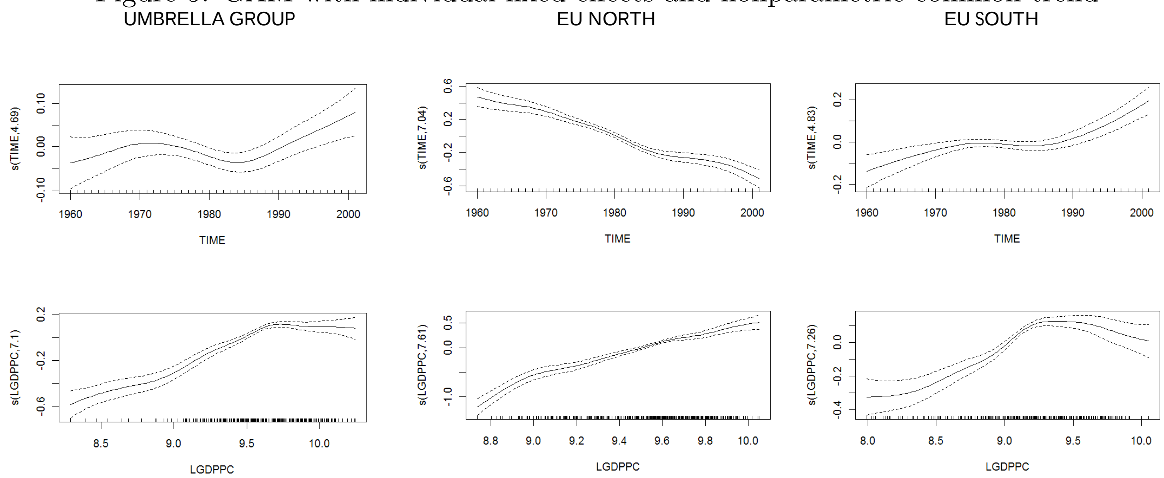
We believe that the issue is not what penalizes northern EU with regard to income related dynamics, but what has advantaged northern EU regarding the time related effects (over the all period, from the energy shock in the 70's 80's to the environmental policy era in the 90's). Some well known stylised facts can be advanced to explain such results. A strong pattern of green technological investments in some countries, exemplified primarily by Germany and also by UK/Scandinavian performances above all, which often intertwined with (higher than average) stringency of environmental policies. Scandinavian countries were in fact the only ones to implement full ecological tax reforms in the early 90's with the aim to achieve 'double dividends' (Andersen and Ekins, 2009). As a final remark here, we present in the appendix the findings related to the functional specification $y_{it} = c_i + f(x_{it}, t) + \varepsilon_{it}$.

Next, we focus on the third specification (IFE_IT), $y_{it} = c_i + f(x_{it}) + g_i(t) + \varepsilon_{it}$, which consists at generalising the previous specification by interacting the country's indicator (factor) variable with the nonparametric trend. This specification is often labelled as *"factor-by-curve interaction"* (Ruppert et al., 2003), and given our data structure (large T, small N) there is not any identification problems in estimating such a model which involves $N + 1$ nonparametric functions.

Looking at the results (tables 2,3 and 4, column "IFE_IT", fig. 6), it can be firstly noticed that the CO_2-GDP relation become in all cases more linear (the edf is now 1, 1.28 and 3.87 for Umbrella, EU-North and EU-South, respectively. We recall that edf=1 means the relationship is linear) and clearly monotonic. This provides more evidence on the fallacy of EKC and on the biased evidence that homogeneous and parametric panel settings may present. Secondly, this new piece of investigation clearly shows, at least for Umbrella and EU-South, that also the relation CO_2-time is heterogeneous across countries. Indeed, for the Umbrella, such relation is overall roughly an inverted U for USA, Canada and Japan, while it is positive for the other countries (Australia, Norway and New Zealand).

Different 'Innovation intensities' (especially patented innovation, which historically favours Japan

Figure 5: GAM with individual fixed effects and nonparametric common trend



Notes. s(LGDPPC, edf) indicates the estimated smooth function (and its 95% confidence interval) of log (GDP per capita) and edf represents the estimated degrees of freedom. $s(TIME, edf)$ indicates the estimated smooth function (and its 95% confidence interval) of time and edf represents the estimated degrees of freedom.

and the US, see Johnstone et al., 2012) that characterise the first set of countries, and in addition the energy structure of the economy, namely endowments of carbon intense sources, could well explain such within group differences, that were hidden by the common time factor specification. Countries possessing larger stocks of (fossil fuel) resources have comparatively less incentives to increase efficiency through innovation and to apply policies that reshape the energy structure towards coal-less sources. They are also less exposed to international energy shocks.

For the EU-South, we note that Italy and Spain present an inverted U CO_2-time component relation, while Portugal and Greece show a positive and monotonic relationship. Thus, the monotonic relation CO_2-common time factor relation slighting out in the previous section appear specifically driven by the poorest within the poorer set of countries confirming a ‘development’ oriented interpretation.

For the EU-North group, instead, the CO_2-time component relation is much more homogeneous across countries: it is clearly negative in all cases, even if some differences regarding the degree of nonlinearity appear. This indicates that the unobserved factors have negatively and primarily impacted CO_2 emissions. The factors explaining this evidence are largely linked to the way EU northern countries reacted to oil shocks, some well back in the mid 80’s, mainly through energy saving and innovation actions. Such countries were then later also characterised by a more effective adoption of environmental policy, including a relatively larger use of market based instruments as carbon taxes in the 90’s (Andersen and Ekins, 2009). The EU-North countries in fact present negative, robust and consistent CO_2-unobserved time factors relation. This evidence is coherent with recent evidence on the average EU performance (EEA, 2008).

As a final step to the analysis focusing on ‘country-specific time effects’, we can set both income and time effects as heterogeneous across countries, and focus on the fourth specification $y_{it} = f_i(x_{it}) + g_i(t) + c_i + \varepsilon_{it}$. The results (tables 2, 3 and 4, column "IFE_IT_IG" and figure 6) are fully coherent with what presented so far, but still deserve some comments. In fact, if on the side of statistical performances (AIC, BIC) it does improve very marginally upon the random growth – homogeneous income effect specification, on the side of economic significance, we highlight that the only two countries showing an inverted U EKC for the income-carbon relationship are Sweden and Finland. It is worth noting that the evidence is absolutely coherent with the results of the EU COMETR project that ex post evaluates the impact of carbon taxation through modelling exercises (Andersen, 2007). This is a clear example of how income-carbon (and time-carbon) dynamics present highly idiosyncratic and heterogeneous contents that deserve specific attention and can differentiate potentially similar countries.

Finally, we use AIC (Akake Information Criterion) and BIC (Bayesian Information Criterion) to assess the statistical validity of the different specifications. Both criteria incorporate a trade-off between model fit and model complexity. In particular the BIC presents an heavier 'penalty' than AIC regarding degrees of freedom losses, and tend to select the simplest models. For all groups, both AIC and BIC (see tables 2, 3 and 4) slightly increase (in absolute value) when moving from the benchmark specification to the specification with common trend. Then, we can note that including individual time effects is very important from a statistical point of view since both the AIC and BIC strongly increase (in absolute value) when moving from a common time effect to country-specific time effects. The comparison of heterogeneous gdp - heterogeneous time versus homogeneous gdp-heterogeneous time in terms of economic and statistical significance deserves a final note. Though the more refined specification (heterogeneous GDP - heterogeneous time) offers some interesting economic insights that show that country differences (e.g. policy implementation, policy stringency, energy sources) matter even among 'equals' and give food for thought to environmental policy, it does not clearly dominate the former (homogeneous gdp-heterogeneous time) in terms of statistical validity.

5 Conclusions

The paper aims at disentangling income and time related nonlinear effects in the analysis of a long run income-environment relationships. We devote strong attention to heterogeneity. To achieve this goal, we exploit recent advances in GAMs and make use of interaction models.

Empirically speaking, we focus on advanced economies given their role as leader in the current climate change agenda. We analyse relevant groups for what concerns economic and policy features – namely a first group including North America and Oceania, South Europe and North Europe.

We find that when time effects are not accounted for, only northern European countries show an inverted U pollution-income relation, whereas the other groups present a monotonic positive relation. These results relate to a global effect of GDP on CO2, which is nevertheless including the indirect effects linked to the omitted (or unobserved) variables, energy prices, technological change, environmental policies, among others.

Interestingly enough, when introducing in the model a nonparametric time effect, even if homogeneous across countries, results are importantly affected. The most important result is that we are able to show that the global long run income-environment is driven more by the unobserved common factors related to various time effects, rather than by economic development per se.

This demonstrates the fallacy of the simplistic 'environmental Kuznets curves' argument when it does not account for time effects. The income-environment relationship is indeed driven and eventually reversed in sign by time related factors. Those might present idiosyncratic elements at country/groups of countries level.

We in fact note that allowing for time effects to vary across cross-sections, an additional interesting insight emerges. From both a statistical and economic point of view, this conclusive model dominates the 'common time effect' specification. It provides detailed country based insights on what lies behind common unobservable time effects. Idiosyncratic elements related to energy, policy, innovation issues characterise the heterogeneity both across groups of countries and within groups of homogeneous countries as well. This matters when policy making set national targets and design policies. It also matter to explain the differences that may clash together when trying to reach international agreements on climate issues.

Heterogeneous time effects make the CO2-GDP relation more linear. In fact, we show as example that time components have been actually behind the reduction of CO2 in Northern Europe - even during growth periods. Time related factors have been able for such countries to more than counterbalance GDP scale effects.

Finally, a full heterogeneous specification (i.e. heterogeneous income effects and heterogeneous time effects) highlights that only Sweden and Finland within the EU have witnessed a 'full' negative CO2-income relationships, namely in relation to both income and time factors. Those two countries appear to be 'leaders among the leaders'.

In the end, we thus claim that the omitted country-specific time related factors bias is found to be empirically very relevant. One main message of the paper is that the negative pollution-development "global" relationship that appears for some advanced countries is explained to a large extent by country-specific time related factors, whose specific innovation, policy and energy contents deserve careful investigation in the future.

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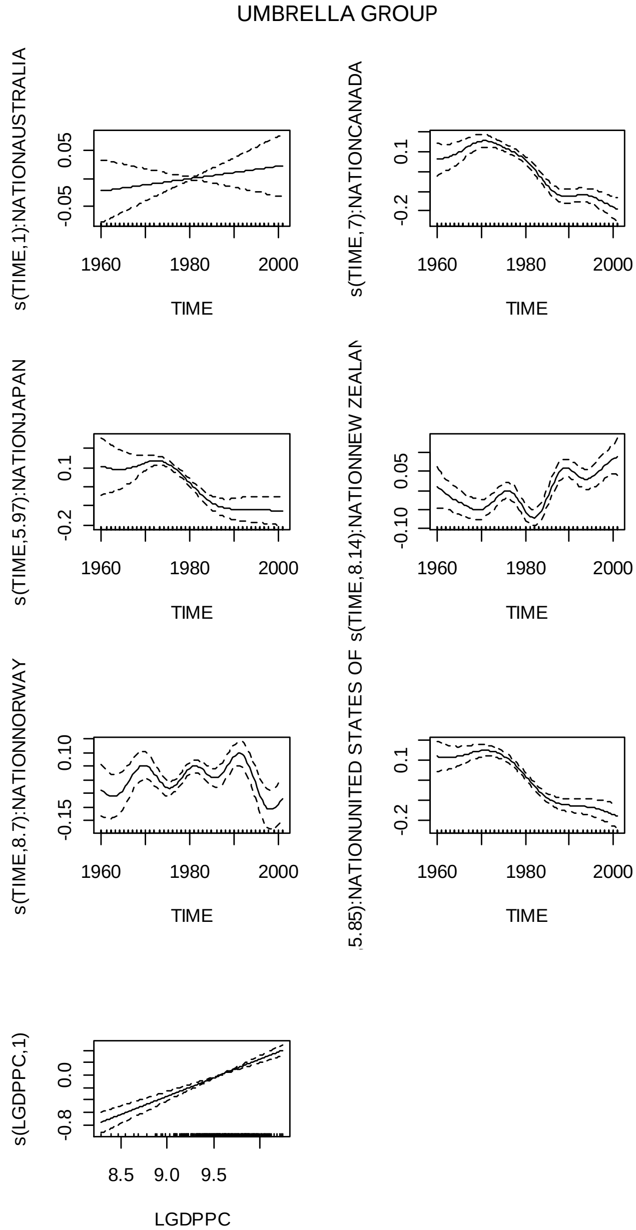
A Appendix 1: Estimating a partially non separable model

As a starting point for further research, we avoid assuming that the income effect and the time effect are separable by estimating $y_{it} = c_i + f(x_{it}, t) + \varepsilon_{it}$.

The 3D framework sketches (diverse angles are available upon request) provide some additional insights. For both UMBRELLA and EU SOUTH, the first part of the time dynamics, say roughly 1960-1973, present carbon income monotonic shapes. In the middle of the 'time evolution', say 1974-1987, U shapes for umbrella and non linear N–like shape for southern EU seem to emerge. The final part of the observed period, say 1988-2001, does not show remarkable changes, and confirms that income effects, if any, are of a positive nature.

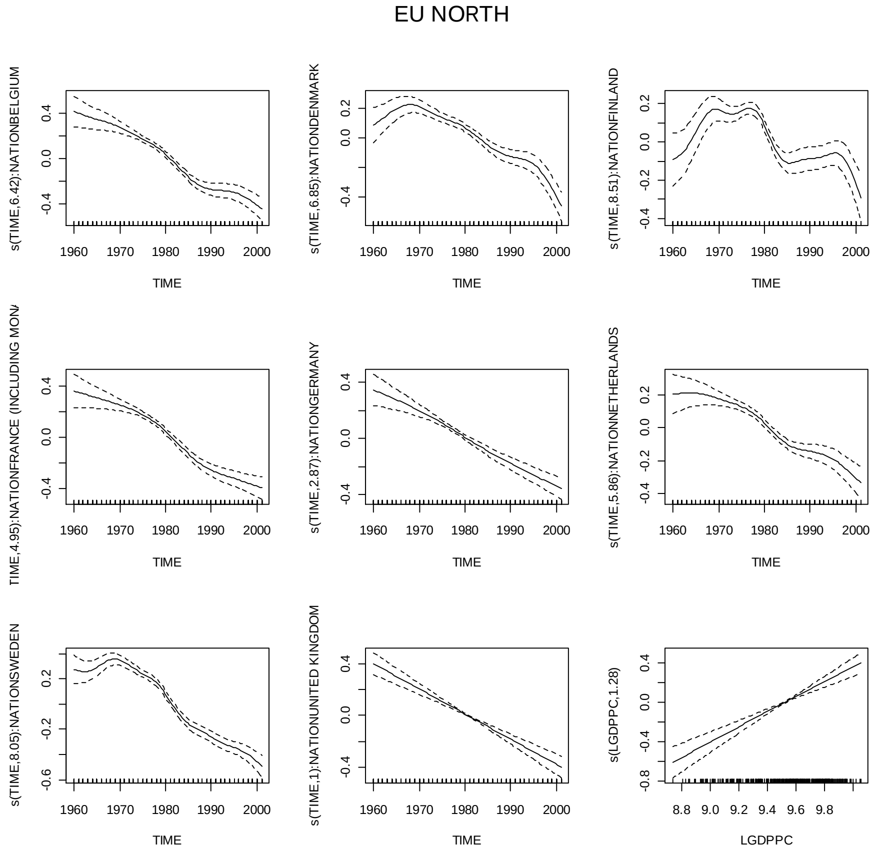
As far as EU NORTH is concerned, we note that in the first phase the shape is non linear (N-like), turning to a U shape in the second part, then concluding with a (globally negative) non linear shape, that nevertheless may hide some heterogeneity. Egli and Steger (2007) provide an interesting policy based motivation for non linear shapes: if the economy develops along the increasing path, a policy breaking stimulus may reduce the level of emissions, but after that pollution again follows a (lower) increasing path, before reaching a turning point in the income-environment relationship.

Figure 6: GAM with individual fixed effects and nonparametric individual trend



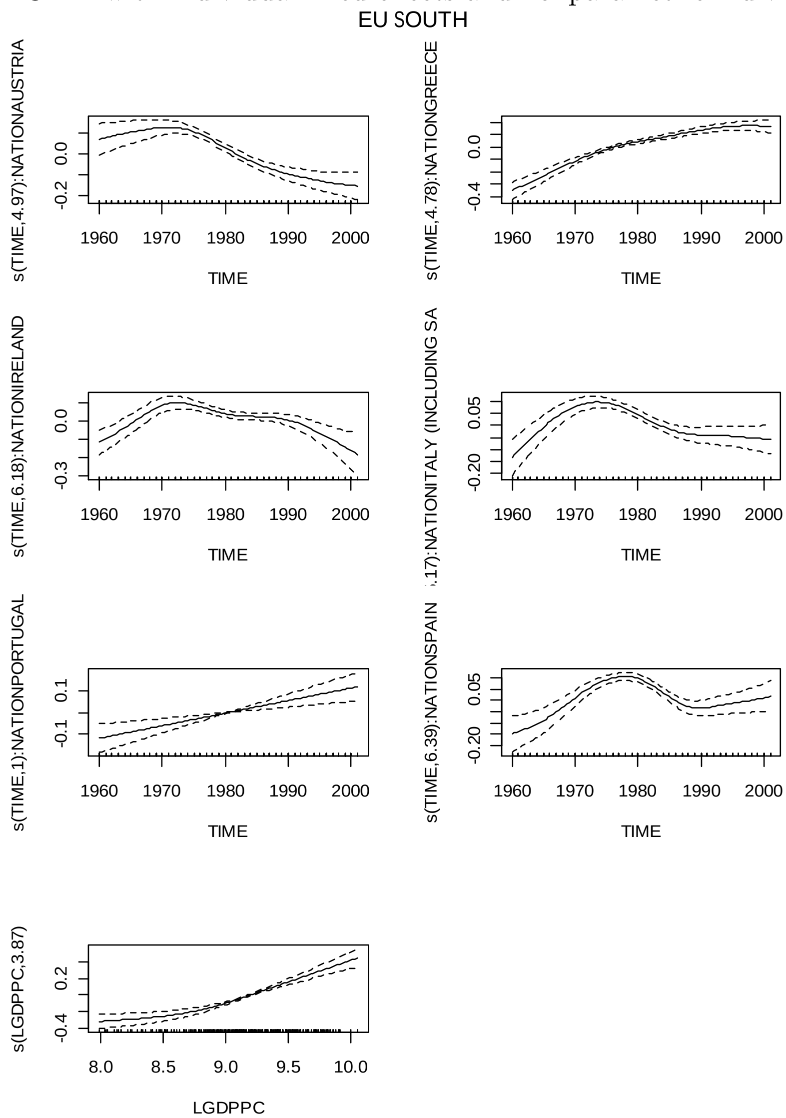
Notes. s(LGDPPC, edf) indicates the estimated smooth function (and its 95% confidence interval) of log (GDP per capita) and edf represents the estimated degrees of freedom.
s(TIME, edf)NATION "NAME OF THE COUNTRY" indicates the estimated smooth function (and its 95% confidence interval) of the "factor-by-curve interaction" (interaction between the common trend and the country's indicator variable) and edf represents the estimated degrees of freedom.

Figure 7: GAM with individual fixed effects and nonparametric individual trend



Notes. s(LGDPPC, edf) indicates the estimated smooth function (and its 95% confidence interval) of log (GDP per capita) and edf represents the estimated degrees of freedom.
s(TIME, edf)NATION "NAME OF THE COUNTRY" indicates the estimated smooth function (and its 95% confidence interval) of the "factor-by-curve interaction" (interaction between the common trend and the country's indicator variable) and edf represents the estimated degrees of freedom.

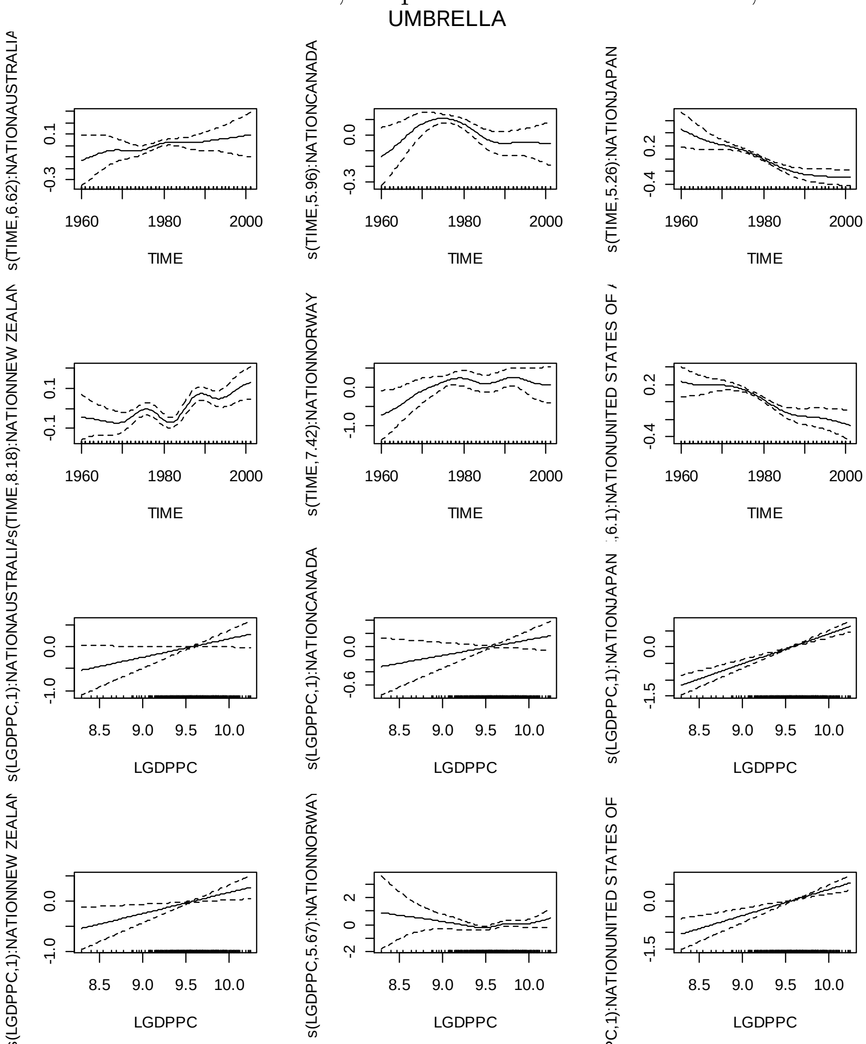
Figure 8: GAM with individual fixed effects and nonparametric individual trend



Notes. s(LGDPPC, edf) indicates the estimated smooth function (and its 95% confidence interval) of log (GDP per capita) and edf represents the estimated degrees of freedom.

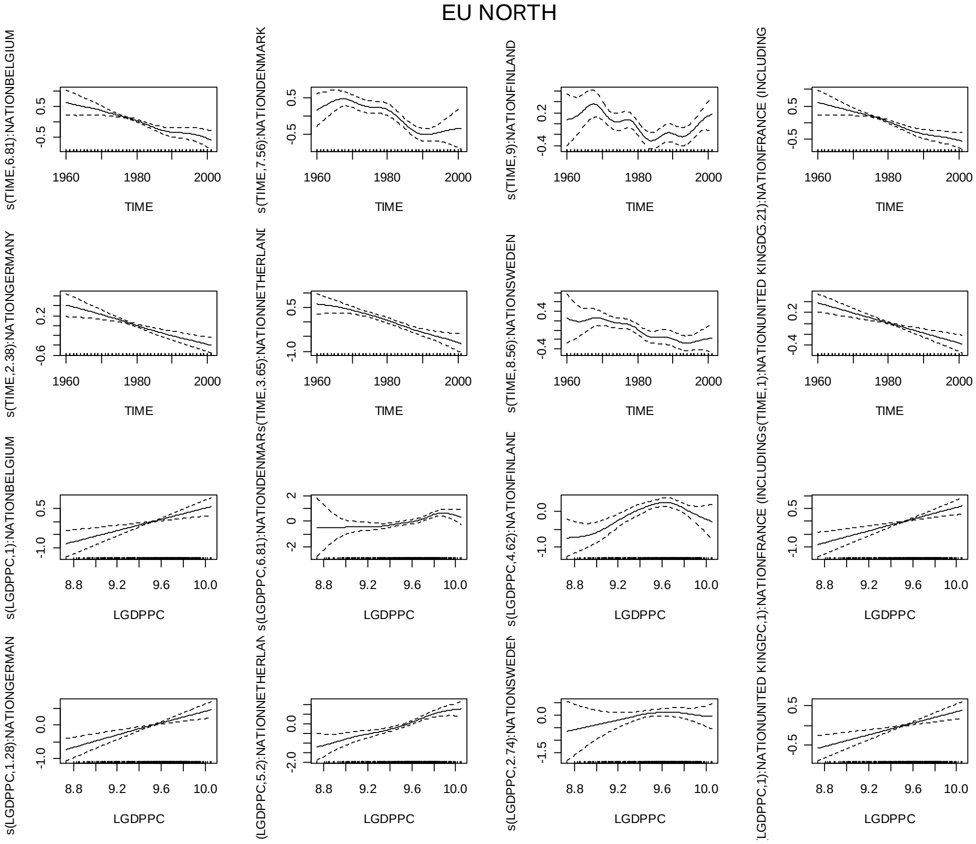
s(TIME, edf)NATION "NAME OF THE COUNTRY" indicates the estimated smooth function (and its 95% confidence interval) of the "factor-by-curve interaction" (interaction between the common trend and the country's indicator variable) and edf represents the estimated degrees of freedom.

Figure 9: GAM with individual fixed effects, nonparametric individual trend, and individual GDP effects



Notes. s(LGDPPC, edf) NATION “NAME OF THE COUNTRY” indicates the estimated smooth function (and its 95% confidence interval) of the “factor-by-curve interaction” (interaction between log(GDP per capita) and and the country’s indicator variable) and edf represents the estimated degrees of freedom.
s(TIME, edf)NATION “NAME OF THE COUNTRY” indicates the estimated smooth function (and its 95% confidence interval) of the “factor-by-curve interaction” (interaction between the common trend and the country’s indicator variable) and edf represents the estimated degrees of freedom.

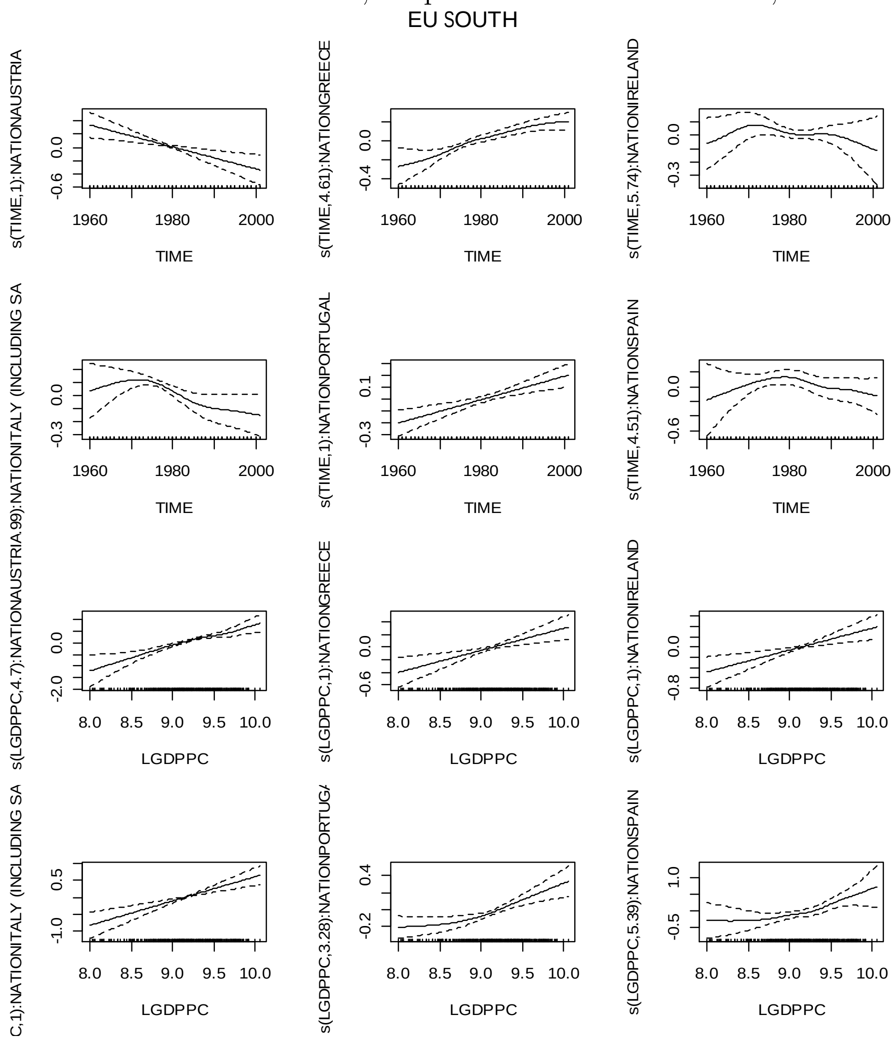
Figure 10: GAM with individual fixed effects, nonparametric individual trend, and individual GDP effects



Notes. s(LGDPPC, edf) NATION "NAME OF THE COUNTRY" indicates the estimated smooth function (and its 95% confidence interval) of the "factor-by-curve interaction" (interaction between log(GDP per capita) and and the country's indicator variable) and edf represents the estimated degrees of freedom.

s(TIME, edf)NATION "NAME OF THE COUNTRY" indicates the estimated smooth function (and its 95% confidence interval) of the "factor-by-curve interaction" (interaction between the common trend and the country's indicator variable) and edf represents the estimated degrees of freedom.

Figure 11: GAM with individual fixed effects, nonparametric individual trend, and individual GDP effects



Notes. s(LGDPPC, edf) NATION "NAME OF THE COUNTRY" indicates the estimated smooth function (and its 95% confidence interval) of the "factor-by-curve interaction" (interaction between log(GDP per capita) and and the country's indicator variable) and edf represents the estimated degrees of freedom.

s(TIME, edf)NATION "NAME OF THE COUNTRY" indicates the estimated smooth function (and its 95% confidence interval) of the "factor-by-curve interaction" (interaction between the common trend and the country's indicator variable) and edf represents the estimated degrees of freedom.

Figure 12: GAM with individual fixed effects and bivariate frame (time, GDP per capita). Other perspectives are available upon request.