Unveiling structural breaks in long-run economic development-CO2 relationships

January 18, 2016

Abstract

The paper assesses the effect of the 1992 United Nations Rio Convention on environment and development and other unknown structural time breaks on the long-run carbon dioxide-economic development relationship for different groups of advanced countries. Using an interrupted time series approach, three patterns of the dynamics of carbon dioxide are obtained: one is market-led, one is market- and policy-led, and one is more development-oriented.

JEL classification: C22; Q53.

Keywords: Carbon Kuznets curves, UN Rio convention, policy events, oil shocks, intervention analysis, structural breaks

1 Introduction

The relationship between climate change and economic development (Grossman and Krueger 1995, Carson, 2010) has received attention since the establishment of climate change policy discourses such as the Rio 1992 Convention, which paved the way for the Kyoto summit in 1997. Since then, the world economy has witnessed the economic upturn of most emerging economies, which has brought about massive increases in greenhouse gas (GHG) emissions. Most developed countries have often played a leadership role in GHG abatement strategies, with Northern Europe standing first in this ranking (Mazzanti and Musolesi, 2013). On this basis, the EU launched the new binding target for 2030 in January 2014. In 2015, The United Nations Climate Change Conference (COP21), was organised in Paris. It might represent a policy turning point if financial and policy schemes will be cooperatively implemented. There is still a strong necessity for learning from the past to to develop future targets and international agreements.

Mazzanti and Musolesi (2014) recently analyzed various groups of advanced countries within the OECD area. In particular, they focus on the 'Umbrella group' (Barrett, 2003 for a definition) comprising North America, Japan and Oceania; Northern Europe (NE); and Southern Europe (SE)) and concluded that nonlinear time effects weigh more than income does in driving carbon emissions. These time-related factors explain the reduction of CO2 levels in Northern Europe, where a bell-shaped carbon-income relationship is observed only for Scandinavian countries. This evidence highlights the fallacy of simplistic environmental Kuznets curve (EKC) interpretations (Harbaugh et al. 2002; Brock and Taylor, 2010) and necessitates further investigations of specific time-related events. Indeed, separating income and time effects by using a smoothing nonparametric approach is useful for capturing complex nonlinear dynamics; however, the specific time events that had (eventually abrupt) effects on emissions trends remain unexplored.

This paper aims to investigate the impact of temporal structural breaks on the above-mentioned groups of advanced countries. Currently, though with heterogenous targets and policy approaches, these countries play a leadership role in GHG reduction proposals. Reactions to historical shocks, such as major policy events and oil price shocks, may strongly differ between such groups and, in turn, may heterogeneously affect emissions. We primarily focus on a key historical policy event, i.e., the 1992 UN Framework Convention on environment and development that was held in Rio (henceforth defined 92RC in comments and tables), and consider other unknown time breaks that might have shaped the long-term trends.

2 Methodology

2.1 Basic econometric set-up

We use an interrupted time series approach (Box and Tiao, 1975; Pankratz, 1991). In the spirit of Musolesi and Mazzanti (2014), it is assumed that the evolution over time of per capita CO2 emissions, taken as a proxy of GHG can be decomposed as a function of economic development (GDP) and a function of time plus an autocorrelated disturbance:

$$y_t = f\left(\mathbf{x}_t;\theta\right) + g\left(t, \mathbf{\Upsilon};\beta\right) + \varepsilon_t \tag{1}$$

where x_t is the per capita GDP (in log form), t denotes time, and $f\left(\mathbf{x}_t,\theta\right)$ is a third-order polynomial function:

$$f\left(\mathbf{x}_t;\theta\right) = \theta_0 + \theta_1 x_t + \theta_2 x_t^2 + \theta_3 x_t^3 \tag{2}$$

The main original focus of this paper is that $g\left(t, \mathbf{\Upsilon};\beta\right)$ allows for both a nonlinaer (polynomial) effect of time, $\beta_1 t + \beta_2 t^2 + \beta_3 t^3$, and also for a finite number of interventions / unknown structural time breaks, $\mathbf{\Upsilon}$:

$$g\left(t, \mathbf{\Upsilon};\beta\right) = \beta_1 t + \beta_2 t^2 + \beta_3 t^3 + \sum_{j=1}^{k} \Upsilon_j \tag{3}$$

The error vector ε is distributed as $N(\mathbf{0}, \sigma^2\Lambda)$, where Λ is diagonal and ε has the covariance matrix Λ. The serial error correlation is modeled using a mixed autoregressive and moving average (ARMA) process. An ARMA(p,q) can be written as

$$\varepsilon_t = \sum_{j=1}^{p} \rho_j \varepsilon_{t-j} + \sum_{l=1}^{q} \xi_l v_{t-l} + v_{it} \tag{4}$$

where ρs and ξs are the autoregressive and moving average parameters, respectively, and v_{it} is random Gaussian white noise.

2.2 The 92RC intervention and unknown structural breaks

92RC is supposed to have brought about a 'gradual start, permanent duration' effect on the long-run carbon-income trend. This can be modeled combining a step function with an exponential (or first-order) transfer function, that (eventually) allows for a non-linear effect of the intervention:

$$\psi_t^s = step\_1993_t = \begin{cases} 1, \text{ if } t \geq 1993 \\ 0, \text{ otherwise} \end{cases}, \tag{5}$$

$$\Upsilon_1 = \left[\omega \mathbf{B} / \left(1 - \delta \mathbf{B}\right)\right] \psi_t^s$$

where $\mathbf{B}$ is the backward shift operator such that $\mathbf{B}^i y_t = y_{t-i}$. The magnitude of the impact that occurred after the event is given by ω,and δ is the rate of decay of the variation (see Box and Tiao, 1975, p. 71-72).[1] A *linear and permanent* effect can be modeled directly (in a more parsimonious way) using a 'ramp' function:

$$\psi_t^r = ramp\_1993_t = \begin{cases} t - 1992, \text{ if } t \geq 1993 \\ 0, \text{ otherwise} \end{cases}, \tag{6}$$
$$\Upsilon_1 = \lambda \psi_t^r$$

where λ measures the magnitude of the change in the trend of the series.

Other unknown structural breaks, namely $\sum_{j=2}^{k} \Upsilon_j$, are detected based on the methods described by de Jong and Penzer (1998). This allows the detection of eventual additive outliers (AOs), level shift outliers (LSOs) or transitory change outliers (TCOs), all of which contribute to the shape of a nonlinear long-run carbon relationship.

3 Data and econometric results

3.1 Data

We use the same group definitions and the same data used by Mazzanti and Musolesi (2013, 2014), who analyzed carbon dioxide-income relationships in a panel setting. We refer to these studies for a more detailed presentation of the data and samples. The countries are categorized according to specific structural features related to the climate change issues. We consider three groups: the 'Umbrella group' formed by North America, Japan and Oceania; Northern Europe (NE); and Southern Europe (SE). The sample covers the period 1950-2001. For the specific purpose of this paper, that is, studying the aggregate behavior of the above-defined areas, the countries are aggregated, which results in time series variables for each group of countries.

3.2 Preliminary unit root tests

Before estimating the model, a preliminary statistical analysis is conducted to detect the order of integration of the variables. This has relevant implications for model building. For GDP, we also provide tests for the polynomial powers (quadratic and cubic). We then perform the Augmented Dickey-Fuller (ADF) test as a benchmark, including a linear time trend in the auxiliary regression and setting the lag order (p) by using the AIC starting from an AR(5) model. The ADF tests

[1]When $\delta < 1$ the series will reach a new steady state and the steady state gain is $\omega/(1-\delta)$. When $\delta = 1$, a step change in the input produces instead a ramp function in the output of magnitude ω. Finally, $\delta > 1$ will produce an exponential pattern decay. Depending on the value of δ, the intervention will produce a *permanent* or *transitory* effect

provide evidence that favors the unit root hypothesis for all of the time series. However, because unit roots tests applied to time series of moderate sample sizes may suffer from size distortion, we simulate the p-value for the ADF test using an AR(p) Gaussian model. Based on Kwiatkowski et al. (1992), who argue that the standard unit root tests are not very powerful against relevant alternatives, we propose using the so-called KPSS test in which the unit root is the null hypothesis to be tested. Finally, because the failure of the ADF tests to reject the unit root null hypothesis could arise due to breaks or nonlinearities in the trend function, which are clearly observed in our data, we also use the Bierens (1997) revised nonlinear Dickey-Fuller test. The results of these tests clearly contradict the benchmark ADF tests and allow us to conclude that the series are stationary (detailed results are available upon request). Consequently, we develop our analysis without using first-difference techniques or cointegration. Detailed results are available upon request.

3.3 Model Identification

We use a two-step selection procedure as follows.

Step one: selection of the income and time components - $f(\mathbf{x}_t;\theta)$ and $g(t, \boldsymbol{\Upsilon};\beta)$ - of the model. We adopt a general-to-specific procedure starting from a model containing i) a cubic polynomial function of both income and time, ii) the 92RC intervention (alternating between the ramp and the step function), and iii) unknown breaks selected using the de Jong and Penzer (1998) approach. At this stage, we use an AR(1) term as the initial proxy for the disturbance series autocorrelation pattern (see, e.g., Pankratz, 1991, p. 173-177).

Step two: selection of the serial correlation structure of the error term. We use the ACF/PACF/IACF functions and white noise diagnostics to deduct the appropriate error structure (e.g., Hamilton 1994). Because the estimated autocorrelation pattern does not generally provide a unique indication of possibly being consistent with different processes, we also use information criteria (AIC and BIC) to choose the most appropriate error process. These criteria are also used to compare the two alternative specifications for the 92RC intervention.

3.4 Estimation results

We find that both the 92RC and other unknown structural time breaks have a relevant impact and influence the groups in different ways (Table 1, Figure 1).

Regarding the 92RC intervention, we first note that the model based on a ramp function is always preferred over one based on a step function with an exponential transfer function. For the Umbrella group, the analyses show a positive effect of the Rio Convention Ramp function over a general negative linear trend. On the contrary, for Northern Europe, 92RC had a negative effect on the emissions. Finally, Southern Europe did not show a specific reaction to this temporal event. The evidence shows how different world areas heterogeneously reacted to the 92RC, which was one of the pillars of the Kyoto Protocol targets 5 years later.

It is worth noting that all three areas present a monotonic carbon-income relationship that is linear for NE and quadratic for Umbrella and SE; the turning point is well above the range of observed incomes. It is worth noting, however, that overall, the only group that shows global non-monotonic carbon dynamics is NE. This is mainly explained by a negative non-linear LSO, detected using the de Jong and Penzer (1998) approach and modeled using a combination of a step function with an exponential transfer function.[2] This shift occurred after the second oil shock. This result adds a new relevant insight with respect to Mazzanti and Musolesi (2013, 2014).

In addition, the search procedure for the unknown breaks contributes to outlining the overall evolution of emissions. The most important ones, except for the above-mentioned breaks, relate to temporally specific positive effects on emissions that characterize the Umbrella group and SE: the effects are linked to the oil shocks of the 1970s, followed by negative effects on emissions in the 1980s. These breaks are either AOs or TCOs. The above-mentioned areas thus reacted to market shocks: a more intense use of coal could explain the positive effect in strict relation to oil shocks, which after a while contributed towards reducing the carbon levels of those economies in the mid-1980s.

[table 1 here]

[figure 1 here]

Finally, more heterogeneity is observed when focusing on individual countries. Table 2 presents a summary of the 92RC effects. The country-specific results show that overall, the RC92 effect is coherent with the group aggregate effect, but some countries show specific effects. SE does present some country-based positive effects, contrary to the aggregate not significant effect. Within NE, the following three countries show significant negative effects in terms of emissions: Finland, Netherlands and Germany, the latter being the (green) technological leader. Finally, among the Umbrella group, it is worth noting that although Norway largely followed the North American tendency towards climate policies, it seems to be aligned with the NE trends of a negative RC92 effect on emissions. Indeed, its economic and policy connections with the UK and Scandinavia were and still are strong. Overall, only four countries show a negative RC92 effect, which shows the possible relevance of policy events, on the one hand, and the difficult challenge of reverting GHG trends, on the other, which we still witness.

[table 2 here]

[2] Thus we introduce the following intervention:

$$\psi_t^{s80} = step\_1980_t = \begin{cases} 1, \text{ if } t \geq 1980 \\ 0, \text{ otherwise} \end{cases},$$
$$\Upsilon_2 = [\omega_{80}\mathbf{B}/\left(1 - \delta_{80}\mathbf{B}\right)]\psi_t^{s80}$$

4 Conclusions

This note sheds light on the structural breaks that might have affected the long-run carbon evolution. By using an interrupted time series approach, the paper captures the relevance of market- and policy-related time events, thus complementing some recent works that have used panel datasets to analyze the role of income and time effects. The analyses highlight two main messages. First, historical carbon dynamics are strongly affected by structural breaks rather than being smoothly influenced by income effects. This evidence further supports the fallacy of a simplistic environmental Kuznets-like argument. Emissions trends seem to be the result of a series of heterogeneous reactions to market and policy shocks, which ultimately determine complex nonlinear paths. Second, these paths seem to be categorized into three 'development models'. A 'market-led' model characterizes the Umbrella group, whose GHG emission pattern is mainly explained by reactions to market (oil) shocks. A 'market- and policy-led model' characterizes Northern Europe, which promptly reduced emissions after the second oil shock and afterwards presented a negative effect in terms of emissions driven by policy stimuli in the early 1990s. Southern Europe follows a more standard 'development-driven' model, where both income and time appear to have a nonlinear effect on the emissions.

The main message of this study is that carbon dynamics are largely explained by structural temporal breaks. The Northern EU countries seem to have taken earlier actions to achieve climate-oriented economic restructuring by reacting both to market and policy events in a consequential and complementary manner. In contrast, whereas the Umbrella group reacted with some delay to oil shocks through enhanced carbon efficiency, NE promptly reacted to the second oil shock and subsequently to the 92RC, ultimately becoming a leading actor in the climate change policy agenda.

The fact that some specific exogenous shocks matter is relevant for future climate negotiations and for stimulating other, possibly country-specific, policy evaluations.

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Table 1 - Main Econometric results

Variable	Umbrella			Southern Europe			Northern Europe		
	estimate	s.e.	t value	estimate	s.e.	t value	estimate	s.e.	t value
constant	-49.099	9.036	-5.43	-66.434	6.964	-9.54	-5.630	0.698	-8.06
AR1	0477	0.167	2.85				0.555	0.149	3.73
LGDP	9.667	2.021	4.78	13.214	1.503	8.79	0.711	0.075	9.47
LGDP2	-0.459	0.113	-4.05	-0.636	0.080	-7.91			
RC92-ramp	0.008	0.002	2.88						
trend	-0.009	0.004	-2.34	-0.068	0.010	-6.55			
trend2				0.001	0.0003	4.71			
trend3				-0.00001	0.0000003	-3.74			
STEP80 (magnitude)							-0.091	0.018	-5.01
STEP80 (rate of decay)							0.774	0.052	14.65
TC7273	0.027	0.011	2.38						
TC8388	-0.052	0.009	-5.28						
TC6970							0.046	0.025	1.85
AO80	0.03493	0.01218	2.87						
AO76				0.03414	0.01105	3.09			
AO79				0.04169	0.01129	3.69			
AO88				-0.03888	0.01104	-3.52			
AO91							0.07030	0.02652	2.65
AO96							0.08803	0.02639	3.34

Notes.

Dependent variable: CO_2 per capita (in logs); AR1 is the first-order autoregressive component.

LGDP and LGDP2 refer to per capita GDP and its square.

Trend, trend2 and trend3 are linear, quadratic and cubic trends, respectively.

STEP80 (magnitude) and STEP80 (rate of decay) refer to the parameters $\omega_{80}$and δ_{80} in footnote 2.

TCs and AOs indicate additive outliers and transitory change outliers, respectively.

Table 2 - Within groups heteroegenous effects

group	country	92RC Rio Effect	Aggregate 92RC Effect
Umbrella	USA	weakly positive significant*	positive effect
Umbrella	Japan	positive effect	positive effect
Umbrella	Canada	not significant	positive effect
Umbrella	Australia	not significant	positive effect
Umbrella	New Zealand	Positive effect	positive effect
Umbrella	Norway	negative effect	positive effect
NE	Sweden	not significant	negative effect
NE	Denmark	not significant	negative effect
NE	Finland	negative effect	negative effect
NE	Germany	negative effect	negative effect
NE	UK	not significant	negative effect
NE	The Netherlands	negative effect	negative effect
SE	France	positive effect	no effect
SE	Italy	not significant	no effect
SE	Ireland	positive effect	no effect
SE	Austria	not significant	no effect
SE	Greece	not significant	no effect
SE	Portugal	not significant	no effect

Notes.

Significance is intended at 10% level

*: For USA, the p-value associatet with RC92 is 0.2283.

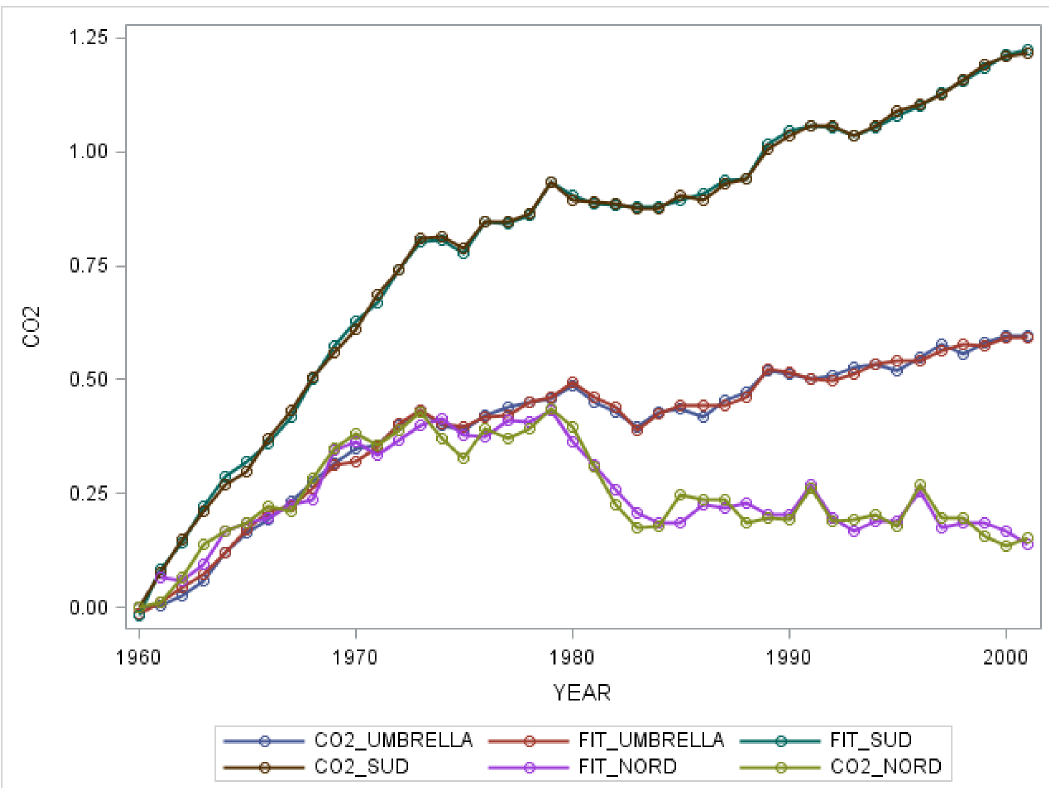

Figure 1: Real and fitted values