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The Kuznets Environmental Curve Using Fractional Integration and Long Range Dependence Techniques

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ABSTRACT

This paper investigates empirically the Kuznets environmental curve in nineteen industrialized countries by using updated techniques in time series analysis and based on the concepts of long range dependence and fractional integration. Unlike most of the literature that focuses on integer degrees of differentiation, we consider more flexible approaches allowing, for example, for mean reverting nonstationary behaviour using fractional integration. The results indicate first that the orders of integration of the series substantially change across the series and the countries examined, and mean reversion is found in a number of cases. When looking at the relationship between emissions and economic activity, evidence of the Kuznets curve is found in some countries, this hypothesis being strongly supported in the cases of Denmark, Norway, Sweden, the UK and the USA.

1. Introduction

The environmental Kuznets curve refers to the relationship between the economic activity and the environment. Since the seminal works by Grossman and Krueger (1995) and Holtz-Eatkin and Selden (1995) many articles have been written in connection with this issue. The Environmental Kuznets Curve (hereafter, EKC) postulates that there exists an inverted U-shaped relationship between the economic activity and indicators of environmental degradation. According to this theory, in the early stages of economic growth pollution and environmental degradation increase, but beyond a certain level of income the trend reverses and high-income levels of economic growth lead to environmental improvement. The term EKC is accredited to Kuznets (1955) who first postulated the U-shaped relationship between income inequality and growth. It is evident that the EKC is an empirical phenomenon and therefore it must be tested throughout appropriate statistical techniques. However, since the very beginning this theory has been widely criticized particularly in relation to the econometric model specifications and the estimation and testing methods employed. This study contributes to this literature by studying in a very detailed way the statistical properties of the time series examined (GDP per capita and CO_2 and SO_2 emissions). First we look individually at each series by using fractionally integrated or I(d) techniques, which are more flexible than the standard methods that use integer degrees of differentiation, and only consider the dichotomy of stationarity I(0) or nonstationarity I(1). To check the robustness of our results we will employ here parametric, semiparametric and even nonparametric techniques of I(d) behaviour. Then, in the multivariate work, we will look at the relationship between income and pollution by employing a multiple linear regression model with the regression errors displaying long range dependence.

The structure of the paper is as follows: Section 2 briefly describes the EKC relationship and the methods examined in the paper. Section 3 presents a short review of the literature on long range dependence (or long memory) in the context of the variables under study. Section 4 introduces the data and the main empirical results, while Section 5 concludes the paper.

2. The EKC and the methodology proposed

The model behind the EKC is as follows:

$$e_t \;=\; \alpha \;+\; \beta t \;+\; \gamma_1 y_t \;+\; \gamma_2 y_t^2 \;+ u_t \,, \qquad t \;=\; 1, 2, ... \tag{1}$$

Where e_t is the log per capita emissions of either CO_2 or SO_2 and y_t is log per capita GDP. The unknown coefficients α and β correspond respectively to the intercept and a time trend, and γ_1 and γ_2 are the coefficients related with the EKC hypothesis, expected to be significantly positive and negative respectively to satisfy the U-shape form. However, based on the strong degree of persistence observed in GDP, it is generally accepted that both y_t and its squared transformation (y_t^2) are integrated of order 1 processes, and assuming that the error term u_t is I(0) the literature has focussed on the analysis of the cointegrating relationships among the variables (Perman and Stern, 2003; Dinda and Coondoo, 2006; Jalil and Mahmud, 2009; Esteve and Tamarit, 2012; etc.). Perman and Stern (2003) for instance argue that there is little evidence in favour of the EKC and they argue that the statistical analysis conducted so far was not robust. In a recent paper, Wagner (2015) also criticizes the use of standard models based on the fact that the power of an I(1) process is not an integrated process, and proposes a new modelling framework for cointegrating polynomial regressions. We take a different approach in this paper and examine first the statistical properties of the series by looking at the order of integration of each of the series individually from a fractionally integrated approach. Then, in a multivariate setting, we assume that GDP is exogenous in the relation in (1) and consider that u_t may be I(d) with d non-necessarily constrained to be 0 or 1.That is:

$$(1 - L)^d \, u_t \;=\; \varepsilon_t \,, \qquad t \;=\; 1, 2, ... \tag{2}$$

where ε_t is an I(0) process, defined for the purpose of the present work as a covariance stationary process with a spectral density function that is positive and finite at the zero frequency. Alternatively, anI(0) process can be defined in the time domain by saying that it is a covariance stationary process where the infinite sum of the autocovariances is finite. Thus, it canbe a white noise process but also we allow for any type of weak autocorrelation of the stationary ARMA form.

With respect to the methodology to be used, we rely on a very general testing procedure suggested by Robinson (1994) that is very convenient in the context of the present work. It is a Lagrange Multiplier (LM) test that uses a linear regression model of form:

$$y_t = \theta^T z_t + x_t, \quad t = 1, 2, ... \qquad (3)$$

wherey_t is the observed time series data (in our case each of the variables to be examined, i.e., log of CO_2 and SO_2 emissions and log of per capita GDP); θ is a (kx1) vector of unknown parameters; z_t is a (kx1) vector of deterministic (or weakly exogenous) regressors; and the regression errors, x_t, are supposed to be I(d), i.e.,

$$(1 - L)^d x_t = u_t, \quad t = 1, 2, ... \qquad (4)$$

with I(0) errors u_t. He proposed testing the null hypothesis,

$$H_o : d = d_o \qquad (5)$$

in the model given by the equations (3) and (4) for any real value d_o, and the test statistic follows asymptotically a standard Normal distribution. This procedure has several advantages compared with other methods. First, it is the most efficient method in the Pitman sense against local departures from the null;[1]Second, it allows us to include deterministic terms in equation (3) and the limit distribution of the test statistic is unaffected by the inclusion of these terms, unlike what happens in most unit root procedures with the distribution changing with features of the regressors (Schmidt and Phillips, 1992). In a similar way, it will allow us to test H_o (5) in a model given by (1) and (2) with no changes in its limiting distribution. There also exist Wald and Likelihood Ratio (LR) test statistics against fractional alternatives and obviously they have the same null and limit theory as the LM tests of Robinson (1994). Thus, for example, Lobato and Velasco (2007) essentially employed such a Wald testing procedure and though this and other methods like the one proposed by Demetrescu et al. (2008) are found to be robust to even unconditional heteroskedasticity (Kew and Harris, 2009), they require an efficient estimate of d, and therefore the LM test of Robinson (1994) seems computationally more attractive.[2]

Finally, we will also implement a semiparametric method (Robinson, 1995) that is basically a "local" Whittle estimate in the frequency domain, with the frequencies degenerating to zero. This is implicitly defined by:

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[1]. That is, when directed against local departures from the null of form: H_a: $d = d_o + \delta T^{-1/2}$, the limit distribution is normal with variance 1 and a mean which cannot be exceeded in absolute value by that of any rival regular statistic.(See, Robison, 1994).

[2]. See Gil-Alana and Robinson (1997) and Gil-Alana and Hualde (2009) respectively for an application of this method and a survey of fractional integration and cointegration methods.

$$\hat{d} = \arg\min_d \left(\log \overline{C(d)} - 2d \frac{1}{m} \sum_{s=1}^{m} \log \lambda_s \right), \qquad (6)$$

$$\overline{C(d)} = \frac{1}{m} \sum_{s=1}^{m} I(\lambda_s)\, \lambda_s^{2d}, \qquad \lambda_s = \frac{2\pi s}{T}, \qquad \frac{m}{T} \to 0,$$

where $I(\lambda_s)$ is the periodogram of the raw time series, x_t, given by:

$$I(\lambda_s) = \frac{1}{2\pi T} \left| \sum_{t=1}^{T} x_t\, e^{i \lambda_s t} \right|^2,$$

and $d \in (-0.5, 0.5)$. Under finiteness of the fourth moment and other mild conditions, Robinson (1995) proved that:

$$\sqrt{m}\,(\hat{d} - d_o) \to_d N(0, 1/4) \quad as\ T \to \infty,$$

Where m is a bandwidth number and d_o is the true value of d.[13] This estimator is robust to a certain degree of conditional heteroscedasticity (Robinson and Henry, 1999) and is more efficient than other more recent semi-parametric competitors.

3. Long memory in GDP and environmental variables

One claim for long memory and more in particular for fractional integration in GDP comes from the observation by Granger (1966) of the "typical" shape of the spectra of many economic variables. He noticed that for many economic aggregates, the estimator of the spectral density function tended to infinity at the lowest frequency, consistent with unit root behaviour; however taking first differences the spectra was close to zero at the zero frequency, which was an indication of over differentiation. Later on, Robinson (1978) and Granger (1980) theoretically justified this type of processes by means of aggregation of heterogeneous AR processes.[24]

Nowadays, there are many empirical studies showing that fractional integration provides a better fit than the ARMA(I) models to describe the dynamic behaviour of economic series. Diebold and Rudebusch (1989) and Sowell (1992) were the first to report evidence of long memory in macro series; their results were confirmed by Gil-Alana and Robinson (1997) and by Abadir, Caggiano and Talmain (2013). These authors found that I(d) models outperform classical methods in the analysis of Nelson and Plosser's (1982) dataset. Focussing on GDP,

[3].This method has been further examined and refined by Velasco (1999), Velasco and Robinson (2000), Phillips and Shimotsu (2004, 2005), Abadir et al. (2007) and many others. These methods, however, require additional user-chosen parameters and the results may be very sensitive to the choice of these parameters; in that respect, Robinson's (1995) approach seems to be more appropriate.

[2.] Other authors have also used the argument of aggregation to explain fractional integration and long memory. See, e.g. Croczek-Georges and Mandelbrot (1995), Taqqu et al. (1997), Chambers (1998) and Lippi and Zaffaroni (1999) and Parke (1999), and more recently, Hassler (2011) and Haldrup and Vera Valdes (2015).

Michelacci and Zaffaroni (2000) found evidence of fractional integration in the real output in a group of OECD countries. They show that extending the standard Solow model to allow for cross-sectional heterogeneity in the adjustment speed resulted in output exhibiting long memory and per capita output was well represented by a mean reverting long memory process with $0.5 < d < 1$. Mayoral (2006) examined annual real GNP and GNP per capita in the US for the time period 1869-2001, using both parametric and semiparametric I(d) methods, and her results though slightly different depending on the technique used, also suggest orders of integration in the interval [0.5, 1). Evidence of fractional integration in output was also found in many other papers including Koop et al. (1997), Candelon and Gil-Alana (2004), Caporale and Gil-Alana (2009) and others.

In the context of environmental variables, the evidence is less abundant.Barassi et al. (2011) examined the convergence of CO_2 emissions within the OECD over the period 1870-2004 using fractional integration. Their results indicated evidence of long memory in thirteen out of the eighteen countries examined. More recently, Barros et al. (2016) examined global carbon dioxide emissions and its components (gas, liquids, solids, cement production and gas flaring) as well as global per capita emissions allowing for structural breaks in I(d) contexts, finding support for higher orders of integration after World War II.[15]

4. Data and empirical results

We use exactly the same dataset as Wagner (2015) referring to nineteen early industrialized countries (Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, the Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, the UK and the USA) over the period 1870 – 2000. The variables examined are carbon dioxide emissions (CO_2), sulphur dioxide emissions (SO_2) and real GDP, and the three variables are in per capita terms and transformed to logarithms.[26]

This section is divided into two parts. The first one deals with the univariate analysis examining the order of integration of the individual series by using parametric, semiparametric and nonparametric methods of fractional integration. The second subsection deals with the multivariate work, relating the environmental variables with the economic activity.

4.1. Univariate analysis

[1.] The literature on the degree of persistence in CO_2 emissions has mainly focused on testing for unit roots with the aim of identifying long run equilibrium relationships between the emissions and the use of energy or even GDP, see, e.g. among others Aslanidis (2009). Fodha and Zaghdoud (2010), Jaunky (2011) and Magazzino (2014). Other papers showing long memory in emissions and energy consumption are Apergis and Tsoumas (2011, 2012) and Belbute and Pereira (2015).

[2.] The GDP data are obtained from Angus Maddison homepage (http://www.ggdc.net/maddison); the CO_2 emissions were downloaded from the Carbon Dioxide Information Analysis Center homepage (http://cdiac.ornl.gov) and those for the SO_2 data from Stern (2006). They can also be found at the Journal of Applied Econometrics data archive.

We start analyzing the individual series. We consider the model given by (3) and (4) with $z_t = (1, t)^T$ to allow for an intercept and a linear time trend. Thus, the estimated model is:

$$y_t = \theta_1 + \theta_2 t + x_t ; \qquad (1-L)^d x_t = u_t , \qquad t = 1, 2, ... \quad (7)$$

and we suppose first that u_t in (7) is a white noise process, though later we will also permit weak autocorrelation throughout the model of Bloomfield (1973). This is a non-parametric approach to I(0) processes in the sense that the model is implicitly described by its spectral density function, and it produces autocorrelations decaying exponentially as in the AR(MA) case.

Tables 1–6 display the estimates of d in the model given by (7) using the Whittle function in the frequency domain (Dahlhaus, 1989). Along with the estimates we report the 95% confidence bands of the non-rejection values of d using Robinson's (1994) LM approach as described in Section 2. We consider here the three standard cases examined in the literature, corresponding to the model with no deterministic terms (i.e., $\theta_1 = \theta_2 = 0$ a priori in (7), ii) an intercept (θ_1 unknown and $\theta_2 = 0$ a priori), and iii) with an intercept and a linear time trend (θ_1 and θ_2 unknown). We discriminate between these deterministic terms using,once again, Robinson's (1994) tests. Under H_o (5) in (7), the null model becomes:

$$\tilde{y}_t = \theta_1 \tilde{1}_t + \theta_2 \tilde{t}_t + u_t , \qquad t = 1, 2, ... \quad (8)$$

Where, $\tilde{y}_t = (1-L)^{d_o} y_t$; and similarly, $\tilde{1}_t = (1-L)^{d_o} 1_t$ and $\tilde{t}_t = (1-L)^{d_o} t$, where 1 represents a vector of ones, and t is the time trend, and based on the fact that u_t in (8) is I(0) by construction, we can estimate θ_1 and θ_2 by least squared methods and the corresponding t-values will remain valid.

Tables 1–3 refer to the case of white noise errors, respectively for the CO_2 and SO_2 emissions and the per capita GDP. Tables 4 – 6 presents the same structure under autocorrelated (Bloomfield) errors.

[Insert Tables 1 – 3 about here]

Starting with the results reported in Table 1 (CO_2 emissions with white noise errors) the first thing we observe is that the time trend is required in all countries except for Austria, Belgium and Italy, and the unit root null hypothesis (i.e., d = 1) cannot be rejected in the majority of the series. Evidence of mean reversion (i.e., d < 1)[17] is found in the cases of the U.K. (0.43), Germany (0.68), the Netherlands (0.75), Sweden and Switzerland (0.77) and Denmark (0.81). For the SO_2 emissions, only for Australia, Finland, Portugal and Spain is a linear trend required, and Portugal and Switzerland are the only countries with significant evidence of mean reversion. Finally, for the per capita GDP, the time trend seems to be required in all cases except for Germany, and we can distinguish three groups of countries according to the order of integration. Thus, New Zealand (0.82) is the only country where d is found to be statistically

[1]. We refer here to the cases where the confidence intervals explicitly exclude the values of d =1 in favour of d > 1.

smaller than 1. Then, there is a group of eleven countries where the unit root null of d = 1 cannot be rejected: Denmark (0.94), Austria (0.99), Switzerland and Norway (1.03), the Netherlands (1.04), Japan and Australia (1.07), France (1.09), the USA (1.12) and Germany and Finland (1.13). Finally, for the remaining seven countries the unit root null is rejected in favour of d >1: Portugal (1.06), Sweden (1.12), Belgium (1.13), Italy (1.15), Canada (1.17) Spain (1.20) and the UK (1.22)

[Insert Tables 4 – 6 about here]

Tables 4–6 reproduces the analysis of Tables 1–3 but using the nonparametric approach of Bloomfield (1973) for the I(0) disturbance term u_t in (7). Starting again with the CO_2 emissions, (Table 4), the time trend is now always required, and we clearly distinguish two blocks here: those with d < 1 (Austria, Belgium, Finland, Germany, Italy, the Netherlands, Norway, Spain, Switzerland and the UK) and those where we cannot reject the null of d = 1 (Australia, Canada, Denmark, France, Japan, New Zealand, Portugal, Sweden and the USA). For the SO_2 emissions (Table 5), however, the time trend is only required in three cases (Finland, Japan and Portugal) and only Japan and the UK display estimates of d significantly above 1. Finally for the per capita GDP, (in Table 6) the time trend is required in all cases, and evidence of mean reversion (d < 1) is found in the cases of the USA (0.55), Italy (0.62), New Zealand (0.66), the Netherlands (0.71) and Finland (0.79). For the rest of the cases, the unit root null hypothesis cannot be rejected.

[Insert Tables 7 – 9 about here]

Tables 7–9 displays the estimates of d with the semiparametric Whittle estimate of Robinson (1995) using three potential values for the bandwidth number m = 11, 12 and 13.[16] Starting with the CO_2 emissions, evidence of mean reversion is found in a number of countries, including Austria, Belgium, France, Germany, Italy, the Netherlands, Norway and Sweden. However, for the SO_2 emissions (Table 8) evidence of d < 1 is only found for Portugal with m = 12. For the per capita GDP evidence of mean reversion takes place for Canada, Germany and the USA.

[Insert Tables 10 –12 about here]

Tables 10 to 12 summarize the results collected in the previous tables, choosing for each one of the three specifications (white noise, Bloomfield and the semiparametric Whittle method) the selected estimate of d. For the CO_2 emissions we observe a large number of cases where d is found to be significantly smaller than 1. In fact, only for Australia, Canada, Japan, New Zealand, Portugal and the USA we obtain evidence of unit roots for the three methods examined. A different picture emerges for the SO_2 data, where the unit root null is almost never rejected. In fact, evidence of mean reversion is only observed for Portugal and Switzerland. Finally, for the per capita GDP data, evidence of mean reversion is found in half of the

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[1.] The choice of the bandwidth shows the trade-off between bias and variance: the asymptotic variance is decreasing with m while the bias is growing with m. We have chosen values close to $(T)^{0.5} \approx 12$.

countries, and the unit root null cannot be rejected with any method in the cases of Australia, Canada, Denmark, Japan, New Zealand, Portugal, Spain, Switzerland, the UK and the USA.

As a conclusion, something that clearly emerges from these results is that the imposition of the same structure (based on unit roots or I)(1) behaviour) in all cases may lead to inadequate specifications of the series and thus incorrect statistical inference.

4.2. Multivariate analysis

As mentioned earlier we examine in this section the model given by the equations (1) and (2) under the assumption that ε_t in (2) is both white noise and autocorrelated throughout the model of Bloomfield (1973). We employ Robinson's (1994) tests again, and so, the estimated model under the null hypothesis (5) is:

$$e_t = \alpha + \beta t + \gamma_1 y_t + \gamma_2 y_t^2 + u_t ; \quad (1-L)^{d_o} u_t = \varepsilon_t , \quad t = 1, 2, \ldots \quad (9)$$

Where, e_t refers to the CO_2 emissions across Tables 13 and 14 and to the SO_2 emissions in Tables 15 and 16.

[Insert Tables 13 and 14 about here]

Starting with the CO_2 emissions, and assuming that the errors are uncorrelated (Table 13) the first thing we observe is that the EKC is satisfied in a number of countries, including Belgium, Canada, Denmark, Finland, France, Germany, the Netherlands, Norway, Sweden, the UK and the USA. Also, for all these countries (except Canada and Germany) the estimated value of d is found to be smaller than 1, and,in fact, only for Switzerland is the value of d significantly smaller than 1 and the EKC hypothesis not satisfied. Still with the CO_2 emissions, if we allow for autocorrelated errors, see Table 14, we see now that for Canada and Denmark the EKC hypothesis cannot be satisfied, and the contrary happens for Spain and Italy where this hypothesis is now satisfied but it was not before with uncorrelated errors. For the remaining countries, we get the same conclusions as in Table 13, with Belgium, Denmark, Finland, France, the Netherlands, Norway, Sweden, the UK and the USA satisfying the EKC.

[Insert Tables 15 and 16 about here]

Tables 15 and 16 refer to the SO_2 emissions respectively for white noise and Bloomfield errors. In general, we observe fewer cases where the EKC hypothesis is satisfied. They are now Austria, Canada, Denmark, Norway, Sweden, the UK and the USA. Allowing for weak dependence, we observe that Canada was included with uncorrelated errors though it was not with the model of Bloomfield. On the other hand, Belgium, Finland and France are included now in the group of countries satisfying the EKC, but they were not with uncorrelated errors. For the remaining countries, the results remain more or less the same so that the hypothesis of EKC is satisfied in both cases of uncorrelated and autocorrelated for Austria, Denmark, Norway, Sweden, the UK and the USA.

[Insert Table 17 about here]

Table 17 summarizes the results for the multivariate work. We observe that there are five countries where the EKC hypothesis is satisfied irrespectively of the method and the type of the emissions used. They are Denmark, Norway, Sweden, the USA and the UK. That is, countries a very high level of income. For Finland and France, this hypothesis is satisfied in three out of the four cases presented; for Belgium and the Netherlands, the EKC is satisfied with the CO_2 emissions but not with the SO_2 ones and it is the contrary for Austria; for Canada, the hypothesis is satisfied for the two types of emissions with uncorrelated errors but not under the nonparametric model of Bloomfield (1973) and for Germany and Spain, it is satisfied in a single case (CO_2emissions with uncorrelated errors in case of Germany, and with autocorrelated ones for Spain). For the remaining six countries, which are Australia, Italy, Japan, New Zealand, Portugal and Switzerland, we do not find any single evidence of this hypothesis being satisfied.

5. Conclusion and policy implications

In this paper we have tested the environmental Kuznets curve in nineteen early industrialized countries (namely, Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, the Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, the UK and the USA) by using long range dependence techniques. As a preliminary step, we examined the order of integration of the series from a univariate fractional viewpoint using parametric (Robinson, 1994) along with semiparametric (Robinson, 1995) and nonparametric (Bloomfield) techniques. The results show that for the CO_2 emissions there are many countries where mean reversion takes place. In fact, only for Australia, Canada, Japan, New Zealand, Portugal and the USA we obtain evidence of unit roots for the three methods examined; for the SO_2 emissions there is more support of the unit root hypothesis, and only for Portugal and Switzerland do we find some evidence of mean reversion; finally, for the per capita GDP the evidence is mixed and evidence of mean reversion is found in nine out of the nineteen series and evidence of unit roots in the remaining ten. Testing the EKC hypothesis, strong supporting evidence is found for Denmark, Norway, Sweden, the UK and the USA, since this hypothesis cannot be rejected irrespectively of the modelling and the type of emissions used; partial evidence of this hypothesis is obtained for the cases of Finland, France, Belgium, the Netherlands, Austria, Canada, and to a lesser extent in Germany and Spain; and there is no evidence at all to support the EKC hypothesis in the remaining countries, which are Australia, Italy, Japan, New Zealand, Portugal and Switzerland.

Comparing our results with others in the literature, many authors have found evidence in favour of the EKC hypothesis using standard time series techniques. Wagner (2015), however, employed a cointegrating polynomial regression as suggested in Hong and Wagner (unpublished manuscript) and a non-linear dynamic OLS estimation method developed in Choi and Saikkomen (2010) and his results supported the EKC hypothesis in Austria, Belgium, Finland and the UK for the CO_2 emissions and in the UK only for the SO_2 emissions. In our paper, we find evidence supporting the EKC in all these countries along with others like Norway, Sweden, Denmark and the USA.

Finally, note that the analysis carried out in this paper has nothing to do with the analysis of long run equilibrium relationships between the variables of interests since income is taken as an exogenous variable in the regression model in equation (9). In this respect the analysis of the EKC throughout the use of fractional cointegration techniques (Hualde and Robinson, 2003, 2007; Johansen and Nielsen, 2012) is another avenue for further research in this work.

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Appendix

Table 1. Estimates of d for CO_2 with white noise errors

Country	No regressors	Anintercept	A linear trend
AUSTRALIA	0.99 (0.89, 1.14)	0.90 (0.76, 1.05)	0.93 (0.85, 1.04)
AUSTRIA	0.99 (0.87, 1.15)	0.95 (0.79, 1.16)	0.95 (0.79, 1.16)
BELGIUM	0.96 (0.86, 1.11)	0.89 (0.72, 1.11)	0.89 (0.72, 1.11)
CANADA	1.01 (0.91, 1.16)	1.04 (0.94, 1.16)	1.03 (0.95, 1.15)
DENMARK	0.93 (0.83, 1.07)	0.80 (0.72, 0.93)	0.81 (0.71, 0.93)
FINLAND	0.85 (0.70, 1.04)	0.86 (0.75, 1.03)	0.85 (0.71, 1.03)
FRANCE	0.98 (0.87, 1.12)	0.96 (0.83, 1.14)	0.96 (0.84, 1.13)
GERMANY	0.96 (0.85, 1.10)	0.66 (0.56, 0.80)	0.68 (0.59, 0.81)
ITALY	0.90 (0.84, 1.16)	1.08 (0.86, 1.38)	1.07 (0.86, 1.38)
JAPAN	1.11 (0.95, 1.31)	1.25 (1.12, 1.43)	1.22 (1.10, 1.38)
NETHERLANDS	0.95 (0.84, 1.10)	0.75 (0.64, 0.96)	0.75 (0.60, 0.96)
NEW ZEALAND	1.03 (0.92, 1.18)	1.12 (1.00, 1.27)	1.11 (1.01, 1.25)
NORWAY	0.92 (0.82, 1.04)	0.82 (0.69, 0.99)	0.82 (0.70, 0.99)
PORTUGAL	1.10 (0.99, 1.27)	1.09 (0.93, 1.26)	1.08 (0.95, 1.24)
SPAIN	0.96 (0.85, 1.10)	0.87 (0.76, 1.07)	0.87 (0.74, 1.07)
SWEDEN	0.94 (0.83, 1.08)	0.75 (0.66, 0.89)	0.77 (0.68, 0.90)
SWITZERLAND	0.96 (0.85, 1.10)	0.75 (0.65, 0.91)	0.77 (0.67, 0.92)
UK	0.98 (0.87, 1.12)	0.42 (0.36, 0.50)	0.43 (0.35, 0.53)

USA	0.98 (0.87, 1.12)	0.91 (0.81, 1.02)	0.92 (0.85, 1.02)

In bold the significant cases according to the deterministic terms. In parenthesis, the 95% confidence intervals of the non-rejection values of d using Robinson 's (1994) approach.

Table 2. Estimates of d for SO_2 with white noise errors

Country	No regressors	Anintercept	A linear trend
AUSTRALIA	1.10 (0.97, 1.22)	0.99 (0.85, 1.17)	0.99 (0.87, 1.16)
AUSTRIA	1.08 (0.97, 1.24)	1.18 (1.07, 1.34)	1.18 (1.07, 1.34)
BELGIUM	0.96 (0.86, 1.11)	1.16 (1.06, 1.32)	1.16 (1.06, 1.32)
CANADA	1.01 (0.93, 1.14)	1.02 (0.86, 1.26)	1.03 (0.90, 1.23)
DENMARK	0.94 (0.84, 1.07)	1.04 (0.94, 1.17)	1.04 (0.94, 1.17)
FINLAND	1.10 (1.00, 1.23)	1.12 (1.02, 1.28)	1.12 (1.02, 1.27)
FRANCE	1.02 (0.91, 1.15)	1.10 (1.00, 1.21)	1.10 (1.00, 1.22)
GERMANY	0.89 (0.79, 1.01)	0.92 (0.85, 1.02)	0.92 (0.85, 1.02)
ITALY	1.36 (1.21, 1.56)	1.37 (1.21, 1.57)	1.37 (1.21, 1.57)
JAPAN	0.89 (0.76, 1.07)	0.92 (0.79, 1.09)	0.93 (0.82, 1.09)
NETHERLANDS	1.04 (0.93, 1.18)	1.22 (1.11, 1.28)	1.22 (1.11, 1.38)
NEW ZEALAND	1.03 (0.91, 1.18)	1.06 (0.96, 1.22)	1.06 (0.96, 1.22)
NORWAY	1.05 (0.95, 1.18)	1.05 (0.95, 1.18)	1.05 (0.95, 1.18)
PORTUGAL	0.83 (0.74, 0.98)	0.77 (0.69, 0.90)	0.75 (0.69, 0.90)
SPAIN	0.96 (0.85, 1.09)	1.02 (0.93, 1.14)	1.02 (0.93, 1.14)
SWEDEN	0.95 (0.88, 1.04)	0.95 (0.88, 1.04)	0.95 (0.88, 1.04)
SWITZERLAND	0.83 (0.75, 0.96)	0.83 (0.75, 0.96)	0.84 (0.75, 0.96)
UK	0.92 (0.80, 1.06)	0.92 (0.86, 1.01)	0.92 (0.86, 1.01)
USA	0.97 (0.88, 1.10)	1.04 (0.96, 1.15)	1.04 (0.96, 1.15)

In bold the significant cases according to the deterministic terms. In parenthesis, the 95% confidence intervals of the non-rejection values of d using Robinson 's (1994) approach.

Table 3. Estimates of d for GDP with white noise errors

Country	No regressors	Anintercept	A linear trend
AUSTRALIA	0.98 (0.86, 1.12)	1.06 (0.96, 1.20)	1.07 (0.96, 1.21)

AUSTRIA	0.97 (0.86, 1.12)	0.99 (0.88, 1.16)	0.99 (0.87, 1.16)
BELGIUM	0.97 (0.87, 1.12)	1.12 (1.01, 1.30)	1.13 (1.01, 1.30)
CANADA	0.97 (0.86, 1.12)	1.17 (1.00, 1.38)	1.17 (1.00, 1.39)
DENMARK	0.97 (0.86, 1.12)	0.96 (0.88, 1.08)	0.94 (0.84, 1.09)
FINLAND	0.97 (0.85, 1.12)	1.11 (0.99, 1.34)	1.13 (0.99, 1.34)
FRANCE	0.97 (0.87, 1.12)	1.09 (0.96, 1.28)	1.09 (0.96, 1.28)
GERMANY	0.97 (0.86, 1.12)	1.13 (0.96, 1.39)	1.13 (0.95, 1.39)
ITALY	0.97 (0.86, 1.11)	1.14 (1.02, 1.32)	1.15 (1.02, 1.33)
JAPAN	0.96 (0.85, 1.11)	1.07 (0.97, 1.20)	1.07 (0.97, 1.21)
NETHERLANDS	0.97 (0.86, 1.12)	1.04 (0.91, 1.25)	1.04 (0.90, 1.25)
NEW ZEALAND	0.98 (0.88, 1.12)	0.84 (0.77, 0.98)	0.82 (0.72, 0.98)
NORWAY	0.97 (0.86, 1.11)	1.03 (0.96, 1.14)	1.03 (0.94, 1.16)
PORTUGAL	0.97 (0.86, 1.11)	1.05 (1.00, 1.13)	1.06 (1.00, 1.15)
SPAIN	0.99 (0.88, 1.13)	1.19 (1.09, 1.35)	1.20 (1.10, 1.35)
SWEDEN	0.97 (0.86, 1.12)	1.11 (1.01, 1.28)	1.12 (1.01, 1.29)
SWITZERLAND	0.97 (0.86, 1.12)	1.03 (0.91, 1.23)	1.03 (0.90, 1.23)
UK	0.98 (0.87, 1.13)	1.21 (1.03, 1.50)	1.22 (1.04, 1.50)
USA	0.97 (0.87, 1.12)	1.12 (0.94, 1.38)	1.12 (0.93, 1.38)

In bold the significant cases according to the deterministic terms. In parenthesis, the 95% confidence intervals of the non-rejection values of d using Robinson 's (1994) approach.

Table 4. Estimates of d for CO_2 with autocorrelated (Bloomfield) errors

Country	No regressors	Anintercept	A linear trend
AUSTRALIA	0.95 (0.77, 1.20)	0.94 (0.64, 1.19)	0.95 (0.81, 1.16)
AUSTRIA	0.85 (0.67, 1.12)	0.62 (0.44, 0.96)	0.62 (0.41, 0.96)
BELGIUM	0.92 (0.71, 1.17)	0.49 (0.38, 0.68)	0.36 (0.14, 0.69)
CANADA	0.93 (0.78, 1.15)	1.05 (0.89, 1.24)	1.04 (0.91, 1.19)
DENMARK	0.88 (0.69, 1.09)	0.80 (0.68, 1.03)	0.81 (0.64, 1.03)
FINLAND	0.55 (0.44, 0.94)	0.72 (0.61, 0.97)	0.56 (0.23, 0.96)

FRANCE	0.94 (0.76, 1.22)	0.71 (0.55, 1.05)	0.75 (0.54, 1.06)
GERMANY	0.91 (0.74, 1.15)	0.63 (0.50, 0.92)	0.69 (0.51, 0.92)
ITALY	0.77 (0.54, 1.02)	0.58 (0.49, 0.75)	0.49 (0.32, 0.75)
JAPAN	0.70 (0.28, 1.08)	0.95 (0.41, 1.21)	0.99 (0.80, 1.17)
NETHERLANDS	0.91 (0.73, 1.15)	0.55 (0.46, 0.67)	0.35 (0.12, 0.63)
NEW ZEALAND	1.00 (0.81, 1.24)	1.15 (0.95, 1.41)	1.14 (0.96, 1.38)
NORWAY	0.93 (0.78, 1.15)	0.60 (0.49, 0.92)	0.66 (0.45, 0.94)
PORTUGAL	0.96 (0.72, 1.21)	0.33 (0.24, 0.41)	0.16 (-0.14, 1.21)
SPAIN	0.90 (0.72, 1.17)	0.64 (0.52, 0.77)	0.56 (0.37, 0.75)
SWEDEN	0.91 (0.71, 1.18)	0.76 (0.61, 1.04)	0.80 (0.61, 1.05)
SWITZERLAND	0.90 (0.72, 1.16)	0.67 (0.55, 0.91)	0.68 (0.51, 0.91)
UK	0.94 (0.75, 1.18)	0.53 (0.42, 0.69)	0.68 (0.51, 0.91)
USA	0.95 (0.78, 1.21)	1.05 (0.86, 1.26)	1.03 (0.91, 1.20)

In bold the significant cases according to the deterministic terms. In parenthesis, the 95% confidence intervals of the non-rejection values of d using Robinson 's (1994) approach.

Table 5. Estimates of d for SO_2 with autocorrelated (Bloomfield) errors

Country	No regressors	Anintercept	A linear trend
AUSTRALIA	1.01 (0.79, 1.31)	0.94 (0.66, 1.26)	0.94 (0.75, 1.27)
AUSTRIA	0.94 (0.76, 1.16)	1.04 (0.88, 1.28)	1.04 (0.87, 1.27)
BELGIUM	0.87 (0.68, 1.16)	1.05 (0.89, 1.28)	1.05 (0.89, 1.29)
CANADA	1.00 (0.86, 1.19)	1.00 (0.88, 1.18)	1.00 (0.89, 1.16)
DENMARK	0.96 (0.73, 1.21)	1.17 (0.95, 1.41)	1.18 (0.95, 1.41)
FINLAND	1.07 (0.95, 1.30)	0.97 (0.84, 1.12)	0.97 (0.84, 1.12)
FRANCE	0.98 (0.78, 1.25)	1.06 (0.90, 1.30)	1.06 (0.90, 1.29)
GERMANY	0.89 (0.70, 1.16)	1.14 (0.99, 1.34)	1.15 (0.99, 1.34)
ITALY	1.05 (0.78, 1.42)	1.05 (0.78, 1.43)	1.05 (0.78, 1.43)
JAPAN	1.00 (0.83, 1.23)	1.15 (1.00, 1.35)	1.14 (1.00, 1.31)
NETHERLANDS	0.95 (0.78, 1.18)	1.08 (0.91, 1.32)	1.08 (0.91, 1.32)
NEW ZEALAND	0.90 (0.75, 1.14)	0.96 (0.82, 1.18)	0.97 (0.84, 1.18)

NORWAY	1.04 (0.89, 1.26)	1.04 (0.89, 1.26)	1.04 (0.89, 1.25)
PORTUGAL	0.78 (0.66, 0.99)	0.73 (0.64, 0.90)	0.67 (0.52, 0.90)
SPAIN	0.92 (0.71, 1.16)	1.09 (0.93, 1.31)	1.08 (0.93, 1.29)
SWEDEN	1.00 (0.97, 1.22)	1.00 (0.97, 1.24)	1.00 (0.97, 1.23)
SWITZERLAND	0.80 (0.66, 0.98)	0.81 (0.68, 0.99)	0.81 (0.68, 0.99)
UK	0.86 (0.67, 1.09)	1.19 (1.06, 1.35)	1.20 (1.06, 1.36)
USA	0.97 (0.81, 1.19)	1.10 (0.96, 1.30)	1.09 (0.96, 1.28)

In bold the significant cases according to the deterministic terms. In parenthesis, the 95% confidence intervals of the non-rejection values of d using Robinson 's (1994) approach.

Table 6. Estimates of d for GDP with autocorrelated (Bloomfield) errors

Country	No regressors	Anintercept	A linear trend
AUSTRALIA	0.95 (0.77, 1.21)	1.10 (0.92, 1.49)	1.14 (0.91, 1.51)
AUSTRIA	0.93 (0.75, 1.16)	0.87 (0.76, 1.09)	0.84 (0.69, 1.10)
BELGIUM	0.93 (0.76, 1.19)	0.93 (0.80, 1.10)	0.92 (0.80, 1.10)
CANADA	0.92 (0.74, 1.19)	0.85 (0.75, 1.20)	0.78 (0.50, 1.20)
DENMARK	0.94 (0.74, 1.18)	0.89 (0.79, 1.01)	0.81 (0.66, 1.01)
FINLAND	0.93 (0.74, 1.18)	0.86 (0.79, 0.98)	0.79 (0.67, 0.97)
FRANCE	0.93 (0.75, 1.19)	0.85 (0.73, 1.07)	0.80 (0.64, 1.07)
ITALY	0.92 (0.74, 1.17)	0.71 (0.62, 0.89)	0.62 (0.45, 0.86)
GERMANY	0.91 (0.72, 1.18)	0.94 (0.83, 1.12)	0.93 (0.79, 1.15)
JAPAN	0.91 (0.72, 1.18)	1.05 (0.90, 1.27)	1.05 (0.89, 1.29)
NETHERLANDS	0.92 (0.75, 1.18)	0.78 (0.71, 0.95)	0.71 (0.56, 0.93)
NEW ZEALAND	0.94 (0.76, 1.19)	0.76 (0.68, 0.88)	0.66 (0.53, 0.86)
NORWAY	0.93 (0.73, 1.17)	0.98 (0.91, 1.11)	0.97 (0.82, 1.16)
PORTUGAL	0.93 (0.76, 1.19)	1.20 (1.10, 1.36)	1.23 (1.12, 1.40)
SPAIN	0.95 (0.76, 1.21)	1.08 (0.97, 1.26)	1.10 (0.98, 1.28)
SWEDEN	0.92 (0.74, 1.21)	0.98 (0.89, 1.15)	0.98 (0.83, 1.19)
SWITZERLAND	0.92 (0.73, 1.17)	0.84 (0.77, 0.99)	0.75 (0.58, 1.00)
UK	0.93 (0.74, 1.17)	0.88 (0.79, 1.03)	0.81 (0.68, 1.05)

USA	0.92 (0.75, 1.18)	0.75 (0.68, 0.96)	0.55 (0.32, 0.96)

In bold the significant cases according to the deterministic terms. In parenthesis, the 95% confidence intervals of the non-rejection values of d using Robinson 's (1994) approach.

Table 7. Estimates of d for CO_2 with a semiparametric method

Country	m = 11	m = 12	m = 13
AUSTRALIA	1.140	1.090	1.117
AUSTRIA	0.504*	0.531*	0.549*
BELGIUM	0.500*	0.500*	0.500*
CANADA	1.352	1.312	1.313
DENMARK	0.930	1.004	0.979
FINLAND	0.500*	0.500	0.550*
FRANCE	0.713*	0.758*	0.795
GERMANY	0.578*	0.595*	0.613*
ITALY	0.587*	0.601*	0.602*
JAPAN	1.115	1.093	1.142
NETHERLANDS	0.500*	0.510*	0.551*
NEW ZEALAND	1.110	1.155	1.180
NORWAY	0.593*	0.580*	0.596*
PORTUGAL	0.990	0.997	1.000
SPAIN	0.768	0.832	0.834
SWEDEN	0.722*	0.746*	0.791
SWITZERLAND	0.816	0.820	0.854
UK	0.912	0.938	0.961
USA	1.270	1.225	1.280
Lower I(1) 95%	0.752	0.762	0.771
Upper I(1) 95%	1.247	1.237	1.228

*: Evidence of mean reversion ($d < 1$) at the 95% level.

Table 8. Estimates of d for SO_2 with a semiparametric method

Country	m = 11	m = 12	m = 13
AUSTRALIA	0.852	0.826	0.846
AUSTRIA	1.145	1.101	1.111
BELGIUM	1.134	1.184	1.179
CANADA	1.138	1.117	1.143
DENMARK	1.082	1.128	1.168
FINLAND	1.096	1.131	1,157
FRANCE	1.154	1.183	1.207
GERMANY	1.224	1.237	1.312
ITALY	0.792	0.819	0.837
JAPAN	1.328	1.309	1.325
NETHERLANDS	1.133	1.199	1.202
NEW ZEALAND	1.039	1.015	1.053
NORWAY	1.017	1.040	1.056
PORTUGAL	0.761	0.738*	0.785
SPAIN	1.292	1.365	1.411
SWEDEN	1.337	1.344	1.281
SWITZERLAND	1.029	1.026	1.051
UK	1.283	1.342	1.405
USA	1.319	1.315	1.350
Lower I(1) 95%	0.752	0.762	0.771
Upper I(1) 95%	1.247	1.237	1.228

*: Evidence of mean reversion ($d < 1$) at the 95% level.

Table 9. Estimates of d for GDP with a semiparametric method

Country	m = 11	m = 12	m = 13
AUSTRALIA	0.934	0.965	1.030
AUSTRIA	0.780	0.793	0.780
BELGIUM	1.001	1.012	1.058

CANADA	0.500*	0.516*	0.587*
DENMARK	0.901	0.941	0.999
FINLAND	0.886	0.929	0.973
FRANCE	0.784	0.774	0.816
GERMANY	0.606*	0.633*	0.677*
ITALY	1.036	0.995	0.969
JAPAN	1.105	1.073	1.054
NETHERLANDS	0.815	0.827	0.808
NEW ZEALAND	0.971	1.011	1.011
NORWAY	1.065	1.107	1.114
PORTUGAL	1.470	1.423	1.424
SPAIN	1.369	1.315	1.239
SWEDEN	1.047	1.086	1.113
SWITZERLAND	0.852	0.888	0.879
UK	0.773	0.818	0.844
USA	0.500*	0.500*	0.500*
Lower I(1) 95%	0.752	0.762	0.771
Upper I(1) 95%	1.247	1.237	1.228

*: Evidence of mean reversion ($d < 1$) at the 95% level.

Table 10. Summary estimates with different methods for the CO_2 series

Country	White noise	AR (nonparametric)	Semiparametric
AUSTRALIA	0.93 (0.85, 1.04)	0.95 (0.81, 1.16)	1.090
AUSTRIA	0.95 (0.79, 1.16)	0.62 (0.41, 0.96)*	0.531*
BELGIUM	0.89 (0.72, 1.11)	0.36 (0.14, 0.69)*	0.500*
CANADA	1.03 (0.95, 1.15)	1.04 (0.91, 1.19)	1.312
DENMARK	0.81 (0.71, 0.93)*	0.81 (0.64, 1.03)	1.004
FINLAND	0.85 (0.71, 1.03)	0.56 (0.23, 0.96)*	0.500*
FRANCE	0.96 (0.84, 1.13)	0.75 (0.54, 1.06)	0.758*

GERMANY	0.68 (0.59, 0.81) *	0.69 (0.51, 0.92) *	0.595*
ITALY	1.08 (0.86, 1.38)	0.49 (0.32, 0.75) *	0.601*
JAPAN	1.22 (1.10, 1.38)	0.99 (0.80, 1.17)	1.093
NETHERLANDS	0.75 (0.60, 0.96) *	0.35 (0.12, 0.63) *	0.510*
NEW ZEALAND	1.11 (1.01, 1.25)	1.14 (0.96, 1.38)	1.155
NORWAY	0.82 (0.70, 0.99) *	0.66 (0.45, 0.94) *	0.580*
PORTUGAL	1.08 (0.95, 1.24)	0.16 (-0.14, 1.21)	0.997
SPAIN	0.87 (0.74, 1.07)	0.56 (0.37, 0.75) *	0.832
SWEDEN	0.77 (0.68, 0.90) *	0.80 (0.61, 1.05)	0.746*
SWITZERLAND	0.77 (0.67, 0.92) *	0.68 (0.51, 0.91) *	0.820
UK	0.43 (0.35, 0.53) *	0.68 (0.51, 0.91) *	0.938
USA	0.92 (0.85, 1.02)	1.03 (0.91, 1.20)	1.225

*: Evidence of mean reversion ($d < 1$) at the 95% level.

Table 11. Summary estimates with different methods for the SO_2 series

Country	White noise	AR (nonparametric)	Semiparametric
AUSTRALIA	0.99 (0.87, 1.16)	0.94 (0.75, 1.27)	0.826
AUSTRIA	1.18 (1.07, 1.34)	1.04 (0.88, 1.28)	1.101
BELGIUM	1.16 (1.06, 1.32)	1.05 (0.89, 1.28)	1.184
CANADA	1.02 (0.86, 1.26)	1.00 (0.86, 1.19)	1.117
DENMARK	1.04 (0.94, 1.17)	1.17 (0.95, 1.41)	1.128
FINLAND	1.12 (1.02, 1.27)	0.97 (0.84, 1.12)	1.131
FRANCE	1.10 (1.00, 1.21)	1.06 (0.90, 1.30)	1.183
GERMANY	0.92 (0.85, 1.02)	1.14 (0.99, 1.34)	1.237
ITALY	1.37 (1.21, 1.57)	1.05 (0.78, 1.42)	0.819
JAPAN	0.92 (0.79, 1.09)	1.14 (1.00, 1.31)	1.309
NETHERLANDS	1.22 (1.11, 1.28)	1.08 (0.91, 1.32)	1.199
NEW ZEALAND	1.06 (0.96, 1.22)	0.96 (0.82, 1.18)	1.015
NORWAY	1.05 (0.95, 1.18)	1.04 (0.89, 1.26)	1.040

PORTUGAL	0.75 (0.69, 0.90)*	0.67 (0.52, 0.90)*	0.738*
SPAIN	1.02 (0.93, 1.14)	1.09 (0.93, 1.31)	1.365
SWEDEN	0.95 (0.88, 1.04)	1.00 (0.97, 1.22)	1.344
SWITZERLAND	0.83 (0.75, 0.96)*	0.80 (0.66, 0.98)*	1.026
UK	0.92 (0.86, 1.01)	1.19 (1.06, 1.35)	1.342
USA	1.04 (0.96, 1.15)	1.10 (0.96, 1.30)	1.315

*: Evidence of mean reversion (d < 1) at the 95% level.

Table 12. Summary estimates with different methods for the GDP series

Country	White noise	AR (nonparametric)	Semiparametric
AUSTRALIA	1.07 (0.96, 1.21)	1.14 (0.91, 1.51)	0.965
AUSTRIA	0.99 (0.87, 1.16)	0.84 (0.69, 1.10)	0.793
BELGIUM	1.13 (1.01, 1.30)	0.92 (0.80, 1.10)	1.012
CANADA	1.17 (1.00, 1.39)	0.78 (0.50, 1.20)	0.516*
DENMARK	0.94 (0.84, 1.09)	0.81 (0.66, 1.01)	0.941
FINLAND	1.13 (0.99, 1.34)	0.79 (0.67, 0.97)*	0.929
FRANCE	1.09 (0.96, 1.28)	0.80 (0.64, 1.07)	0.774
GERMANY	1.13 (0.96, 1.39)	0.62 (0.45, 0.86)*	0.633*
ITALY	1.15 (1.02, 1.33)	0.93 (0.79, 1.15)	0.995
JAPAN	1.07 (0.97, 1.21)	1.05 (0.89, 1.29)	1.073
NETHERLANDS	1.04 (0.90, 1.25)	0.71 (0.56, 0.93)*	0.827
NEW ZEALAND	0.82 (0.72, 0.98)*	0.66 (0.53, 0.86)*	1.011
NORWAY	1.03 (0.94, 1.16)	0.97 (0.82, 1.16)	1.107
PORTUGAL	1.06 (1.00, 1.15)	1.23 (1.12, 1.40)	1.423
SPAIN	1.20 (1.10, 1.35)	1.10 (0.98, 1.28)	1.315
SWEDEN	1.12 (1.01, 1.29)	0.98 (0.83, 1.19)	1.086
SWITZERLAND	1.03 (0.90, 1.23)	0.75 (0.58, 1.00)	0.888
UK	1.22 (1.04, 1.50)	0.81 (0.68, 1.05)	0.818
USA	1.12 (0.93, 1.38)	0.55 (0.32, 0.96)*	0.500*

*: Evidence of mean reversion (d < 1) at the 95% level.

Table 13. Estimated coefficients in the model in (9) for CO_2 emissions and uncorrelated errors

	d	α	β	γ_1	γ_2
AUSTRALIA	0.89 (0.89, 1.20)	-13.8136 (-0.92)	0.0292 (4.60)	4.0633 (1.17)	-0.2218 (-1.09)
AUSTRIA	0.98(0.77, 1.23)	-40.3695 (-1.39)	0.0116 (0.45)	10.8620 (1.49)	-0.6231 (-1.36)
BELGIUM	0.63(0.38, 0.98)	-39.7637 (-4.56)	-0.0065 (-2.14)	10.0555 (5.04)	-0.5202 (-4.47)
CANADA	0.39 (0.82, 1.06)	-24.2376 (-2.29)	0.0188 (2.28)	6.3766 (2.50)	-0.3380 (-2.21)
DENMARK	0.64(0.52, 0.82)	-37.5493 (-4.92)	0.0060 (1.41)	9.2583 (5.37)	-0.4788 (-4.98)
FINLAND	0.61(0.43, 0.86)	-79.1727 (-6.18)	-0.0352 (-3.11)	17.4802 (5.73)	-0.4788 (-4.98)
FRANCE	0.77(0.61, 0.98)	-19.9077 (-3.35)	0.0012 (0.35)	5.5846 (3.86)	-0.2864 (-3.25)
GERMANY	0.50(0.37, 1.12)	-17.7040 (-2.20)	0.0040 (1.28)	5.4414 (2.85)	-0.2924 (-2.58)
ITALY	0.93(0.74, 1.26)	-17.8301 (-0.89)	-0.0034 (-0.19)	3.6335 (0.72)	-0.1021 (-0.32)
JAPAN	1.20(1.09, 1.35)	-10.6699 (-0.60)	0.0878 (1.64)	1.7825 (0.37)	-0.0742 (-0.23)
NETHERLANDS	0.50(0.38, 0.67)	-35.4891 (-5.72)	0.0038 (1.75)	8.669 (6.15)	-0.4583 (-5.47)
NEW ZEALAND	1.12 (1.01, 1.26)	34.0650 (2.39)	0.0182 (1.57)	-6.8002 (-2.07)	0.4018 (2.13)
NORWAY	0.88(0.78, 0.99)	-40.1219 (-2.72)	-0.0167 (-1.38)	9.1974 (2.60)	-0.4170 (-1.99)
PORTUGAL	1.10(0.97, 1.26)	-25.4966 (-1.06)	0.0557 (1.38)	6.0535 (0.96)	-0.3386 (-0.83)
SPAIN	0.80(0.65, 1.02)	-15.7639 (-1.76)	0.0063 (1.04)	3.9795 (1.78)	-0.1703 (-1.23)
SWEDEN	0.74(0.63, 0.90)	-61.0257 (-4.01)	-0.0216 (-2.14)	13.7987 (3.86)	-0.6680 (-3.20)
SWITZERLAND	0.72(0.59, 0.89)	-3.1747 (-0.20)	0.0107 (1.31)	1.3558 (0.38)	-0.0439 (-0.21)
UK	0.22(0.10, 0.37)	-32.6766 (-6.35)	-0.0056 (-3.51)	8.7012 (7.98)	-0.4582 (-8.11)
USA	0.78(0.70, 0.89)	-32.8436 (-5.53)	0.0042 (1.56)	8.4347 (6.26)	-0.4343 (-5.74)

In bold, statistical evidence in favour of the EKC hypothesis at the 95% level.

Table 14. Estimated coefficients in the model in (9) for CO_2 emissions and autocorrelated errors

	d	α	β	γ_1	γ_2
AUSTRALIA	0.97(0.80, 1.17)	-4.7586 (-0.29)	0.0282 (3.34)	1.9564 (0.51)	-0.1002 (-0.45)
AUSTRIA	0.33(-0.11, 0.84)	-16.6878 (-1.70)	-0.0078 (-1.94)	4.6362 (2.02)	-0.2097 (-1.57)
BELGIUM	-0.09 (-0.08, 0.20)	-56.0978 (-9.95)	-0.0065 (4.44)	13.8056 (11.2)	-0.7329 (-11.2)
CANADA	1.09 (0.95, 1.24)	-7.7262 (-0.65)	0.0185 (1.21)	2.3998 (0.83)	-0.1026 (-0.59)
DENMARK	0.55(0.29, 1.01)	-39.9749 (-6.18)	0.0053 (1.35)	9.7935 (6.82)	-0.5070 (-6.47)
FINLAND	0.09 (-0.14, 0.40)	-84.2681 (-1.23)	-0.0392 (-5.99)	18.6772 (12.2)	-0.8948 (-11.2)

FRANCE	0.59 (0.20, 1.06)	-27.4955 (-6.56)	0.0022 (1.13)	7.4141 (7.43)	-0.3950 (-6.66)
GERMANY	1.18 (0.46, 1.33)	136.973 (6.47)	-0.0266 (-0.77)	-32.434 (-6.20)	2.0054 (6.23)
ITALY	0.41(0.16, 0.67)	-27.9265 (-4.27)	-0.0010 (-0.21)	8.7098 (4.20)	-0.4130 (-3.47)
JAPAN	1.04(0.89, 1.22)	-21.8166 (-1.44)	0.0694 (2.39)	4.7621 (1.18)	-0.2675 (-1.01)
NETHERLANDS	0.31(0.12, 0.60)	-38.8688 (-8.21)	0.0035 (2.35)	9.6496 (9.01)	-0.5026 (-8.32)
NEW ZEALAND	1.13(0.96, 1.36)	30.2798 (2.27)	0.0191 (0.13)	-5.9333 (-1.93)	0.3517 (1.99)
NORWAY	0.93(0.78, 1.14)	-40.1564 (-2.49)	-0.0173 (-1.25)	9.1617 (2.35)	-0.4127 (-1.77)
PORTUGAL	0.79(0.39, 1.23)	-15.9023 (-0.82)	0.0389 (2.61)	3.9549 (0.82)	-0.2209 (-0.74)
SPAIN	0.50(0.29, 0.78)	-22.6017 (-3.56)	0.0100 (3.62)	5.7841 (3.81)	-0.2900 (-3.24)
SWEDEN	0.79(0.56, 1.07)	-60.0583 (-3.56)	-0.0251 (-2.17)	13.4658 (3.37)	-0.6411 (-2.72)
SWITZERLAND	0.65(0.46, 0.90)	-7.6097 (-0.56)	0.0086 (1.17)	2.3008 (0.73)	-0.0910 (-0.50)
UK	0.26(0.09, 0.57)	-29.4703 (-5.80)	-0.0050 (-3.09)	8.0142 (7.42)	-0.4226 (-7.50)
USA	1.12(0.98, 1.28)	-17.3788 (-2.02)	0.0396 (0.39)	4.8641 (2.46)	-0.2312 (-2.07)

In bold, statistical evidence in favour of the EKC hypothesis at the 95% level.

Table 15. Estimated coefficients in the model in (9) for SO_2 emissions and uncorrelated errors

	D	α	B	γ_1	γ_2
AUSTRALIA	0.99(0.87, 1.15)	-8.7948 (-0.44)	0.0154 (1.49)	2.2121 (0.47)	-0.1121 (-0.41)
AUSTRIA	1.09 (0.97, 1.24)	-31.4138 (-1.90)	-0.0106 (-0.55)	7.7989 (1.87)	-0.4450 (-1.70)
BELGIUM	1.12(0.96, 1.28)	-20.4115 (-1.10)	-0.0162 (-0.98)	4.6586 (1.04)	-0.2211 (-0.83)
CANADA	0.96(0.19, 1.22)	-54.8411 (-2.61)	0.0221 (1.24)	12.7251 (2.50)	-0.7182 (-2.35)
DENMARK	0.90(0.76, 1.09)	-105.359 (-4.56)	-0.0221 (-1.80)	23.4460 (4.34)	-1.2480 (-3.99)
FINLAND	1.11(0.97, 1.28)	-12.9099 (-0.92)	-0.0078 (-0.27)	1.4522 (0.40)	0.0120 (0.06)
FRANCE	1.11(1.00, 1.22)	-0.6412 (-0.05)	-0.0168 (-1.20)	-0.4885 (-0.16)	0.0935 (0.51)
GERMANY	1.12(1.01, 1.22)	119.626 (5.82)	-0.0418 (-1.57)	-28.989 (-5.71)	1.7803 (5.71)
ITALY	1.24(1.08, 1.44)	3.2620 (0.16)	-0.0264 (-0.64)	-2.0576 (-0.41)	0.2213 (0.69)
JAPAN	1.29 (1.21, 1.39)	-4.9056 (-0.67)	0.0302 (1.01)	0.0958 (0.04)	0.0405 (0.31)
NETHERLANDS	1.23(1.10, 1.37)	-8.9116 (-0.60)	-0.0180 (-0.82)	1.6913 (0.46)	-0.0466 (-0.21)
NEW ZEALAND	1.08(0.96, 1.23)	17.9012 (1.23)	0.0015 (0.13)	-3.7727 (-1.12)	0.2193 (1.12)
NORWAY	0.86(0.69, 1.08)	-80.4056 (-6.24)	-0.0182 (-1.74)	18.1538 (5.90)	-0.9742 (-5.37)
PORTUGAL	0.70(0.58, 0.86)	-14.3591 (-1.63)	0.0121 (2.04)	2.7579 (1.27)	-0.1182 (-0.90)
SPAIN	0.99 (0.88, 1.12)	-3.6985 (-0.45)	0.0056 (0.69)	0.7872 (0.37)	-0.0180 (-0.13)

SWEDEN	0.85(0.73, 0.99)	-100.596 (-5.52)	-0.0300 (-2.41)	22.2170 (5.10)	-1.1636 (-4.49)
SWITZERLAND	0.79 (0.65, 0.95)	-24.8949 (-0.88)	-0.0060 (-0.39)	5.4004 (0.82)	-0.2761 (-0.72)
UK	0.74(0.63, 0.89)	-114.370 (-8.20)	-0.0089 (-2.27)	26.3262 (8.38)	-1.4546 (-8.26)
USA	0.92(0.81, 1.04)	-40.6324 (-5.30)	-0.0097 (-2.13)	9.2604 (5.29)	-0.4732 (-4.79)

In bold, statistical evidence in favour of the EKC hypothesis at the 95% level.

Table 16. Estimated coefficients in the model in (9) for SO_2 emissions and autocorrelated errors

	D	**α**	**β**	**γ_1**	**γ_2**
AUSTRALIA	0.96(0.77, 1.28)	-8.4364 (-0.46)	0.0150 (1.63)	2.1280 (0.50)	-0.1071 (-0.43)
AUSTRIA	1.09 (0.93, 1.32)	-31.4138 (-1.90)	-0.0106 (-0.55)	7.7989 (1.87)	-0.4450 (-1.70)
BELGIUM	0.81(0.26, 1.22)	-68.6759 (-5.25)	-0.0037 (-0.66)	16.0898 (5.24)	-0.8950 (-4.97)
CANADA	0.92(0.51, 1.19)	-59.9908 (-2.97)	0.0220 (1.42)	14.0023 (2.82)	-0.7951 (-2.72)
DENMARK	1.07(0.70, 1.47)	-77.2487 (-4.56)	-0.0291 (-1.31)	16.8924 (4.34)	-0.8724 (-2.15)
FINLAND	0.87(0.43, 1.13)	-43.3513 (-3.67)	0.0100 (0.77)	9.2434 (3.14)	-0.4803 (-2.64)
FRANCE	1.27(1.10, 1.41)	14.3978 (1.10)	-0.0197 (-0.74)	-4.2412 (-13.1)	0.3266 (1.62)
GERMANY	1.28(1.17, 1.38)	143.820 (6.96)	-0.0376 (-0.72)	-34.946 (-6.83)	2.1443 (6.80)
ITALY	1.09(0.83, 1.46)	-6.8712 (-0.37)	-0.0201 (-0.87)	2.3846 (0.08)	0.0761 (0.26)
JAPAN	1.33(1.20, 1.47)	-3.4900 (-0.47)	0.0371 (1.06)	-0.2793 (-0.14)	0.0647 (0.49)
NETHERLANDS	1.16(0.85, 1.41)	-16410 (-1.14)	-0.0161 (-0.96)	3.5160 (1.01)	-0.1573 (-0.74)
NEW ZEALAND	0.98(0.82, 1.19)	12.8853 (0.86)	0.0013 (0.18)	-2.6118 (-0.75)	0.1528 (0.76)
NORWAY	0.71(0.42, 1.32)	-95.4058 (-9.24)	-0.0164 (-2.06)	21.7633 (9.11)	-1.1867 (-8.75)
PORTUGAL	0.54(0.30, 0.79)	-13.7048 (-1.83)	0.0124 (2.80)	2.6564 (1.46)	-0.1147 (-1.08)
SPAIN	1.17(0.95, 1.40)	7.4364 (0.72)	0.0004 (0.28)	-2.0899 (-0.78)	0.1663 (0.96)
SWEDEN	1.00(0.74, 1.20)	-73.7779 (-3.24)	-0.0412 (-2.16)	15.5259 (2.81)	-0.7490 (-2.24)
SWITZERLAND	0.75(0.29, 1.00)	-31.6207 (-1.20)	-0.0077 (-0.55)	6.8642 (1.12)	-0.3521 (-0.99)
UK	0.88(0.60, 1.23)	-109.033 (-6.10)	-0.0119 (-2.08)	24.9931 (6.14)	-1.3715 (-5.94)
USA	1.16(1.01, 1.30)	-24.0124 (-2.71)	-0.0105 (-0.85)	5.4351 (2.6)	-0.2564 (-2.22)

In bold, statistical evidence in favour of the EKC hypothesis at the 95% level.

Table 17. Countries satisfying the EKC hypothesis

CO_2emissions		**SO_2emissions**	
Uncorrelation	Autocorrelated	Uncorrelation	Autocorrelated
		AUSTRIA	AUSTRIA

BELGIUM	BELGIUM		
CANADA		CANADA	
DENMARK	DENMARK	DENMARK	DENMARK
FINLAND	FINLAND		FINLAND
FRANCE	FRANCE		FRANCE
GERMANY			
NETHERLANDS	NETHERLANDS		
NORWAY	NORWAY	NORWAY	NORWAY
	SPAIN		
SWEDEN	SWEDEN	SWEDEN	SWEDEN
UK	UK	UK	UK
USA	USA	USA	USA

In bold evidence of the EKC in all the cases examined.