The EKC: Some really disturbing Monte Carlo evidence

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Abstract

In many fields of the economics discipline, much of the empirical work includes a thorough analysis of time series data. In environmental economics, however, such an analysis is often neglected. This is unfortunate for two reasons. First, as Lee and List (2004. Examining trends of criteria air pollutants: are the effects of government intervention transitory? *Environmental and Resource Economics* 29 (1), 21–37) argue, time series analysis can provide many new insights relevant in modelling work or in forwarding policy advice. Secondly, the nature of the time series has a profound impact on the modelling work. This paper shows that such an analysis is a necessity. We illustrate this with a Monte Carlo investigation of an Environmental Kuznets type of transition between non-stationary variables.

The Environmental Kuznets Curve hypothesis posits an inverse U-shaped relation between environmental pollution and income. Although both pollution and income may be stochastically trending, the empirical literature has largely ignored this property. Through Monte Carlo experiments we show that with stochastically trending series, regression analysis spuriously confirms the EKC hypothesis in 40% of the cases.

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1. Introduction

As Lee and List (2004) argue, the analysis of environmental time series data has been sparse. Although there are some notable exceptions,¹ this is unfortunate for two reasons. First, an analysis of the properties of environmental time series can provide many new insights relevant in modelling work or in forwarding policy advice.

Secondly, the nature of the time series has a profound impact on the modelling work.

Environmental and economic time series may be stationary or non-stationary. A series $\{X_t\}$ is stationary if it has a constant finite mean ($E[X_t] = \alpha < \infty$), constant and finite variance ($E[(X_t - \alpha)^2] = \sigma^2 < \infty$) and autocovariances which depend only upon the distance in time between observations ($E[(X_t - \alpha)(X_{t-k} - \alpha)] = \rho_k < \infty$ for $k = 1, 2, 3, \dots$) (see Verbeek, 2000).² A non-stationary process that becomes stationary after first

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¹ See for instance the following works: Nunnari et al. (2004) who model SO₂ concentrations at a point in space and analyse the ability of various statistical techniques to forecast critical episodes; Kurunç et al. (2005) where the focus is on the forecasting ability of two stochastic approaches for water quality and streamflow; Mora-López et al. (2005) who propose a new model to predict climate parameters or Romanowicz et al. (in press) who perform a non-stationary time series and spatio-temporal analysis on NO data.

² To be more precise, a process with finite and constant mean and variance and autocovariances which depend only upon the distance in time is said to be weakly stationary or covariance stationary. A stochastic process is strictly stationary if the joint distribution is not affected by an arbitrary shift in time. However, it is common to refer to a weakly stationary process as just a stationary process (see Verbeek, 2000). In this paper we will use stationary and weak stationarity interchangeably.

differencing is said to be integrated of order one or is $I(1)$. More generally a non-stationary process that requires differencing d times before it becomes stationary is integrated of order d or is $I(d)$. The trend of an integrated process is a stochastic trend. A series which is stationary is integrated of order 0 i.e. it is $I(0)$ or levels stationary. An $I(1)$ process is also referred to as a difference stationary process and its trend is a simple random walk. It is also possible that the non-stationarity is due to a deterministic trend. If that is the case, it is sufficient to remove the trend from the series for the variable to become stationary. Such a process is referred to as a trend stationary process.

Consider for instance a series $\{X_t\}$. Suppose that at time t , the value for x is given by

$$x_t = \alpha + \gamma t + \delta x_{t-1} + \xi_t \quad (1)$$

where ξ_t is a stationary random error process with mean zero and t is a linear deterministic trend. The process in Eq. (1) is stationary if $\gamma = 0$ and $|\delta| < 1$ and non-stationary if $\delta = 1$. As the first difference of Eq. (1) equals $\Delta x_t = \alpha + \xi_t$ if $\delta = 1$ and $\gamma = 0$, the process is an $I(1)$ process and x is a random walk with drift. If $\gamma \neq 0$ but $|\delta| < 1$, the process is trend stationary. If $\gamma \neq 0$ and $\delta = 1$ the first difference of the process is trend stationary.

It makes an enormous difference if a series is $I(0)$, trend stationary or $I(1)$. First of all, there is a huge difference in terms of the ‘memory’ of the past behaviour of a series. Consider for instance again the process in Eq. (1) with $\gamma = 0$. A stochastic shock has a permanent effect on the series if $\delta = 1$. Hence, an $I(1)$ series has an infinitely long memory of its past behaviour and it can wander around widely without reversing back to some specific value. If $|\delta| < 1$ on the other hand, the impact of a shock is only temporary and the series moves back to its mean α . An $I(0)$ series has only a limited memory of its past behaviour and shows a tendency to move back towards its mean. A trend stationary process will move back towards an upward or downward sloping trend. Note that trend stationarity does not imply that the trend is constant. As a matter of fact, the intercept, slope or both can change over time (Perron, 1997).

In terms of environmental modelling, the nature of a time series can be revealing in terms of the success of environmental policies. Assume for instance that an emission series is trend stationary and that the trend is positive. The implication of such a finding is that environmental policies have not had a permanent impact on emissions. Although it might be possible that emissions decreased over some period of time following the introduction of these policies, the implication of trend stationarity with a constant positive trend is that they did not affect emission levels permanently. After an initial policy shock, the emissions’ series moves back to its upward sloping trend. The impact of policies on

emissions can also be investigated by examining whether the trend in a trend stationary process has changed. Lee and List (2004) use such an analysis to argue that the 1970 Clean Air Act had a permanent effect on per capita NO_x emission in the US. Ng and Yan (2004) apply the variance intervention method of intervention analysis to study sharp discontinuities of the level or the slope in models of non-stationary air quality data.

Secondly, consider two time series, $\{X_t\}$ and $\{W_t\}$. If $\{X_t\}$ is an $I(1)$ process and $\{W_t\}$ is $I(0)$ or trend stationary, then $\{X_t\}$ can never be the cause of $\{W_t\}$ or vice versa. If the causality would run from $\{X_t\}$ to $\{W_t\}$, one would expect the stochastic trend to show up in the process for $\{W_t\}$. As the latter is $I(0)$, this is not the case and hence, the process $\{X_t\}$ cannot be its cause. If causality would run in the opposite direction, then the $\{W_t\}$ process would not be able to cause a stochastic trend in $\{X_t\}$. Causation could, however, run from the first difference of $\{X_t\}$ to $\{W_t\}$ or vice versa. The direction of causation between two $I(0)$ variables can be examined using Granger causality tests (for an application to environmental series see for instance the work of Stern and Kaufmann, 1999 or Coondoo and Dinda, 2002).

If the series $\{X_t\}$ and $\{W_t\}$ are both $I(1)$, regression analysis might be spurious. Suppose for instance that both $\{X_t\}$ and $\{W_t\}$ are random walks with a positive drift and that one estimates a regression such as $x_t = \beta_0 + \beta_1 w_t + \varepsilon_t$. It would not be that surprising to find a positive and significant value for β_1 even if both processes are completely independent. This phenomenon is known as spurious regression (Granger and Newbold, 1974). The problem is due to the fact that if both $\{X_t\}$ and $\{W_t\}$ contain a stochastic trend, the error series ε_t is often non-stationary as well. An important exception to this result exists when the error series is $I(0)$. If that is the case, the processes are cointegrated. The relationship between two cointegrated processes indicates that there is a long-run equilibrium between $\{X_t\}$ and $\{W_t\}$. The long-run equilibrium for x_t equals $\beta_0 + \beta_1 w_t$. As ε_t is $I(0)$ the equilibrium error fluctuates around zero, i.e. the system is, on average, in equilibrium. In the case of spurious regression, ε_t is $I(1)$ which indicates that $\varepsilon_t = 0$ might be a very rare event as random walks are not attracted towards a particular value. It is therefore difficult to argue that $\beta_0 + \beta_1 w_t$ is an equilibrium value for x_t as it is highly likely that periods in disequilibrium (i.e. $\varepsilon_t \neq 0$) are the rule rather than the exception.

In economic and environmental modelling, an analysis of the nature of the time series and the problem of spurious regression is especially relevant as the evidence suggests that economic and environmental series are often integrated. Nelson and Plosser (1982) found evidence that a lot of economic time series contain a stochastic trend rather than a deterministic one. In the

environmental field, the evidence so far seems to indicate that a lot of environmental time series are either $I(1)$ or $I(2)$. Stern and Kaufmann (1999) for instance analyse the order of integration of the time series for CO_2 , SO_2 , CH_4 , CFC11 , CFC12 , N_2O emissions using 4 different tests. Each of their 4 tests confirms that SO_2 emissions are $I(1)$ while 3 out of 4 tests indicate that CH_4 and N_2O are integrated of order 1. Their evidence further suggests that one cannot accept the hypothesis that CO_2 is not $I(1)$ as 2 out of 4 tests point in this direction. Their analysis also reveals that temperature series in the northern and southern hemisphere are $I(1)$. Lee and List (2004) show that their US per capita NO_x emissions series for 1900–1994 is $I(1)$. Perman and Stern (2003) perform both individual and panel unit root tests for SO_2 emissions and per capita GDP for 74 countries using 30 years of data. They conclude that both these variables are integrated in the majority of countries. This suggests that it is not unreasonable to assume that many environmental series are $I(1)$.

In environmental economics, a large number of studies analyse the so-called Environmental Kuznets Curve (EKC). As Lee and List (2004), however, argue, most of the studies do not take into account the time series properties of the data. In this paper we use the EKC hypothesis to show the importance of a proper understanding of the time series at hand. We investigate the impact of these specific time series properties on the EKC standard empirical strategy. We perform a number of Monte Carlo experiments on independently generated $I(1)$ series which we use to estimate EKC regressions. The results cast a dark shadow over the standard EKC empirical strategy in a pure time series framework as we find EKC-like relations in a large number of cases. It is noteworthy that this number is about the same as the number of cases for which Perman and Stern (2003) find support for the EKC using data for 74 countries for sulphur dioxide emissions (SO_2).

Secondly, we analyse the residuals of our regressions to test if the Engle and Granger (1987) cointegration framework is affected by including both the level and the square of a variable in our regressions. Our results suggest that the critical values reported in MacKinnon (1991) to test the null of no cointegration are too small. This seems to be especially the case if estimates reveal an EKC-like relation.

The two basic results of our paper are the following. Firstly results derived from time series analysis of the EKC are not reliable without information with respect to the properties of the time series used. If the estimates were produced from $I(1)$ series, our results suggest that it should not be surprising to find evidence in favour of the EKC. To our knowledge, most empirical papers do not report whether the series are integrated or not. Basically, this means that there is no way to tell if the reported results are due to the EKC or are spurious.

This is especially worrying since the spuriousness favours the EKC.

Secondly, if researchers use cointegration analysis, they should be very cautious when interpreting the results in an Engle–Granger framework. The critical values to determine if the null of no cointegration can be rejected are higher if the EKC cannot be rejected.

Note that this paper does not argue in favour of or against the EKC. We do not perform tests that would allow accepting or rejecting the EKC. All this paper does is suggesting that EKC regressions could be spurious. Basically, it supports Lee and List's (2004) argument that the analysis of the properties of environmental time series should, following macro-economic literature, become an integral part of environmental economics.

Section 2 gives a brief overview of the EKC. Section 3 details the Monte Carlo experiments; Section 4 discusses the results. Section 5 concludes.

2. The EKC: the issue of spurious regressions

The EKC predicts an inverse U-shaped relationship between environmental pollution and per capita income. This shape is attributed to the scale, composition, income and technique effects. At first, the increasing scale of economic activity as well as its changing composition from agricultural towards industrial activities generates more pollution. However, as income rises, demand for environmental quality increases and more stringent environmental regulation leads to a replacement of old technologies by environmentally less harmful ones. This technology or income effect, together with the changing composition away from an industrial and towards a post-industrial economy puts downward pressure on pollution. Eventually, as income passes some threshold level, the latter effects will start to dominate and environmental quality will increase with growth.

The standard empirical EKC literature captures the scale, composition, income and technique effects through reduced form regressions in a time series or panel framework (see Holtz-Eakin and Selden, 1992; Selden and Song, 1994; Shafik, 1994; Grossman and Krueger, 1995; Stern, 1998; de Bruyn et al., 1998; Stern and Common, 2001; Harbaugh et al., 2002) such as (in a time series context)

$$\ln\left(\frac{E}{P}\right)_t = c + \gamma t + \beta_1 \ln\left(\frac{Y}{P}\right)_t + \beta_2 \ln\left(\frac{Y}{P}\right)_t^2 + \zeta_t. \quad (2)$$

In these regressions the (natural logarithm of the) level of environmental pollution ($\ln(E/P)$) depends on (the natural logarithm of) per capita GDP ($\ln(Y/P)$), per capita GDP squared and a trend (γt). The EKC predicts

that $\beta_1 > 0$ and $\beta_2 < 0$. Following Grossman and Krueger (1995) the log of per capita GDP cubed is often added to the regressands. However, most authors who do so do not discuss it in much detail and many estimates have been done without this term.

Some authors have questioned the use of the standard EKC empirical strategy based on the properties of environmental and income time series. As noted in the previous section, a lot of evidence suggests that environmental time series are I(1). If per capita GDP is I(1), its square is also I(1) (Granger and Hallman, 1988). In line with Nelson and Plosser's (1982) results, Perman and Stern (2003) find evidence that per capita GDP as well as its square are I(1). Hence standard EKC regression results could be spurious if emissions, per capita GDP and GDP squared are not cointegrated (Stern and Common, 2001). Therefore the interpretation of standard EKC empirical results from time series analysis critically hinges on information with respect to the time series properties of the data. Unfortunately, most of the EKC literature ignores or does not report those properties while the literature above suggests that most models are estimated using three variables that are likely to be I(1) (Stern, 2004).

We next turn to the set-up of our Monte Carlo experiments which we use to test the standard EKC empirical strategy.

3. Set-up of the Monte Carlo simulations

To look at the behaviour of the EKC empirical framework in the presence of I(1) series we performed a number of Monte Carlo experiments. The basic set-up of these experiments includes two random walks, possibly with drift, z and y :

$$z_t = z_{t-1} + \alpha_z + \sigma_z \zeta_t^z \quad (3)$$

$$y_t = y_{t-1} + \alpha_y + \sigma_y \zeta_t^y \quad (4)$$

with $\zeta_t^z \rightarrow N(0, 1)$, $\zeta_t^y \rightarrow N(0, 1)$, $E[\zeta_t^z, \zeta_t^y] = 0$ (uncorrelated random shocks), volatility parameters $\sigma_z > 0$, $\sigma_y > 0$ and t a time index. As Granger and Hallman (1988) have shown, if a series such as y_t is I(1), this will also hold for y_t^n for n not too large. These series are used to estimate (variants of)

$$z_t = \delta + \gamma t + \beta_1 y_t + \beta_2 y_t^2 + \varepsilon_t \quad (5)$$

with t a time trend, δ , γ , β_1 , and β_2 , the parameters to be estimated with OLS and ε_t the error term. Given Eqs. (3) and (4) and Granger and Hallman's (1988) results with respect to the powers of y_t , Eq. (5) is only valid if z , y , and y^2 are cointegrated. Using the Engle and Granger (1987) framework, this requires that the estimates from

$$\Delta \hat{\varepsilon}_t = \theta \hat{\varepsilon}_t + \zeta_t^e \quad (6)$$

do not yield an estimate of $\theta = 0$, with $\hat{\varepsilon}_t$ the estimated residuals from Eq. (5) and ζ_t^e a white-noise error term. Critical values to test this hypothesis have been provided by MacKinnon (1991).

We have used a number of different values for α_z , α_y , σ_z , σ_y to test whether these variables had an influence on the results. We allowed the standard deviations to equal 10%, 20% and 30% and growth rates to equal 0%, 2% and 4%. We have used these values to make sure that our assumptions with respect to drift and volatility had no impact on our results. These different parameter values yield 81 different parameter sets.

Both z_0 and y_0 were set at 0. Using Eqs. (3) and (4) we generated 1000 values for z and y . We used the last 250 observations to perform the experiments. As the first 750 observations were never used, the impact of the initial conditions z_0 and y_0 is extremely limited if not inexistent.

With respect to the estimates of Eq. (5), we have experimented with two specifications. First of all, we estimated the full model in Eq. (5). Secondly, we forced the coefficient on the time trend, γ , to equal zero.

For each parameter set and for each specification, we determined the probability that the estimates of Eq. (5) revealed EKC-like behaviour; i.e. the number of times out of 100 that the EKC would not have been rejected if the estimates had been obtained from an analysis with and environmental degradation series and per capita GDP. Estimates were said to reveal EKC-like behaviour if β_1 was positive, β_2 negative and if both were individually significant at a 5% level. For each parameter set and model specification, we performed 100 experiments and determined how many times the 100 estimates of Eq. (5) revealed EKC-like behaviour. If EKC-like behaviour is not rejected in n cases, $n/100$ equals the probability that the EKC would have been falsely accepted. We repeated this procedure 1000 times to analyse the behaviour of n over a large number of observations. Because the series are independent, the probability that one cannot reject the EKC should approach zero. Although we would expect the estimate of β_1 in Eq. (5) to be significant and even positive if the drift terms are added, there is no a priori reason to assume that the estimate of β_2 would be significant or negative.

For each of the regressions, we recorded the t -statistic on θ in Eq. (6). This gives a total of 100,000 t -stats. We have used these to test if the critical values for the rejection of no cointegration as reported by MacKinnon (1991) are affected by the fact that the estimates of Eq. (5) include the square of an I(1) variable as well as the variable itself. Furthermore, we analysed these statistics in those cases where the results revealed EKC-like behaviour to test if this specific type of outcome has an impact on the critical values.

The Eviews 4.1. econometric software package from Quantitative Micro Software was used to run the Monte Carlo experiments.

4. Results

Table 1 shows the mean and standard deviation of the distribution of the number of times the estimates of Eq. (5) revealed EKC-like behaviour if a trend was added to the model. With the exception of those cases where there is no drift in the independent variable ($\alpha_y=0$), the table indicates that in about 35–40% of the estimates, the EKC would not have been rejected at the 5% confidence level. The standard deviations which are included between brackets below the mean suggest that the various means are not significantly different from one another.

Except when $\alpha_y=0$, the results hold if the drift in the dependent variable is smaller or larger than the drift in the independent variable. In terms of the EKC, this is especially worrying as it implies that environmental degradation could be increasing at a higher pace than growth of per capita GDP and still, the estimates could reveal EKC-like behaviour. Table 1 further suggests that our results hold irrespective of the values of the standard deviations.

These conclusions are not affected if Eq. (5) did not include a trend.³ The mean number of times the estimates reveal an EKC-like result is quite similar and is not significantly different from the results presented in Table 1.

It is quite interesting to compare the means presented in Table 1 with the results for sulphur dioxide emissions in 74 countries presented in Perman and Stern (2003). Although one should be very careful comparing results from our Monte Carlo simulations with those from ‘real data’, it is quite striking to note that both methods find a comparable ‘EKC-acceptance rate’. Perman and Stern (2003) estimate an EKC for each country and report the number of times their estimates confirm the EKC. If they include a time dummy but do not allow for an additional trend, 42 estimates out of 74 (56% of the cases) support the EKC. If they do allow for an additional trend, the EKC cannot be rejected in 34 out of 74 estimates (41% of the cases). Confronting these results with our mean in Table 1, their findings seem to be in line with the results from our Monte Carlo experiments. Based on our results, it should not be surprising to find their EKC-acceptance rates using real data as they show that the time series they use are I(1) processes.

In order to assess the results for those experiments where the independent variable has a zero drift rate,

we should look at what the independent variable represents. In an EKC framework, the independent variable is per capita GDP. For the majority of developed countries, one would expect a positive drift for this variable. For developing countries on the other hand, the drift rate might be closer to zero. Perman and Stern (2003) or Stern and Common (2001) find that estimates of an EKC for sulphur dioxide emissions do not support an inverse U-shaped relation if they restrict their sample to non-OECD countries. For their OECD group on the other hand, their estimates seem to support an inverse-U. Based on the evidence presented in Table 1, this result should not be surprising. If per capita GDP drift of the non-OECD group approaches zero for a large number of countries, the probability that one would not reject the EKC is quite low. If, on the other hand, their OECD group’s per capita GDP drift is different from zero, this probability rises and approaches 35–40%.

Turning to the t -statistics on θ in Eq. (6), Table 2 reports the 1st percentile of the distribution for those cases where the EKC could not be rejected when a trend was included in Eq. (5).⁴ With 250 observations, MacKinnon’s critical values equal -4.7430 (1%), -4.1678 (5%) and -3.8714 (10%). Table 2 shows that the largest value for the 1st percentile of the distribution of the t -statistic equals -4.7711 and the smallest -4.8871 . Both estimates are quite different from those presented by MacKinnon.

If we look at the distribution of the t -statistic if all 100,000 observations are included (Table 3), we can see that the 1st percentiles are much closer to MacKinnon’s critical values.⁵

Table 2 also reports where MacKinnon’s critical values are located in the distribution. With the drift of both variables equal to 2% and both standard deviations equal to 20% for instance, the probability that we find a value that is smaller or equal to -4.7430 equals 1.40% instead of 1%. Similar results hold for the 5% and 10% level of significance. These results seem to suggest that the Engle–Granger cointegration framework would lead the researcher to reject the null of no cointegration in too many cases. To make matters even worse, the evidence presented here suggests that this problem is especially relevant in those cases where the estimates suggest that $\beta_1 > 0$ and $\beta_2 < 0$ (Eq. (5)). Hence, even carefully examined empirical results could cause the researcher to accept the

⁴ Table 2A and 2B in the working paper version of this paper contain the 5% and 10% levels. Table 3A–3C in the working paper version of this paper contain the results if no trend was included. The working paper version is available from the corresponding author.

⁵ Table 4A and 4B of the working paper version of this paper contain the 5th and 10th percentiles for the model with trend. For the model without a trend Table 5A–5C of the working paper version can be consulted. The working paper version is available from the corresponding author.

³ Available from the corresponding author.

Table 1

Mean and standard deviation of the number of times $\beta_1 > 0$, $\beta_2 < 0$ in Eq. (5) with $\gamma \neq 0$

	$\sigma_z = 0.10$			$\sigma_z = 0.20$			$\sigma_z = 0.30$		
	$\sigma_y = 0.10$	$\sigma_y = 0.20$	$\sigma_y = 0.30$	$\sigma_y = 0.10$	$\sigma_y = 0.20$	$\sigma_y = 0.30$	$\sigma_y = 0.10$	$\sigma_y = 0.20$	$\sigma_y = 0.30$
$\alpha_z = 0.00$									
$\alpha_y = 0.00$	15.3160 (3.6361)	15.6360 (3.8254)	15.4720 (3.8278)	15.3920 (3.5373)	15.3760 (3.6694)	15.2840 (3.6673)	15.7800 (3.6531)	15.3920 (3.683)	15.7200 (3.3988)
$\alpha_y = 0.02$	39.9320 (4.5969)	36.9840 (4.5593)	33.8320 (4.9944)	39.8320 (4.8788)	37.2480 (4.8415)	33.6920 (4.5537)	39.8560 (4.7865)	37.0000 (4.8313)	34.0160 (5.2854)
$\alpha_y = 0.04$	39.9840 (4.7853)	40.4600 (5.2809)	39.4680 (5.0802)	40.3520 (5.1379)	39.7960 (5.0343)	38.5160 (4.9675)	40.1160 (4.776)	40.6560 (5.1345)	38.2560 (4.3785)
$\alpha_z = 0.02$									
$\alpha_y = 0.00$	15.0120 (3.6255)	15.7280 (3.5338)	15.7840 (3.594)	15.0240 (3.9239)	15.3040 (3.9672)	15.2200 (3.7109)	15.3640 (3.5949)	15.5280 (3.6007)	15.4200 (3.3623)
$\alpha_y = 0.02$	39.8960 (4.9945)	37.2240 (4.9905)	34.1080 (4.8297)	39.6400 (4.6481)	37.2440 (4.4838)	34.0640 (4.659)	39.9640 (4.7087)	37.0400 (4.9962)	34.1720 (4.7658)
$\alpha_y = 0.04$	39.8680 (4.9595)	40.2760 (4.8338)	38.7640 (4.6193)	40.0200 (4.8133)	40.2400 (4.7801)	38.4400 (4.9469)	40.1400 (4.5133)	40.3560 (4.5032)	39.1160 (4.827)
$\alpha_z = 0.04$									
$\alpha_y = 0.00$	15.0520 (3.5206)	15.7600 (3.9125)	15.5640 (3.458)	15.6040 (3.5146)	15.6680 (3.7978)	15.6080 (3.5134)	15.3840 (3.6045)	15.3760 (3.565)	15.4800 (3.5806)
$\alpha_y = 0.02$	39.9640 (5.0007)	37.1280 (4.8445)	34.3800 (4.5145)	39.6200 (4.8664)	36.6960 (4.928)	33.8040 (4.7413)	39.4760 (4.8123)	36.8320 (4.6985)	34.0200 (4.9564)
$\alpha_y = 0.04$	39.6080 (5.0506)	39.9080 (5.2949)	38.7960 (4.7222)	40.2760 (4.9795)	40.1840 (4.8733)	38.6360 (4.9145)	40.2600 (4.4243)	40.1080 (5.0864)	38.5360 (4.8089)

Standard deviation of the mean are given in brackets.

EKC and the cointegration relation among the variables even if this is the wrong conclusion. This clearly indicates that bootstrapped standard errors and critical values are strongly preferred in order to determine if a linear combination of the variables is a cointegrating relation.

5. Conclusion

This paper analyses, with a number of Monte Carlo experiments, how the properties of environmental and economic time series might affect the EKC empirical

Table 2

First percentile of the distribution of the t -statistic on θ in Eq. (6) with trend in Eq. (5) and the percentile associated with the MacKinnon 1% critical value (−4.7430) for the observation where estimates reveal EKC-like behaviour

	$\sigma_z = 0.10$			$\sigma_z = 0.20$			$\sigma_z = 0.30$		
	$\sigma_y = 0.10$	$\sigma_y = 0.20$	$\sigma_y = 0.30$	$\sigma_y = 0.10$	$\sigma_y = 0.20$	$\sigma_y = 0.30$	$\sigma_y = 0.10$	$\sigma_y = 0.20$	$\sigma_y = 0.30$
$\alpha_z = 0.00$									
$\alpha_y = 0.00$	−4.7920 1.20%	−4.8647 1.40%	−4.8456 1.40%	−4.8098 1.40%	−4.8253 1.30%	−4.7711 1.20%	−4.8547 1.40%	−4.8330 1.30%	−4.8228 1.30%
$\alpha_y = 0.02$	−4.8871 1.50%	−4.8385 1.40%	−4.8049 1.30%	−4.8530 1.50%	−4.8204 1.30%	−4.8144 1.30%	−4.8438 1.40%	−4.8360 1.30%	−4.8191 1.30%
$\alpha_y = 0.04$	−4.8105 1.20%	−4.8603 1.40%	−4.8446 1.40%	−4.8083 1.30%	−4.8382 1.40%	−4.8662 1.50%	−4.8292 1.30%	−4.8308 1.40%	−4.8471 1.40%
$\alpha_z = 0.02$									
$\alpha_y = 0.00$	−4.8047 1.20%	−4.8422 1.40%	−4.8338 1.40%	−4.8285 1.40%	−4.8189 1.40%	−4.8687 1.40%	−4.8073 1.30%	−4.8326 1.40%	−4.8134 1.30%
$\alpha_y = 0.02$	−4.8683 1.50%	−4.8470 1.30%	−4.8112 1.30%	−4.8439 1.40%	−4.8449 1.40%	−4.8074 1.30%	−4.8563 1.50%	−4.8243 1.30%	−4.8192 1.30%
$\alpha_y = 0.04$	−4.8161 1.30%	−4.8417 1.40%	−4.8264 1.30%	−4.8435 1.30%	−4.8549 1.40%	−4.8471 1.40%	−4.8004 1.30%	−4.8362 1.40%	−4.8379 1.40%
$\alpha_z = 0.04$									
$\alpha_y = 0.00$	−4.8190 1.30%	−4.8105 1.30%	−4.8252 1.30%	−4.7985 1.20%	−4.8312 1.30%	−4.7797 1.10%	−4.8445 1.40%	−4.7810 1.20%	−4.8364 1.40%
$\alpha_y = 0.02$	−4.8487 1.40%	−4.8116 1.30%	−4.8348 1.30%	−4.8193 1.30%	−4.8614 1.40%	−4.8497 1.40%	−4.8647 1.40%	−4.8003 1.30%	−4.8732 1.50%
$\alpha_y = 0.04$	−4.8148 1.30%	−4.8481 1.40%	−4.8343 1.40%	−4.8026 1.30%	−4.8370 1.40%	−4.8128 1.30%	−4.8114 1.30%	−4.8265 1.40%	−4.8181 1.30%

Table 3

First percentile of the distribution of the t -statistic on θ in Eq. (6) with trend in Eq. (5) and the percentile associated with the MacKinnon 1% critical value (−4.7430) for all observations

	$\sigma_z=0.10$			$\sigma_z=0.20$			$\sigma_z=0.30$		
	$\sigma_y=0.10$	$\sigma_y=0.20$	$\sigma_y=0.30$	$\sigma_y=0.10$	$\sigma_y=0.20$	$\sigma_y=0.30$	$\sigma_y=0.10$	$\sigma_y=0.20$	$\sigma_y=0.30$
$\alpha_z=0.00$									
$\alpha_y=0.00$	−4.7486	−4.7396	−4.7542	−4.7314	−4.7475	−4.7386	−4.7515	−4.7530	−4.7512
$\alpha_y=0.02$	−4.8262	−4.7912	−4.7691	−4.8049	−4.7821	−4.7714	−4.8175	−4.7950	−4.7764
$\alpha_y=0.04$	−4.7781	−4.8133	−4.8083	−4.7829	−4.8175	−4.8130	−4.7995	−4.7994	−4.8029
$\alpha_z=0.02$									
$\alpha_y=0.00$	−4.7463	−4.7475	−4.7525	−4.7510	−4.7429	−4.7334	−4.7419	−4.7350	−4.7482
$\alpha_y=0.02$	−4.8254	−4.7830	−4.7690	−4.8160	−4.7953	−4.7656	−4.8148	−4.7954	−4.7520
$\alpha_y=0.04$	−4.7956	−4.7892	−4.7923	−4.8029	−4.8073	−4.8085	−4.7777	−4.8132	−4.8035
$\alpha_z=0.04$									
$\alpha_y=0.00$	−4.7418	−4.7521	−4.7512	−4.7394	−4.7464	−4.7274	−4.7424	−4.7538	−4.7473
$\alpha_y=0.02$	−4.8002	−4.7878	−4.7726	−4.8003	−4.8205	−4.7793	−4.8215	−4.7943	−4.7643
$\alpha_y=0.04$	−4.7956	−4.8138	−4.8022	−4.7903	−4.8088	−4.7947	−4.7924	−4.7980	−4.7900

strategy. The results are quite surprising. First of all, our results clearly indicate that it should not come as a surprise to find evidence in favour of the EKC if the environmental and per capita GDP time series used in the empirical work are I(1). Our results indicate that one will not be able to reject the EKC in about 40% of the cases. Secondly, the Engle–Granger cointegration framework has some power deficiencies. More problematic in terms of the EKC, however, is the fact that these deficiencies are larger when the estimates reveal an EKC-like pattern.

Some panel data methods use average results from time series data. Most probably, this means that our results can be extended to those estimates that use panel data techniques if the number of cross-sections is small relative to the number of time series observations. However, one of the areas of future research could focus on the way in which a panel environment affects the results of this paper.

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