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Abstract

The environmental Kuznets curve hypothesis is a theory by which the relationship between per capita GDP and per capita pollutant emissions has an inverted U shape. This implies that, past a certain point, economic growth may actually be profitable for environmental quality. Most studies on this subject are based on estimating fully parametric quadratic or cubic regression models. While this is not technically wrong, such an approach somewhat lacks flexibility since it may fail to detect the true shape of the relationship if it happens not to be of the specified form.

We use semiparametric and flexible nonlinear parametric modelling methods in an attempt to provide more robust inferences. We find little evidence in favour of the environmental Kuznets curve hypothesis. Our main results could be interpreted as indicating that the oil shock of the 1970s has had an important impact on progress towards less polluting technology and production.

Key words and phrases: Environmental Kuznets curve, CO_2 emissions, Partially linear regression model, Flexible parametric inference, Oil shock.

JEL codes: Q53, Q56

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1 Introduction

Since the seminal paper of Grossman and Krueger (1991) on the potential environmental impacts of NAFTA, the works of Shafik and Bandyopadhyay (1992), which provided the backbone for the 1992 World Development Report, and that of Panayotou (1993) for the International Labour Organization, the environmental Kuznets curve (EKC) hypothesis has generated extraordinary research enthusiasm. Essentially, the interest of the EKC hypothesis is dynamic in nature. Indeed, the important question is "What is the evolution of a single country's environmental situation when faced with economic growth?" (Lopèz, 1994, Antel and Heidebrink, 1995, Kristrom and Rivera, 1995, Selden and Song, 1995, McConnell, 1997, Andreoni and Levinson, 2001, Munashinghe, 1999 and Antweiler et al., 2001). Although many researchers, mostly using cross-country panel data, reached the conclusion that the relationship between some pollution indicators and income per capita could be described as an inverted-U curve, the question of the existence of the EKC has not yet been fully resolved.

Indeed, a careful comparison of several papers reveals a great sensitivity of the estimated EKC shapes to the choice of time period and country sample. For example, Harbaugh et al. (2000, 2002), using the database of Grossman and Krueger (1995) extended by 10 years, found a rotated-S function for SO_2 emissions instead of the N curve detected by Grossman and Krueger (1995). Likewise, Stern and Common (2001), using a sample of 73 countries, including several developing ones, found an EKC with a turning point much higher than that found by Selden and Song (1994) with a similar sample containing only 22 OECD countries. Other examples of the sensitivity of empirical results to the chosen sample include the United States state-level based studies of Carson et al. (1997) vs. that of List and Gallet (1999) and the cross-country studies of Cole et al. (1997) vs. that of Kaufman et al. (1998).

One reason for this sensitivity is the use by several early authors of ordinary least squares (OLS) estimation with one-year cross-section data sets. This approach amounts to making the assumption that the environment-income relationship is internationally homogenous (Panayotou, 1993 and Shafik, 1994). Thus, a second wave of papers use panel data sets to include country-specific effects into the estimation, which allows some heterogeneity across cross sectional units. These papers include Cole and Elliott (2003), Cole (2004), Roca et al. (2001), Heerink et al. (2001), Barrett and Graddy (2000), Gale and Mendez (1998), Kaufman et al. (1998), Torras and Boyce (1998) and Panayotou, (1997). Following the same logic, these studies also include other underlying structural determinants, such as structural changes, population density, technological progress, institutional development, inequality, etc.

Still, most of these papers use simple error components models, which amounts to forcing the turning point of the hypothetical Kuznets curve to be the same for all units. Attempts to relax this restriction by using random coefficients models were made by List and Gallet (1999), Koope and Tole (1999) and Halos (2003). Their conclusions are to the effect that different countries appear to have different turning points and that the one-form-fit-all EKC curves obtained with standard panel data techniques should be used with great caution.

This state of affairs has prompted some authors to use country-specific regional panel data sets (Vincent, 1997 on Malaysia, Auffhammer, 2002, de Groot et al., 2004 and He, 2008 on China and Lantz and Feng, 2006 on Canada). The assumption here is that there is less heterogeneity between the regions of one country than between different nations. Although this assumption is very likely true, this approach merely tones down the heterogeneity problem without actually solving it.

Evidently, the only way to completely avoid the heterogeneity issue is to use single country time series data. Because of the scarcity of this type of data, only a few studies have chosen this path. They include Roca et al. (2001) on CO_2, SO_2 and NO_X emissions in Spain (1973-1996), Friedl and Getzner (2003) on CO_2 emissions in Austria (1960-1999) and Lindmark (2002) on CO_2 emission in Sweden (1870-1997). These three studies indicated that the appearance of a delinking between pollution and income should be attributed to country-specific characteristics such as technological progress, structural evolution or external shocks like the 1970s oil crisis.

The rigidity of the quadratic or cubic parametric functional forms used by most investigators has also been criticised. For example, Harbaugh et al. (2002) found that the location of the turning points, as well as their very existence, are sensitive both to slight variations in the data and to reasonable changes of the econometric specification. This has motivated the use of semi and nonparametric techniques, which do not specify a functional form *a priori*. Important papers in this category include Schmalensee et al. (1998) who used spline regressions, Taskin and Zaim (2000) and Azomahou et al. (2005), who used nonparametric regressions to investigate the EKC for CO_2 emissions with cross-country data, Millimet et al. (2003) and Roy et al. (2004), who employed semi-parametric partially linear models for US data and Bertinelli and Strobl (2005), who also estimated a partially linear model for the CO_2 emission for international experience.

We test the EKC hypothesis for per capita CO_2 emissions in Canada using the nonlinear parametric model introduced by Hamilton (2001). This method is extremely versatile and yields consistent estimates of the investigated functional form under very unrestrictive assumptions. It also allows one to easily identify which regressors affect the dependant variable nonlinearly. The results obtained with this method are compared to the results from a cubic parametric model as well as a partially linear regression model.

The contribution of this paper is threefold. First we contribute to the empirical literature on the EKC for CO_2 emissions. Due to its particularity as a global pollution problem and its closer links with anthropological activities, different from some local pollution cases, such as SO_2 or Particulate Matters (PM), the evidence for the EKC hypothesis is "at best mixed" (Galeotti et al. 2006). On the one hand, several studies, revealing ever-increasing trends, failed to detect the inverted-U relationship between this pollution indicator and per capita GDP (Agras and Chapman, 1999; Roca et al., 2001 and Egli, 2002 among others). On the other hand, some empirical investiguations revealed relatively high turning points or an N-shaped curve indicating the re-increasing trend of CO_2 emission after income reaches a certain level. For example, Holtz-Eakin and Selden (1995) find a turning point at 36 048$ using a level model and over 8 million $ with a logarithmic model. Similarly, Heil and Selden (2001), using a level model for CO_2 emissions, find a turning point at 36 044$ but an ever-increasing trend with a logarithmic model. Unruh and Moomaw (1998) find an N-shaped curve with lower turning point but report a very narrow income range for CO_2 declines. Friedl and Getzner (2003) find a cubic N curve for CO_2 emissions in Austria, with an obvious structural break point in the mid-1970s, and a resuming of an increasing trend starting in 1982. Our paper therefore aims to contribute to this debate and offer more empirical evidence to support or refute the EKC hypothesis.

Our second contribution is to provide an analysis of the relationship between economic growth and CO_2 emissions in Canada. Several empirical studies among those mentioned above are based on international panel data, in which Canadian macro data are very often included. Some of these studies, such as Unruh and Moomaw (1997), have highlighted some particularity of Canada compared to the other OECD members. While benefiting, just like other OECD member countries, from the technological progress following the oil crisis, Canada and its neighbour, the United States, seemed to be the only two nations that contributed to the re-increasing trend of CO_2 emissions after the turning point of 1973, possibly owing to their better oil resources. The best way to analyse this particularity is to directly study Canadian data. To our knowledge, at the time of writing this, the only paper concentrating on Canadian CO_2 emissions is Lantz and Feng (2006), who investigate the EKC hypothesis with a 5-region panel data set from 1970-2000. Their findings suggest that CO_2 emissions are not related to GDP per capita, but to population and technology.

Finally, and perhaps most importantly, we use the nonlinear parametric model introduced by Hamilton (2001) for the first time in the EKC literature. The main advantage of this method is that it does not require any assumption about the functional form of the investiguated relationship and allows one to test which variables have a nonlinear impact on the dependant variable. We also provide comparisons with results obtained from the parametric and semiparametric methods.

The rest of the paper is organized as follows. Section 2 briefly introduces our data while section 3 is given over to the estimation of the fully parametric model. The estimation results based on semiparametric and nonlinear models are presented in sections 4 and 5. Section 6 concludes.

2 Data

To carry out our analysis we employ time-series data on Canada CO_2 emissions from 1948 to 2004. These are published by the World Resources Institute (WRI), Washington, DC.[1] The WRI calculates carbon dioxide emissions from 3 sources: International Energy Annual (IEA) 2002[2], CO_2 Emissions from Fuel Combustion (2004 edition)[3] and Marland, Boden and Andres (2005). All other data series, that is, GDP, population and a set of control variables, were obtained from Statistics Canada.

Table 1. Descriptive statistics.

Variable	Mean	Std. Dev.	Max. (year)	Min. (year)
CO_2pc	14.64	2.45	17.90 (1978)	10.56 (1960)
GDPpc	22.46	7.74	37.15 (2004)	10.79 (1948)
Poil	11.14	8.86	36.77 (2004)	2.51 (1950)
Ind. Share	26.78	1.98	30.34 (1965)	21.78 (1992)
Xo	0.036	0.03	0.10 (1974)	0.00 (1949)
Mo	0.04	0.02	0.10 (1975)	0.02 (1998)
Xus	0.68	0.10	0.84 (2002)	0.49 (1948)
Mus	0.71	0.03	0.77 (1998)	0.67 (1950)

Table 1 shows descriptive statistics for the variables used in our study while figure 1 shows the evolution of GDP per capita (GDPpc) and CO_2 emissions per capita (CO_2pc). As time passes and GDPpc increases, the gap between the two series widens. This corresponds to the decreasing of the emission intensity trend which has already been observed for OECD countries by Roberts and Grimes (1997) and Unrhu and Moomaw (1998), among others. This could be interpreted as evidence in favour of the EKC hypothesis.[4] Of course, this type of simple visual analysis can be quite misleading as several factors besides GDPpc may affect CO_2pc emissions. For example,

[1]Climate Analysis Indicators Tool (CAIT) version 3.0., available at http://cait.wri.org.

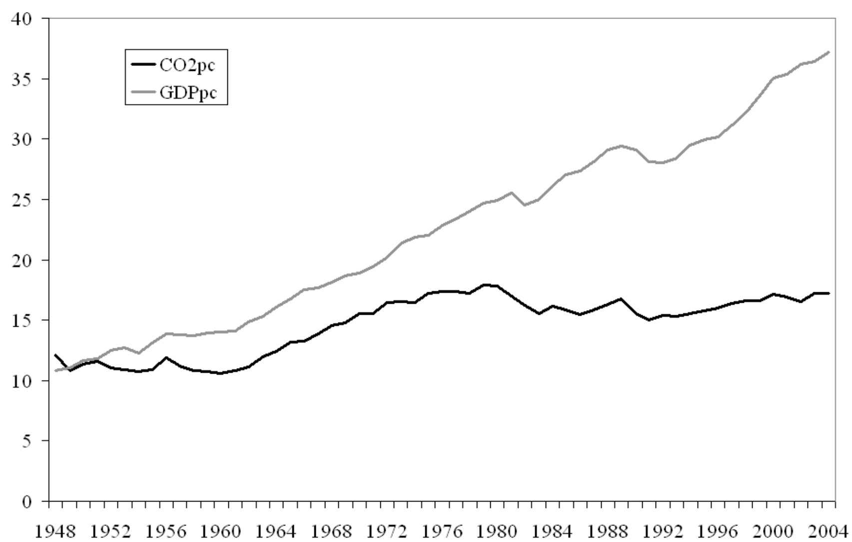
[2]Available online at: http://www.eia.doe.gov/iea/carbon.html.

[3]Available online at: http://data.iea.org/ieastore/CO_2 main.asp

[4]It is not surprising, therefore, that a very simple cubic parametric model estimated in the next section does not clearly reject the EKC hypothesis.

technological improvement may very well have an effect on CO_2pc. Indeed, technological improvement has been well documented as a possible environment-friendly factor. For instance, Lindmark (2002) emphasized the important role played by technology in the CO_2 emissions decreasing trend in Sweden after the oil crisis of the early 1970s. Also, Unruh and Moomaw (1997), based on scatter plot analysis and spline structure transition models with 16 countries' data during 1950-1992, indicated the existence of a structural break point in 1973. We explore this issue in the next three sections.

Figure 1. Evolution of GDPpc and CO_2pc.



3 Cubic parametric models

We begin our analysis by considering a parametric model that is quite standard in the EKC literature and takes the following form:

$$E_t = \alpha_0 + \alpha_1 t + \beta_1 y_t + \beta_2 y_t^2 + \beta_3 y_t^3 + \gamma X_t + u_t \tag{1}$$

where E_t is per-capita CO_2 emissions, y_t is per capita real GDP and X_t is a vector of variables that may affect E_t. The deterministic time trend (and sometimes its square) is included as a crude proxy of technological progress. For various reasons, mainly data availability or small sample sizes, several empirical studies omit the vector X_t altogether. This of course may lead to biased and inconsistent inferences and parameter estimation. Nevertheless, to form a benchmark for our analysis, we estimated model (1) with the restriction γ=0. At first glance, the results, which are reported in column 2 of table 2, seem to support at least weakly the EKC hypothesis. Indeed, according to heteroscedasticity robust asymptotic and bootstrap tests, α_1, β_1

and β_2 are statistically significant and have the expected signs while β_3 is statistically insignificant at a 5% nominal level. Thus, one may use these results to reject y_t^3 and conclude that the relationship between E_t and y_t, after controlling for linearly increasing technology, has an inverted U shape with a peak around 22 615$ GDPpc.

Evidently, the probable under-specification of this regression model makes the robustness of this result highly questionable. Some authors propose including a quadratic trend in the regression to allow for a nonlinear effect of technology (see Lantz and Feng, 2006, among others). Doing so in the present case yields quite different results (see column 3 in table 2). The signs of the estimated parameters associated to the trend and quadratic trend imply that technological progress first decreases and then increases per capita emissions. A similar result is found by Lantz and Feng (2006), "implying that technological changes have shifted from enhancing more environmentally friendly production techniques (Kaufman et al., 1998) to encouraging CO_2 emissions enhancing production techniques (Shafik, 1994)". More importantly, β_3 now appears to be positive and statistically significant. This implies that the pollution / per-capita income relationship is either monotonically increasing or N-shaped, which means that any beneficial effects economic growth may ave on per-capita pollution is transitory. This finding echoes the conclusion of Unruh and Moomaw (1997), which suggest that Canada contributed to the re-increasing trend of world CO_2 emissions after the 1980s.

Economic common sense and specification tests reported at the bottom of the table suggest that this second model is also badly specified. We therefore considered the addition of several explanatory variables. One is the price of crude oil, P_t. This variable has often been used in CO_2 related EKC estimation (Agras and Chapman, 1999; Heil and Selden, 2001, etc.). It is often expected to carry a negative coefficient to capture the price elasticity of demand. The interest of including this variable in the case of Canada is two-fold. First, more expensive petrol may induce people and industries to switch to less energy consuming, and thus less polluting, technologies. However, Canada is a producer of oil, so that increasing oil prices may cause extraction and refining activities to increase. Since these are pollution intensive activities, the link between P_t and E_t may be positive.

A second variable is the share of industrial production in total GDP (S_t). The inclusion of this variable aims to capture the composition effect, by which per capita emissions decrease through a movement from pollution intensive industries towards less polluting ones. York et al. (2003), Friedl and Getzner (2003) and Egli (2002) also include similar variables in their studies. To further isolate the composition effect, we have used variables that describe Canada's international trade. These variables are the share of oil exports in total Canadian exports (XO_t) and the share of oil imports in Canadian imports (MO_t). Friedl and Getzner (2003) and Agras and Chapman (1999) used similar variables in their EKC estimate. Because a large proportion of Canadian international trade is done with the United States we have also included measures of the chare of Canadian exports to the US (XUS_t) and imports from the US (MUS_t). [5] However, as discussed in Antweiler et al. (2001), the relationship between trade and environment can go through various channels. It is consequently difficult to give a clear prediction of the estimated sign for their coefficients.

Estimation results for this model are reported in column 4 of table 1. Although it has a higher adjusted R^2, almost all the specification tests indicate that it is misspecified. In particular, the Breusch-Godfrey test detects serial correlation in the residuals. The sample ACF and PACF, which are available from the authors on request, strongly suggest that the residuals follow an AR(1) process. Reestimating model (1) under the hypothesis that its errors are $u_t = \rho u_{t-1} + \varepsilon_t$, where ε_t is a random white noise, yields the results reported in the last three columns of table 1. Notice that the quadratic trend does not appear as significant in any of the dynamic models and is therefore omitted. On the other hand, industry share has a positive sign in model 6, which is as expected.

Models 5 and 6 provide the best fit and appear to be reasonably well specified. Although non-nested hypothesis J tests do not prefer one model over the other, we may consider model 6 as slightly better because it only includes statistically significant control variables. In any case, inference regarding the EKC hypothesis based on these two models does not allow any clear conclusions. As was the case with the simpler models, different statistical significance levels yield different conclusions. Indeed, the U-shape hypothesis is rejected by neither models at 1%, by model 5 at 5% and by both models at 10%. These results illustrate the limits of cubic parametric regressions and motivate the utilisation of more flexible methods considered in the next two sections.

[5] Total Canadian imports and exports were also considered but they did not appear to contain any relevant information.

Table 1. Parametric models

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
C	-16.7868 (0.0001) [0.0005]	-43.5431 (0.0000) [0.0000]	-40.0179 (0.0000) [0.0001]	-21.0875 (0.0213) -	-19.0965 (0.0043) -	-20.2722 (0.0200) -
t	-0.3655 (0.0000) [0.0000]	-0.8616 (0.0000) [0.0000]	-0.7711 (0.0008) [0.0019]	0.0635 (0.7712) -	-0.1218 (0.1052) -	- - -
t^2	- - -	0.0078 (0.0002) [0.0008]	0.0076 (0.0212) [0.0353]	-0.0026 (0.3792) -	- - -	- - -
Y_t	3.1706 (0.0000) [0.0000]	6.8464 (0.0000) [0.0000]	6.2027 (0.0000) [0.0002]	3.0838 (0.0066) -	3.4950 (0.0002) -	3.1698 (0.0042) -
Y_t^2	-0.0701 (0.0059) [0.0092]	-0.1923 (0.0000) [0.0000]	-0.1721 (0.0000) [0.0006]	-0.1003 (0.0218) -	-0.1060 (0.0055) -	-0.1011 (0.0240) -
Y_t^3	0.0006 (0.0554) [0.0674]	0.0019 (0.0000) [0.0002]	0.0016 (0.0002) [0.0006]	0.0012 (0.0311) -	0.0012 (0.0218) -	0.0011 (0.0616) -
P_t	- - -	- - -	-0.0279 (0.0360) [0.0549]	-0.0199 (0.3707) -	- - -	- - -
S_t	- - -	- - -	0.0353 (0.6994) [0.7036]	0.0296 (0.7437) -	- - -	0.1305 (0.0493) -
XO_t	- - -	- - -	3.0363 (0.1201) [0.3941]	3.6954 (0.0621) -	- - -	- - -
MO_t	- - -	- - -	16.3279 (0.0113) [0.0152]	13.4448 (0.1042) -	9.8623 (0.1125) -	- - -
XUS_t	- - -	- - -	-1.2554 (0.6624) [0.7199]	0.6236 (0.7825) -	- - -	- - -
MUS_t	- - -	- - -	0.2481 (0.9690) [0.9706]	4.6581 (0.3940) -	- - -	- - -
u_{t-1}	- - -	- - -	- - -	0.7182 (0.0000) -	0.7006 (0.0000) -	0.7961 (0.0000) -
R^2_{adj}	0.9048	0.9245	0.9314	0.9755	0.9714	0.9674
F BG	23.88 (0.0000)	7.27 (0.0017)	5.66 (0.0066)	1.10 (0.3421)	0.46 (0.631)	0.22 (0.806)
F ARCH	3.57 (0.0350)	3.74 (0.0303)	4.06 (0.0230)	1.35 (0.2689)	0.97 (0.391)	0.55 (0.578)
F White	2.46 (0.0303)	3.29 (0.0045)	1.95 (0.0401)	0.88 (0.6056)	0.40 (0.930)	1.14 (0.354)
RESET	-0.15 (0.879)	5.16 (0.0000)	12.05 (0.0012)	7.79 (0.0079)	9.68 (0.000)	11.74 (0.000)
JB	0.82 (0.6640)	0.12 (0.9426)	4.31 (0.1161)	0.54 (0.7645)	0.26 (0.878)	0.47 (0.789)
Com. Fact.	-	-	-	-	1.441 (0.236)	1.848 (0.294)

Asymptotic P values in parenthesis, bootstrap P values in brackets. For models 1 and 2, heteroscedasticity robust covariance matrices and the wild bootstrap are used.

4 More flexible models

The parametric models of the previous section have several weaknesses. One is that the powers of the deterministic trend and the powers of GDPpc are highly correlated, a fact that may have an adverse effect on the reliability of the parameters estimates. Another is that they impose a given form to the pollution / income relationship. Should the chosen functional form be wrong, then all the analysis may be incorrect.[6] The serial correlation found in the residuals of the static models may be a symptom of this[7].

It is therefore preferable to use more flexible models that do not specify the shape of the relationship and do not require the use of powers of the explanatory variables. Specifically, we would like to consider a model such that

$$E_t = \alpha_0 + \alpha_1 t + \mu(y_t) + \gamma X_t + u_t, \qquad (2)$$

where $\mu()$ is some unspecified, possibly nonlinear function and X_t is as before. One such model is the partially linear regression (PLR) model, in which the function $\mu(y_t)$ has to be estimated nonparametrically. We use the method proposed by Robinson (1988), which allows one to obtain consistent estimators of $\mu(y_t)$ and the linear parameters. This requires nonparametric kernel-density estimation of the expectation of the dependent variable, as well as that of the regressors, conditional on y_t.

In all that follows, we have carried-out these computations using local constant Gaussian kernel estimators. The necessary window widths were obtained by cross-validation. Model (2) was estimated without the constant and with standardized data replacing the original observations. This is necessary because the constant and the function $\mu(y_t)$ cannot be jointly identified. See Li and Racine (2007), chapters 2 and 7 for details on these issues. Notice that Millimet et al. (2003) have employed this model on a state-level panel data set of the United State and overwhelmingly rejected the parametric approach.

An alternative approach proposed by Hamilton (2001) consists of considering the function $\mu(y_t)$ as the realisation of a stochastic process called a random field and to use the observed data to form inferences about what this realisation might be. This fully parametric approach allows one to avoid some problems related to nonparametric estimation such as the choice of an appropriate bandwidth. Generaly speaking, the

[6]Theoretically, one could obtain an arbitrarily accurate approximation of the true functional form by adding higher powers of GDPpc. This, however, is not a practical procedure in small samples.

[7]The fact that the common factor restrictions are not rejected does not necessarily imply that the linear model with AR(1) errors is correctly specified.

form of Hamilton's model is:

$$E_t = \mu(Z_t) + \varepsilon_t, \quad \text{where} \quad \mu(Z_t) = Z_t\beta + \lambda m(Z_t^\ell g) \tag{3}$$

where λ is a scalar parameter, β and g are $k \times 1$ and $k-1 \times 1$ vectors of parameters respectively, Z_t denotes a k-vector containing all the regressors (that is, the constant, the deterministic trend, y_t and X_t), Z_t^ℓ denotes the set of regressors excluding the constant and $m()$ is a standard normal random field.

Generation of data from a process element of model (3) proceeds in two steps. First, a realisation of the random field $m(x)$ takes place for all possible values of x, which essentially means that a realisation of the part of the data generating process which is usually considered non-stochastic occurs. Then, values of the dependant variable E_t are generated from (3), according to some distribution for ε_t.

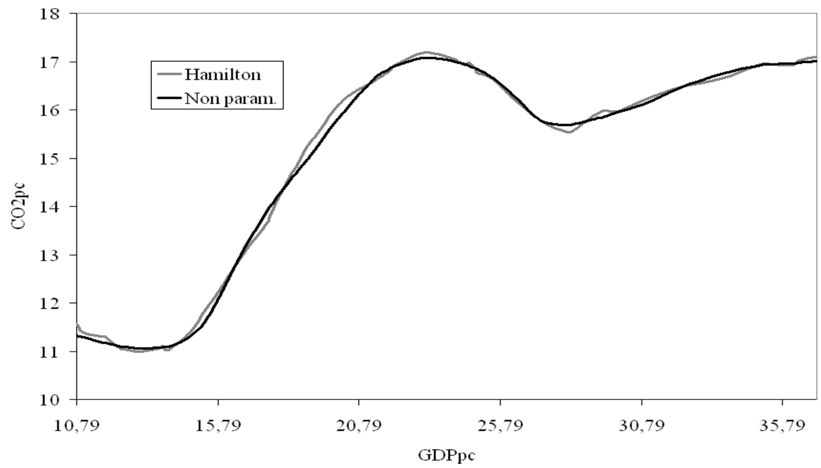
Unless some restrictions are imposed, $2k$ parameters must be estimated. Clearly, $\lambda = 0$ implies that $\mu(Z_t)$ is a linear function. Also, if the i^{th} element of g is 0, then $Z_{i,t}$, the i^{th} regressor, drops out of the function $m()$ and $\mu(Z_t)$ is linear in $Z_{i,t}$. Thus, one may take a statistically significant estimate of the coefficient g_i as a indicator of the necessity to include the variable i in the nonlinear part of the model. Estimation of $m()$ and of the various parameters may either be performed using maximum likelihood or Bayesian methods. We report maximum likelihood estimates although Bayesian estimates turned out to be very similar in every cases.

In this section, we assume that only y_t has a non-zero parameter g_i. This choice is motivated by the facts that it is primarily the GDPpc / CO_2pc relationship that interests us and that we have relatively few observations available. We will consider other specifications in the next section.

4.1 Estimation without control variables

To set a benchmark for our analysis, figure 2 shows the graph of $\mu(y_t)$ as estimated by both methods when all regressors entering linearly are dropped, that is, $\hat{\mu}(y_t)$ is here an estimate of $E(E_t|y_t)$.

Figure 2. Estimates of $\mu(y_t)$.



Even though the two methods rely on quite different estimation principles, their results are similar. A most interesting feature of this function is the hump that occurs near the middle of the sample. Upon closer examination, it can be seen that the function's slope becomes negative at a GDPpc value between 23 000$ and 24 000$, which corresponds to the mid 1970s. This may hold some significance, and we will return to this point in section 5. As we will see next, adding control variables significantly changes the estimated $\mu(y_t)$.

4.2 PLR models

We now turn to the estimation of the PLR model (2) with control variables. Estimation results for the parametric part are reported in table 3.

These share several features with the parametric models results reported in table 2. In both cases, the share of U.S. over total exports and imports is not statistically significant while the share of industry over total production carries a positive sign around 0.1. A similar result has also been found in York et al. (2003) with an international panel data set. On the other hand, the price of oil and imports of oil, which did not appear as clearly significant in the parametric models cannot now be rejected at a 5% nominal level. The sign of their estimated coefficient seems to reveal that the role of petrol on Canada's CO_2 emissions goes through more strongly from the consumption side than from the production side.

Table 3. PLR models

	Model 1	Model 2	Model 3	Model 4
Trend	-0.4796	-0.4836	-0.4688	-0.3868
	(0.0120)	(0.0179)	(0.0240)	(0.0286)
	[0.0104]	[0.0121]	[0.0145]	-
P_t	-0.1158	-0.1185	-0.1171	-0.0065
	(0.0163)	(0.0187)	(0.0196)	(0.9106)
	[0.0537]	[0.0565]	[0.0627]	-
S_t	0.0707	0.0682	0.0731	0.0557
	(0.0394)	(0.0559)	(0.0420)	(0.0949)
	[0.0488]	[0.0685]	[0.0457]	-
XO_t	0.0231	0.0185	-	-
	(0.0371)	(0.1081)	-	-
	[0.3189]	[0.3728]	-	-
MO_t	0.1501	0.1486	0.1525	0.1023
	(0.0005)	(0.0002)	(0.0000)	(0.0045)
	[0.0029]	[0.0051]	[0.0042]	-
XUS_t	-0.0517	-	-	-
	(0.4628)	-	-	-
	[0.4666]	-	-	-
MUS_t	0.0253	-	-	-
	(0.3866)	-	-	-
	[0.4204]	-	-	-
E_{t-1}	-	-	-	-0.1468
	-	-	-	(0.0020)
	-	-	-	-
Li and Stengos (B=9999)	0.3878	0.3253	0.3028	0.0155

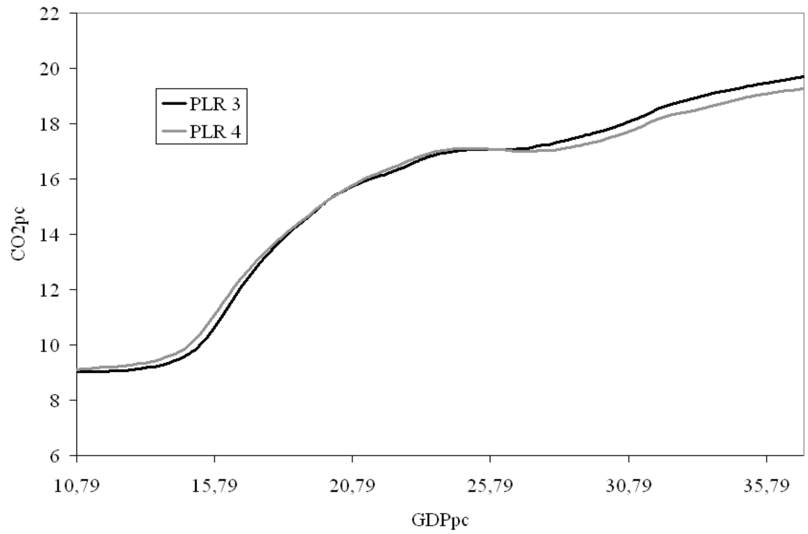
Asymptotic heteroscedasticity robust P values in parenthesis, wild bootstrap P values in brackets.

Evidence on whether or not dynamics should be included in these models is somewhat mixed. According to the test of Li and Stengos (2003), the errors of the static PLR models do not appear to be serially correlated. However, E_{t-1} seems to be statistically significant in model 4, though its inclusion makes the Li and Stengos test reject the null of no autocorrelation in the residuals, which hints at some sort of misspecification. Fortunately, this is not a problem because, as we will see next, models 3 and 4 yield very similar estimates of $\mu(y_t)$.

figure 3 shows the estimated function $\hat{\mu}(y_t)$ from models PLR 3 and PLR 4.[8] These are very similar to one another. The hump around the late 1970s observed in figure 2 was greatly attenuated with the addition of control variables. In fact, $\hat{\mu}(y_t)$ from PLR 3 is monotonically increasing while $\hat{\mu}(y_t)$ decreases slightly for GDPpc values around 27 000$ in PLR 4.

[8] $\hat{\mu}(y_t)$ for PLRs 1 and 2 are virtually identical to that of PLR 3 so we do not report them.

Figure 3. Estimate of function $\mu(y_t)$ with PLM model 3



4.3 Hamilton's model results

Estimating Hamilton's model (3) under the assumption that only y_t enters nonlinearly yields the results reported in table 4. Once again, we have estimated several different specifications and report only the best fitting ones. There are some interesting similarities between these estimates and those obtained earlier. As was the case with the PLR models, P_t and the time trend are statistically significant and affect E_t negatively. Also, MO_t has a positive sign. On the other hand, the share of industrial production over GDP is not significant here. The first lag of per capita emissions also is not statistically significant. Notice that the parameter g is statistically significant at a 1% level in the three static models and at 10% in the dynamic one. This means that the function is statistically significantly nonlinear in y_t.

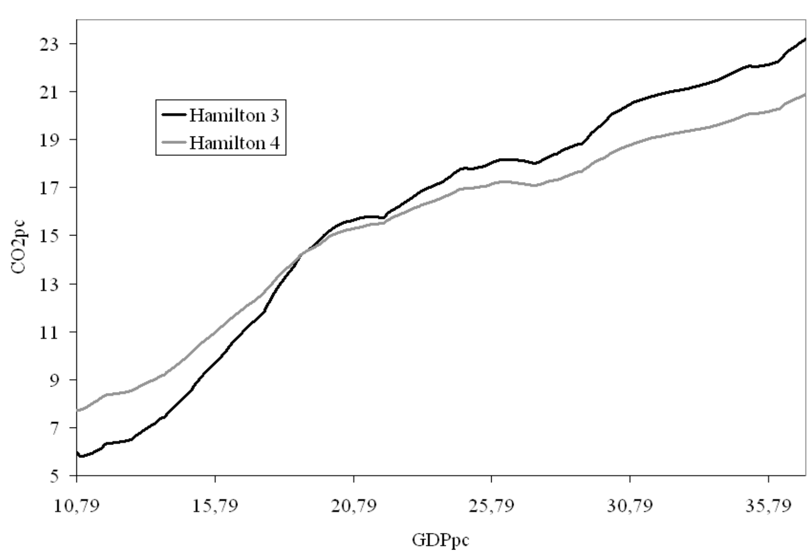
Estimates of the function $\mu(y_t)$ obtained with Hamilton's models 3 and 4 are shown in figure 4. These are computed by setting all the regressors except y_t equal to their sample average and evaluating the function at different values of y_t. There is no evidence of an EKC and the hump seen in figure 2 has almost disappeared, though there seems to be a slight decrease of CO_2pc in model 4 around 26 000$, which is similar to what we found in model PLR 3. The estimated functions are similar to those obtained by the PLR models.

Table 4. Hamilton's models

	Model 1	Model 2	Model 3	Model 4
Constant	0.1153	2.4446	5.3540	6.9617
	(2.6157)	(2.7570)	(1.5310)	(2.1069)
Trend	-0.1866***	-0.1877***	-0.1796***	-0.1267**
	(0.0396)	(0.0347)	(0.0349)	(0.0540)
Y_t	0.6495***	0.6458***	0.6308***	0.3494**
	(0.0935)	(0.0895)	(0.0904)	(0.1398)
P_t	-0.0298**	-0.0335**	-0.0358**	-0.0353**
	(0.0137)	(0.0140)	(0.0140)	(0.0170)
S_t	0.0273	-	-	-
	(0.0506)	-	-	-
XO_t	2.1052	-	-	-
	(1.7476)	-	-	-
MO_t	18.7725***	18.7800***	17.2609***	11.5805*
	(4.7990)	(4.6267)	(4.5344)	(6.8141)
XUS_t	-1.2852	-	-	-
	(1.8145)	-	-	-
MUS_t	7.0156***	3.8557	-	-
	(2.8257)	(3.0669)	-	-
E_{t-1}	-	-	-	0.2335
	-	-	-	(0.1998)
g	-0.2575***	-0.2364***	-0.2342***	0.1398*
	(0.0003)	(0.0109)	(0.0097)	(0.0751)
λ/σ	-3.8751***	-3.6445***	3.6483***	3.6229**
	(1.0933)	(0.9892)	(0.9438)	(1.6195)
$\hat{\sigma}^2$	0.2552***	0.2748***	0.2791***	0.3997***
	(0.0422)	(0.04197)	(0.0417)	(0.0599)

Standard errors in parenthesis. *, ** and *** denote asymptotic statistical significance at the 1%, 5% and 10% levels respectively.

Figure 4. Estimated $\mu(y_t)$ with models Hamilton 3 and 4.

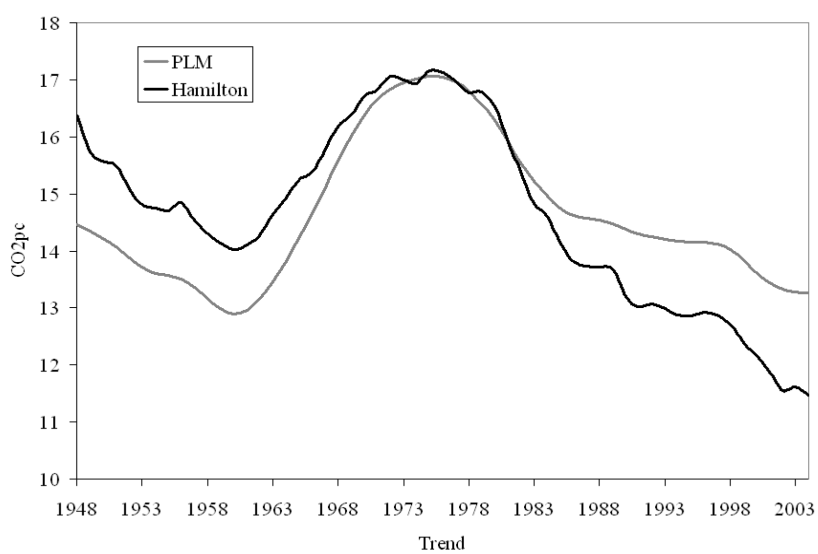


4.4 Nonlinearity with respect to the time trend

Using a panel of Canadian regional data and quadratic parametric regressions, Lantz and Feng (2006) find that the level of CO_2 emissions appears to have a U shaped relationship with the time trend. Our parametric models offered some evidence to that effect. We now investigate this possibility further by estimating the partially linear regression (2) and Hamilton's (3) models with t entering as the sole nonlinear variable and using y_t as a linear variable.

As figure 5 shows, there clearly is nonlinearity between t and CO_2pc. A similar conclusion can be found in Lindmark (2002) for the case of Sweden. It is important to note that Lantz and Feng's sample covers the period from 1970 to 2000, which roughly correspond to the second half of our sample. Considering the shape of the estimated $\mu(y_t)$ shown in figure 5, it is not impossible that a parametric quadratic regression estimated over these years would detect a U shaped relationship. Thus, our results do not contradict theirs.

Figure 5. Estimates of $\mu(t)$ PLM and Hamilton.



There also seems to be a U-shape relationship between t and CO_2pc before 1973. We believe this can be explained by the evolution of emissions and population growth in Canada during this period. The historical statistics registered the period of 1948-1960 as the period of "baby-boom" with a high annual population growth rate of 2.8 %, but during the same time range, the CO_2 emissions growth rate was only 1.4%[9]. It is possible that the decreasing trend of CO_2pc is simply due to the increasing demographic weight of the "baby-boomers" who were, during the first stage of their

[9]Caculated by authors based on available historical statisitcs obtained from Statistics Canada.

life, less Carbon-dependant. Likewise, the positive slope during the 1962-1973 period may be explained by the "baby-boomers" reaching adulthood and thus more active. It is also possible, as suggested by Lindmark (2002), that technological progress during this period lead people to emit more CO_2 through their consumption activities owing to new, more energy consuming living standard.[10]

Of course, the apparent nonlinearity displayed in figure 5 could merely result from the assumption that GDPpc linearly affects CO_2pc, just as the findings about the functional form of the relationship between GDPpc and CO_2pc may depend on that same assumption about the time trend. Thus, there seems to be a need to consider models in which both the time trend and GDPpc are allowed to be nonlinearly related to CO_2pc.

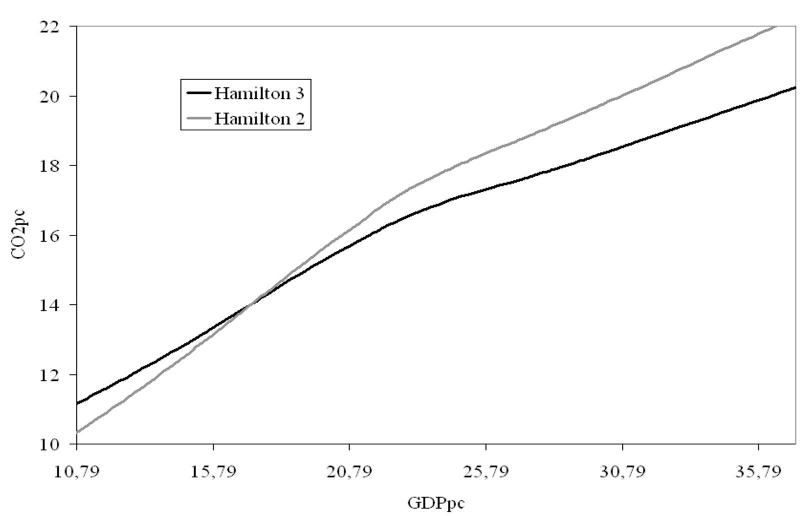
5 Two nonlinear variables

We now consider the model

$$E_t = \alpha_0 + \mu(y_t, t) + \gamma X_t + u_t, \tag{4}$$

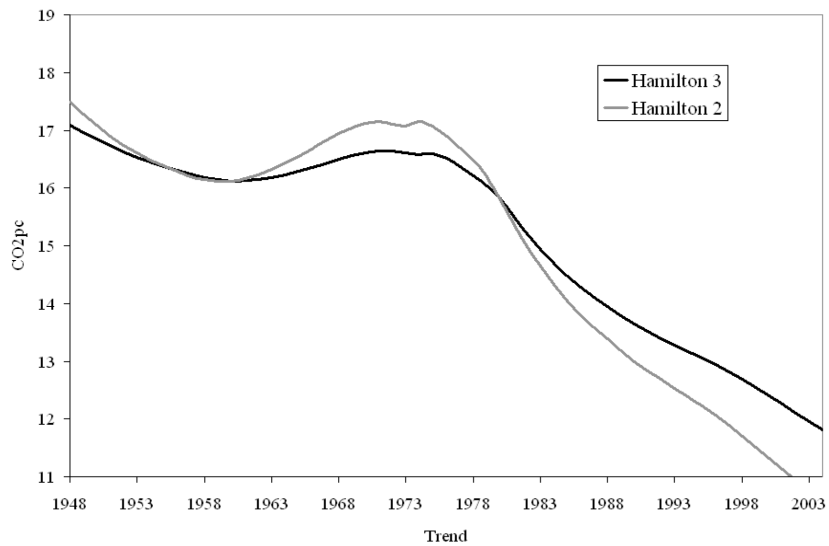
that is, one which allows both y_t and t to enter nonlinearly simultaneously. Both the partially linear regression model and Hamilton's model can be used to estimate an equation such as (4). Unfortunately, perhaps because of our small sample and the high correlation between y_t and t, estimation of the PLR in this context yielded very imprecise results which we decided not to report here.

Figure 6. Function $\hat{\mu}(y_t, \bar{t})$ from Hamilton's model



[10]A prime example of this is the wider accessibility and affordability of the automobile.

Figure 7. Function $\hat{\mu}(\bar{y}_t, t)$ from Hamilton's model



Hamilton's method, on the other hand, worked quite well. figure 6 presents the estimated relationship between GDPpc and CO_2pc while figure 7 shows the estimated relationship between the time trend and CO_2pc. The function reported in figure 6 is the estimated relation between GDPpc and CO_2pc with all the other regressors, including the time trend, fixed at their sample average. figure 7 shows the same thing except that it is now the time trend that is allowed to vary. Parameter estimates along with standard errors are shown in table 5. Notice that we have also estimated the model allowing the other explanatory variables to enter the nonlinear part of the equation, but none turned out to be statistically significant.

According to table 5, the g parameter for GDPpc is not statistically significant while that of the deterministic trend is. This means that, at conventional significance levels, GDPpc is linearly related to CO_2pc while the relationship between the time trend and CO_2pc is nonlinear.

The linearity of the relationship between GDPpc and CO2pc revealed by our estimation actually adds more supporting evidence to the literature suggesting the non-appropriateness of the EKC hypothesis for this case. This is easy to understand given the close relationship of this emission with fossil fuel consumption, which is very often considered as being essential for both production and consumption.[11]

[11]Some studies have also questioned the causality from economic growth to CO_2 emissions. Coondoo and Dinda (2002) find that for developed countries in North America and Western Europe, the causality runs from emissions to income. Heil and Selden (2001) also indicated that CO_2 and income can be simultaneously determined, since "GDP might be at least in part an endogenous function of energy use underlying carbon emission".

Table 5. Hamilton's models with time trend and GDPpc nonlinear

	Model 1	Model 2	Model 3
Constant	6.3707	9.8209***	7.7196***
	(4.4713)	(1.5737)	(2.2591)
Trend	-0.1237	-0.1679	-0.1344*
	(0.0799)	(0.1500)	(0.0697)
Y_t	0.3786**	0.4303***	0.3165**
	(0.1579)	(0.0729)	(0.1543)
P_t	-0.0212	-	-
	(0.0221)	-	-
S_t	0.0591	-	-
	(0.0836)	-	-
XO_t	-0.2287	-	-
	(8.3177)	-	-
MO_t	11.3449	-	-
	(8.8385)	-	-
XUS_t	-1.0304	-	-
	(2.4356)	-	-
MUS_t	3.1445	-	-
	(5.0983)	-	-
E_{t-1}	-	-	0.2539
	-	-	(0.1794)
g (GDP)	0.0674	0.0578	0.0564
	(0.0503)	(0.0416)	(0.0431)
g (tr)	0.0560**	0.0618**	0.0479*
	(0.0285)	(0.0279)	(0.0266)
λ/σ	4.1757***	3.8367***	3.4969***
	(1.3136)	(1.2183)	(1.3499)
σ	0.3414***	0.3640***	0.3868***
	(0.0467)	(0.0508)	(0.0627)

Standard errors in parenthesis. *, ** and *** denote asymptotic statistical significance at the 1%, 5% and 10% levels.

Given this result, we believe that the divergence of CO_2pc and GDPpc observed in Figure 1 of our paper should be explained by some other factors, such as technological progress, which can facilitate the decoupling between economic growth and energy consumption with CO_2 emissions. The nonlinearity of the function between the time trend and CO2pc, clearly seen in figure 7, provides some evidence that technological progress has a mitigating effect on emissions. It is interesting to notice that functions $\hat{\mu}(\bar{y}_t, t)$ in figure 7 and $\hat{\mu}(t)$ in figure 5 both peak around 1973, before becoming negatively sloped. Unruh and Moomaw (1998) and Moomaw and Unruh (1997) obtained similar results with parametric quadratic regressions and a panel of 16 OECD countries. Precisely, they found evidence that exogenous events around 1973, namely the oil shock, are responsible for a change of time path in the CO_2 emissions process. They argue that most reduced-form based evidence of a U shaped relationship between GDPpc and CO_2pc may simply result from technological changes prompted by this exogenous shock. Our results, though they are reduced-form in nature, seem to agree with their analysis.

Even though the estimates shown in table 5 indicate that GDPpc enters linearly, inspection of figure 6 remains interesting. Indeed, the functions presented there look very much like they were generated by threshold models with a smooth transition from a rather sharp slope to a milder one (notice also the similarity with the functions shown in figure 4). The fact that the nonlinearity parameter estimate does not appear to be statistically significant may be due to the small magnitude of this change, which is hard to detect with such a small sample as ours. What makes this interesting is that the transition seems to occur when per capita GDP is in the neighbourhood of 22 000$. Such values correspond to the first half of the 1970s. Hence, if indeed there has been a transition from an initially sharp to a milder GDPpc / CO_2pc relationship, then this has coincided with the oil shock.

Thus, if we are willing to lend to the time trend its common interpretation as a proxy of technological progress, then figures 6 and 7 could be interpreted as indicating a shift from a pre-shock highly polluting technology to a more efficient one (figure 7) which allowed GDPpc growth to continue at a smaller environmental cost (figure 6). Of course, this interpretation would need to be confirmed by a structural model analysis.

6 Conclusion

We investigate the existence of an environmental Kuznets curve for CO_2 emissions in Canada over a period of 57 years. Results obtained from parametric cubic models are somewhat ambiguous and, though they indicate that there probably is no such relationship, they do not allow clear conclusions to be drawn. We apply more flexible estimation methods that do not share the weaknesses of the parametric models and find no evidence of an Environmental Kuznets curve.

Specifically, when we assume that only per capita GDP is nonlinearly related to per capita CO_2 emissions, we find that the relationship between the two is monotonically increasing but that the slope of this function changes often over time. Allowing the time trend to enter nonlinearly as well provides further insights. Indeed, it reveals that important changes in the link between the time trend and CO_2pc and possibly in the link between GDPpc and CO_2pc occurred at a point in time corresponding to the oil shock of the 1970s. In accordance with previous literature, this could be interpreted as an adjustment towards less polluting technology in response to more expensive oil.

Joining many previous studies, our conclusion suggests a positive correlation between CO_2pc and GDPpc. None of the commonly used control variables such as oil price, industrial structural changes and international trade has been proven to be significant determinant for CO2 emission evolution during 1948-2004 in Canada. The only obvious structural break seems to appear after the oil crisis owing to the unexpected roar of oil price, which is an exogenous shock to the world economy. These findings in fact imply that simply waiting for the automatic arrival of the turning point for CO_2 emission suggested by the EKC hypothesis will not be a feasible solution for the battle of Canada against climate changes. Although emission-efficiency seems to improve with time, thanks to the so-called technological progress, until now, we can not yet observe an obvious decreasing trend for carbon pollution in Canada.

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