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Unit Roots, Polynomial Transformations and the Environmental Kuznets Curve

Abstract:
Time-series regressions including non-linear transformations of an integrated variable are not uncommon in various fields of economics. In particular, within the Environmental Kuznets Curve (EKC) literature, where the effect on the environment of income levels is investigated, it is standard procedure to include a third order polynomial in the income variable. When the income variable is an I(1)-variable and this variable is also included nonlinearly in the regression relation, the properties of the estimators and standard inferential procedures are unknown. Surprisingly, such problems have received rather limited attention in applied work, and appear disregarded in the EKC literature. We investigate the properties of the estimators of long-run parameters using Monte-Carlo simulations. We find that the mean of the ordinary least squares estimates are very similar to the true values and that standard testing procedures based on normality behave rather well.

Keywords: Emissions, Environmental Kuznets Curve, Unit Roots, Monte Carlo Simulations

JEL classification: C15, C16, C22, C32, O13

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1. Introduction

It is known that it is not straightforward to generalize properties of linear non-stationary variables to a nonlinear environment (Ermini and Granger 1993, Granger and Hallman 1991, Corradi 1995). In spite of this, nonlinear transformations of non-stationary variables are included in regression analyses within various fields of economics. The study of the relationship between the environment and income, often referred to as the Environmental-Kuznets-Curve-literature[1], provides an example.[2] Here the standard procedure is to regress a measure of environmental quality on a low order polynomial in income. It is often assumed, which seems reasonable, that the emission and the income variable are both integrated of order one. However, powers of the income variable will not possess this feature. Thus the properties of the estimators are unknown and it is not straightforward to apply the same type of inference in a nonlinear model, such as the EKC relation, as one uses within a linear framework. Hence, standard inference procedures based on asymptotic normality could potentially lead to very misleading conclusions.[3]

If standard inference procedures are invalid in the presence of nonlinear transformations of the income variable, still relying on such procedures could result in e.g. accepting the EKC-hypothesis too often. Moreover, as the properties of the estimators in a model with nonlinear transformations of the income variable are unknown, the estimators may not even be consistent. Finally, how do the estimators behave in small samples? In the present paper we use Monte Carlo simulations to illuminate these issues.

Recently, time series EKC-studies acknowledge the implications of non-stationary variables when analyzing the EKC-relation. However, the implications of the simultaneous presence of

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[1] See e.g. Dasgupta et al. (2002), Stern (2004), Dinda (2004), Copeland and Taylor (2004), or Brock and Taylor (2004) for surveys of the EKC-literature.

[2] Although our main point applies to any time series regression including a non-linear transformation of a non-stationary variable, the present paper focuses on the EKC-literature.

[3] Such problems are potentially more serious than the robustness properties of the EKC that are often addressed in the literature. Investigations of the robustness of the empirical EKC have taken many forms, see e.g. Millimet et al. (2003), Roy and van Kooten (2004), or Giles and Mosk (2003) for testing robustness to semi/non-parametric specifications; Harbough et al. (2002) for investigating robustness to choice of functional forms and variations in sample; List and Gallet (1999) for investigating robustness of the assumption of identical functional forms across states; and Perman and Stern (2003), Egli (2004), or Day and Grafton (2003) for investigations of non-stationarity and cointegration. To our knowledge, no previous paper recognizes the fundamental problem raised by the inclusion of power transformations of the non-stationary income variable in the typical EKC-model.

non-stationary variables and power-transformed values of such variables are to a very little extent discussed. It is not clear what are the properties of estimators and test procedures. Perman and Stern (2003), Friedl and Getzner (2003) and Egli (2004) consider single equation modeling, but do not discuss whether the techniques used in the standard linear case are relevant when also polynomial terms are included in the emission equation. Day and Grafton (2003) and Giles and Mosk (2003) apply VAR models. However, the same type of critique can be raised here. There is no discussion of the properties of the inferential procedures. The simultaneous occurrence of a non-stationary variable and polynomial transformations of it implies complications since it leads to an unbalanced equation. It is not clear that econometric techniques valid in a linear environment can be applied in a nonlinear setting.

In the present paper we use Monte Carlo simulations to investigate the properties of estimators and test procedures related to the long-run parameters in an EKC-type relation. In Section 2 we start out by specifying a traditional VAR model for emission, income and some additional variables. In the EKC-literature this relation is viewed as misspecified because of neglected nonlinearities. Thus we modify the model in accordance with the EKC-literature by adding variables which are power transformations of the income variable and argue that the properties of the estimators of the parameters of this modified VAR model are difficult to derive analytically. Hence, we perform a Monte Carlo simulation analysis on this model to assess the properties of inferential procedures frequently used in a linear setting; see Sections 3 and 4. Section 5 concludes.

2. A linear[4] VAR model involving emission and a nonlinear modification

We now, first, recapture the traditional linear VAR model and some properties of the estimators of the parameters in the model. Then we show how inclusion of polynomial transformations of a variable in the model makes it inconvenient to analytically derive the properties of the estimators. This motivates investigating the properties of the estimators using Monte Carlo simulations.

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[4] By the term linear we mean that there is no additional transformation involved after initially having obtained log-transformed per capita variables.

Let z_t be a (2+K)×1 vector defined by $z_t = \left[y_t, \quad m_t^{/} \right]^{/} = \left[y_t, \quad x_t, \quad q_t^{/} \right]^{/}$, where the scalars y_t and x_t denote log of emission per capita and log of GDP per capita, respectively, and where q_t is a vector with K additional variables. We assume that the z_t vector consists of non-stationary variables integrated of order 1, and that the variables follow a second order VAR-process (in equilibrium correction form):

$$\Delta z_t = \mu + \Gamma \Delta z_{t-1} + \Pi z_{t-1} + u_t, \tag{1}$$

where μ is (2+K)×1 vector of intercepts, Γ and Π are (2+K) ×(2+K) matrices with slope parameters and u_t is a (2+K)×1 vector with error terms. We assume that $u_t \sim NIID(0, \Sigma)$, where Σ is a positive-definite covariance matrix. In the case with one cointegrating vector, we can use the representation $\Pi = \alpha\theta^{/}$ where α and θ are both (K+2)×1 vectors. To obtain identification we set the first element in the θ-vector equal to 1. Hence, $\theta = \left[1, \quad \theta_x, \quad \theta_q^{/} \right]^{/}$, where θ_x is a scalar and θ_q is a K×1 vector. An equivalent formulation of this model is obtained by considering (i) the conditional relation for Δy_t given past values and $\Delta m_t = (\Delta x_t, \quad \Delta q_t^{/})^{/}$ and (ii) the marginal model for Δm_t. Our further elaboration is based on the assumptions that

(i) Δm_t is weakly exogenous with respect to the long-run parameters, θ,

(ii) Δm_t is not Granger-caused by Δy_t,

These two assumptions imply that Δm_t is strongly exogenous with respect to the long-run parameters. Hence, we can write the model as

$$\Delta m_t = \mu_m + \Gamma_m \Delta m_{t-1} + u_{m,t} \tag{2}$$

and

$$\begin{aligned} &\Delta y_t = \mu_y + \rho \Delta y_{t-1} + \omega_0 \Delta m_t + \omega_1 \Delta m_{t-1} + \alpha_y \theta^{/} z_{t-1} + u_{y,t} = \\ &\mu_y + \rho \Delta y_{t-1} + \omega_0 \Delta m_t + \omega_1 \Delta m_{t-1} + \alpha_y y_{t-1} + \theta_x^y x_{t-1} + \theta_q^{y/} q_{t-1} + u_{y,t}, \end{aligned} \tag{3}$$

where $\theta_x^y = \alpha_y \theta_x$ and $\theta_q^{y/} = \alpha_y \theta_q^/$. Under these assumptions, consistent and efficient estimates of α_y, θ_x^y and the elements in θ_q^y are obtained using ordinary least squares. The long-run effects of x and q on y are given by $-\theta_x$ and $-\theta_q^/$. Inference on the individual long-run parameters can be carried through using standard procedures.

However, the EKC-literature is implicitly based on the assumption that the above VAR-model is not well-specified since nonlinear effects in the income variable are neglected. The nonlinear modification we consider consists in adding polynomial effects in income both in the short- and long-run part of the model.[5] Thus we are looking at the following equation

$$\Delta y_t = \lambda + \xi \Delta m_t + \xi_{x^2} \Delta x_t^2 + \xi_{x^3} \Delta x_t^3 + \kappa y_{t-1} + \theta_{x^1} x_{t-1} + \theta_{x^2} x_{t-1}^2 + \theta_{x^3} x_{t-1}^3 + \theta_q^/ q_{t-1} + \delta_t . \qquad (4)$$

This relation is clearly unbalanced. Hence, the properties of the estimators in this model are unknown, and it appears difficult to derive these properties analytically. Thus it may be fruitful to use Monte Carlo simulations to look at the properties of the estimators of the parameters in this nonlinear modification of (3) while still sticking to (2) as the data generating process of the m_t-variables.

3. Monte Carlo simulations

Will using traditional testing procedures result in accepting the EKC-hypothesis too often? How do the estimators behave in small samples? These are the questions we set out to illuminate by the simulations presented in this and the next section. In Appendix A we provide a detailed technical description of how the simulations have been carried out. Below we provide a non-technical explanation of the basic steps. To illustrate how the estimators of OLS regression of the EKC-relation behave, we estimate the EKC-relation (4) on a number of simulated datasets. To generate such replicated datasets we first define the true parameters, and then specify a way of generating replications of each of the variables in the dataset - both exogenous and endogenous variables.

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[5] We also impose the additional innocent assumptions that Δm_{t-1} and Δy_{t-1} do not enter the emission equation.

(a) Simulating exogenous variables

We assume that x_t and the elements of q_t are I(1)-variables generated by a linear VAR model. Instead of simply setting some values for the true parameters in the simulation model, we use the estimated results obtained when fitting a VAR model on Norwegian data for the log of GDP per capita, *x*, the log of the percent of overall government expenditures devoted to environmental protection and, *v*, and the log of the share of electricity consumption relative to total energy consumption, *w*. The time series are reported in the three last columns of Table B1 in Appendix B. The simulation is based on these parameter values, which we now view as true, to generate new observations combining the dynamic structure in the VAR model with new error terms drawn from a parametric error distribution. The time series generated in this way (of which there are R replications) may consist of a chosen number of observations. Finally, having obtained the simulated values for x_t and q_t, x^2 and x^3 are calculated.

(b) Simulating the endogenous variable

Log of emissions per capita, y_t, is assumed to be generated by an equilibrium correction model which includes the variables indicated in (a). Thus we implicitly assume that the right hand side variables are strongly exogenous with respect to the parameters in the conditional equation of emission, cf. Engle et al. (1983). In the long run, log per capita emissions (y) depend on x, x^2, x^3 and q. We obtain parameter values by fitting a model to real data. These estimates are used as true parameters in the subsequent simulation analysis. The actual time series y is reported in the first column of Table B1 in Appendix B. Simulated values of y are now obtained by utilizing the simulated values from (a), the dynamic structure of the error correction model and new error terms drawn from a parametric error distribution. Thus having carried through step a) and b) we obtain *R* replicated data sets on y, x, x^2, x^3 and q with a chosen number of observations.

(c) Estimating the EKC-relation using simulated data and making inference

Equipped with *R* simulated data sets, we estimate an EKC-relation corresponding to (4) *R* times, i.e. one time for each of the replicated data sets. Thus we obtain *R* estimates of each parameter in the emission equation and also of the derived long-run parameters of interest in the EKC-literature. We use these R estimates to address the questions raised in the paper.

The first question is how close the mean of the estimated coefficient is to the true value of the corresponding parameter. If the mean of the estimates is similar to the true values, this indicates consistency. Moreover, we elaborate on the small-sample properties of the estimators by investigating the sensitivity to sample size of the discrepancy between the mean of the estimates and the true value.

The second question is about the properties of standard tests. Using data from a particular replication, we test whether the estimates of the long-run parameters are statistically different from the true parameters using standard asymptotic inference. Given the critical value using some significance level, say 0.05, the null hypothesis is either accepted or rejected. We repeat this procedure for each replication $r=1,..,R$. Based on all these tests we can calculate the relative share of rejections out of R replications. If the share turns out to be close to 0.05, we conclude that the test performs well. Otherwise the standard test procedure results in rejection too often or too seldom.

A special case of the test above is also of interest. Suppose we change the process generating simulations of y (under b) by omitting all cubic terms and defining new true values as the estimated coefficients from the emission equation (now excluding x^3) on real data. Simulation of data is hence based on the same model for the strongly exogenous variables (x, q), but on a new model for log emission per capita (y). Again we generate R replications. However, when estimating the EKC-relation on the replicated datasets we now reintroduce the cubic terms. Of special interest is now to test for the significance of the long-term effect of the cubic variable when the true model is quadratic. Given a chosen significance level, how often is the null hypothesis that the coefficient of x^3 is zero retained? If we again let the significance level be 0.05, the cubic term should be retained in 5 per cent of the R replications. If it is retained more or less often, the test is size-distorted.

4. Results: Inference and small-sample properties

We now present the simulation results relevant for the assessment of small sample properties and the properties of standard test procedures estimating EKC-regressions corresponding to (4) using the R simulated data sets. Since the EKC-literature has been concerned with the long-term relationship between emissions and income, we restrict attention to the long-term parameters. According to the Bårdsen formula (Bårdsen, 1989) the long-run effects of the conditioning variables are given as

$$\Xi_{x^j} = -\theta_{x^j} / \kappa, \; j = 1,2,3 \text{ (for } x, x^2 \text{ and } x^3\text{, respectively)},$$

$$\Xi_v = -\theta_v / \kappa \text{ (for } v\text{), and}$$

$$\Xi_w = -\theta_w / \kappa \text{ (for } w\text{).}$$

The true values of these long-run parameters are given in the last row of Table 1. Let $\hat{\Xi}_j^*, j = \{x^1; x^2; x^3; v; w\}$ denote the estimate of $\Xi_j, j = \{x^1; x^2; x^3; v; w\}$ based on data from an arbitrary replication. The remaining part of Table 1 shows summary statistics over R replications. The calculations have been carried through for four different sample sizes (35, 60, 100 and 200 observations).

The results reported in Table 1 show that as the sample size increases, the means are converging towards the true values. This indicates consistency. However, as can be seen from the first row, some small sample bias is present.

Table 1. Mean and empirical standard deviations of long-run parameters estimated on simulated data[a]

No. of obs.	$\hat{\Xi}^*_{x^1}$		$\hat{\Xi}^*_{x^2}$		$\hat{\Xi}^*_{x^3}$		$\hat{\Xi}^*_{v}$		$\hat{\Xi}^*_{w}$	
	Mean	St. dev.	Mean	St. dev.	Mean	St. dev.	Mean	St. dev.	Mean	St. dev.
35	31.1432	28.0171	-6.8981	9.6163	0.4130	1.1099	-0.0676	0.1406	-0.2206	0.2776
60	30.3522	4.2801	-6.6228	1.4824	0.3812	0.1734	-0.0665	0.0720	-0.2205	0.1335
100	30.2200	0.8880	-6.5776	0.2866	0.3761	0.0318	-0.0667	0.0399	-0.2217	0.0713
200	30.2221	0.1405	-6.5784	0.0387	0.3762	0.0039	-0.0668	0.0192	-0.2214	0.0330
True	30.2221		-6.5786		0.3762		-0.0667		-0.2215	

[a]The total number of replications is 10 000.

Below we consider four types of tests, two of which are related to double-sided alternatives and the other two one-sided alternatives. In test types A and B the following hypotheses are tested in each replication:

$$H_{0,Ah}: \ \Xi_h = \Xi_h^0 \ \text{vs.} \ H_{1,Ah}: \ \Xi_h \neq \Xi_h^0; \ h = \left\{x^1; x^2; x^3; v; w\right\},$$

$$H_{0,Bh}: \ \Xi_{h,1} = \Xi_h^0 \ \text{vs.} \ H_{1,Bh}: \ \Xi_h < \Xi_h^0; \ h = \left\{x^1; x^2; x^3; v; w\right\}.$$

Thus we are interested in the probability of rejecting $H_{0,Ah}$ and $H_{0,Bh}$ $\left(h = \left\{x^1; x^2; x^3; v; w\right\}\right)$ when they in fact are true.

As mentioned above we also consider two additional tests (C and D) where the true parameters of the cubic terms are set to zero. However, when estimating on the simulated data, we use a misspecified model in which the cubic terms are included. We focus on making inference on the long-term effect of the cubic term, which leads to the following two hypotheses (one double-sided and one one-sided)

$$H_{0,C}: \ \Xi_{x^3} = 0 \ \text{vs.} \ H_{1,C}: \ \Xi_{x^3} \neq 0,$$

$$H_{0,D}: \ \Xi_{x^3} = 0 \ \text{vs.} \ H_{1,D}: \ \Xi_{x^3} < 0.$$

Again we are interested in the probability of rejecting the hypothesis when it is true. To carry out the tests above we calculate t-values for the estimates of long-run parameters, using the delta method to estimate the standard errors (cf. Bårdsen, 1989). In order to assess the (possible) size distortion we calculate the share out of R replications, in which the hypothesis is rejected given the significance level.

We consider three test levels (α=0.01; α=0.05; α=0.10) and four sample sizes (S=200; S=100; S=60; S=35). The results related to the A hypotheses, B hypotheses, C hypothesis and D hypothesis are reported in Tables 2-5, respectively. According to the results in these four tables, there seem to be no serious size distortions. Besides, the distribution of the long-run estimates across the replications appears to be approximately symmetric.[6]

Table 2. Share of rejections under Monte Carlo simulations.[a] Hypotheses of type A

Test level	No. of obs. (S)	Hypotheses				
		H_{0,Ax^1}	H_{0,Ax^2}	H_{0,Ax^3}	$H_{0,Av}$	$H_{0,Aw}$
α=0.01	200	0.0113	0.0096	0.0091	0.0109	0.0094
	100	0.0095	0.0101	0.0096	0.0101	0.0105
	60	0.0118	0.0115	0.0111	0.0095	0.0110
	35	0.0123	0.0128	0.0132	0.0103	0.0103
α=0.05	200	0.0513	0.0502	0.0515	0.0504	0.0484
	100	0.0529	0.0510	0.0499	0.0487	0.0531
	60	0.0560	0.0566	0.0557	0.0501	0.0505
	35	0.0549	0.0535	0.0537	0.0518	0.0513
α=0.10	200	0.1000	0.1002	0.1001	0.1011	0.0985
	100	0.0991	0.0996	0.1010	0.0978	0.1017
	60	0.1091	0.1085	0.1103	0.1003	0.1031
	35	0.1076	0.1043	0.1052	0.1027	0.1046

[a] For S=200 we apply critical values from the t(187)-distribution, that is 2.602376, 1.972731 and 1.653043 for α=0.01, 0.05 and 0.10. For S=100 we apply critical values from the t(87)-distribution, that is 2.633527, 1.987608 and 1.662557 for α=0.01, 0.05 and 0.10. For S=60 we apply critical values from the t(47)-distribution, that is 2.684556, 2.011741 and 1.677927 for α=0.01, 0.05 and 0.10. For S=35 we apply critical values from the t(22)-distribution, that is 2.818756, 2.073873 and 1.717144 for α=0.01, 0.05 and 0.10.

Table 3. Share of rejections under Monte Carlo simulations.[a] Hypotheses of type B

Test level	No. of obs. (S)	Hypotheses				
		H_{0,Bx^1}	H_{0,Bx^2}	H_{0,Bx^3}	$H_{0,Bv}$	$H_{0,Bw}$
α=0.01	200	0.0107	0.0097	0.0109	0.0098	0.0098
	100	0.0082	0.0126	0.0075	0.0110	0.0104
	60	0.0100	0.0127	0.0105	0.0085	0.0096
	35	0.0086	0.0167	0.0092	0.0103	0.0108
α=0.05	200	0.0496	0.0489	0.0512	0.0509	0.0492
	100	0.0447	0.0541	0.0468	0.0483	0.0517
	60	0.0486	0.0587	0.0514	0.0493	0.0510
	35	0.0444	0.0617	0.0434	0.0516	0.0522
α=0.10	200	0.0963	0.0991	0.1027	0.0979	0.1012
	100	0.0955	0.1068	0.0999	0.0980	0.1003
	60	0.1005	0.1095	0.1015	0.1009	0.1031
	35	0.0884	0.1145	0.0863	0.1011	0.1000

[a] For S=200 we apply critical values from the t(187)-distribution, that is -2.346454,- 1.653043 and -1.286095 for α=0.01, 0.05 and 0.10. For S=100 we apply critical values from the t(87)-distribution, that is -2.369977, -1.662557 and -1.291358 for α=0.01, 0.05 and 0.10. For S=60 we apply critical values from the t(47)-distribution, that is -2.408345, -1.677927 and -1.299825 for α=0.01, 0.05 and 0.10. For S=35 we apply critical values from the t(22)-distribution, that is -2.508325, -1.717144 and -1.321237 for α=0.01, 0.05 and 0.10.

[6] We have also performed calculations (not reported) analogous to those reported in Tables 2-5, but with critical values taken from the standard normal distribution. This yielded some small sample bias when the number of observations was 35 and 60. Thus, there is some gain in taking advantage of the small sample corrections inherent in the t-distribution.

Table 4. Share of rejections under Monte Carlo simulations.[a] Hypothesis C

Test level	No. of observations (S)			
	200	100	60	35
α=0.01	0.0095	0.0113	0.0108	0.0114
α=0.05	0.0491	0.0506	0.0520	0.0533
α=0.10	0.0965	0.0994	0.1019	0.1018

[a] For S=200 we apply critical values from the t(187)-distribution, that is 2.602376, 1.972731 and 1.653043 for α=0.01, 0.05 and 0.10. For S=100 we apply critical values from the t(87)-distribution, that is 2.633527, 1.987608 and 1.662557 for α=0.01, 0.05 and 0.10. For S=60 we apply critical values from the t(47)-distribution, that is 2.684556, 2.011741 and 1.677927 for α=0.01, 0.05 and 0.10. For S=35 we apply critical values from the t(22)-distribution, that is 2.818756, 2.073873 and 1.717144 for α=0.01, 0.05 and 0.10.

Table 5. Share of rejections under Monte Carlo simulations.[a] Hypothesis D

Test level	No. of observations (S)			
	200	100	60	35
α=0.01	0.0090	0.0097	0.0115	0.0123
α=0.05	0.0463	0.0496	0.0531	0.0585
α=0.10	0.0926	0.1033	0.1051	0.1123

[a] For S=200 we apply critical values from the t(187)-distribution, that is -2.346454,- 1.653043 and -1.286095 for α=0.01, 0.05 and 0.10. For S=100 we apply critical values from the t(87)-distribution, that is -2.369977, -1.662557 and -1.291358 for α=0.01, 0.05 and 0.10. For S=60 we apply critical values from the t(47)-distribution, that is -2.408345, -1.677927 and -1.299825 for α=0.01, 0.05 and 0.10. For S=35 we apply critical values from the t(22)-distribution, that is -2.508325, -1.717144 and -1.321237 for α=0.01, 0.05 and 0.10.

5. Concluding remarks

Although it has been known for some time that it is not straightforward to apply econometric techniques for linear relations with unit roots in nonlinear situations, this problem is generally neglected in applied work. We focus on empirical time series studies of the Environmental Kuznets Curve type, where, within a dynamic framework, the three first powers of the log of the per capita income are included. The properties of ordinary least squares estimators are not known in this setting. This motivates our Monte Carlo simulation analysis. The simulations indicate that inconsistency does not appear to be a serious problem, and moreover, that standard inference on long-run parameters based on the t-distribution tends to produce rather small size distortions.

Nevertheless, as our simulations are based on a particular design and on the assumption that the conditioning variables are strongly exogenous with respect to the long-run parameters in the emission equation, their generality can be questioned. Hence, we advice applied researchers working in the EKC-area to use simulation techniques as a tool for assessing the properties of their methods and hopefully, to improve the models.

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A detailed description of the Monte Carlo design

Let us collect x_t (log of GDP per capita in period *t*), v_t (log of the percent of overall government expenditures devoted to environmental protection in period *t*), and w_t (log of the share of electricity consumption relative to total energy consumption in period *t*) in the column vector m_t, that is $m_t = [x_t, \quad v_t, \quad w_t]^{/}$. For these variables we postulate the following 1. order DVAR-model:

$$\Delta m_t = \mu_m + \Gamma_m \Delta m_{t-1} + u_{m,t}, \tag{A1}$$

where $u_{m,t} \sim N(0,\Theta)$ and μ_m, Γ_m and Θ are matrices with unknown parameters. To provide parameters values for the simulation experiment we estimate (A1) on actual data[7] using ordinary least squares. The estimates are reported in Table B2 in Appendix B. Let $\hat{\mu}_m$, $\hat{\Gamma}_m$ and $\hat{\Theta}$ denote the vector and matrices with estimates of the unknown parameters. We simulate data for the right hand side variables in the following way, where * refers to an arbitrary replication

$$m_t^* = \hat{\mu}_m + (I + \hat{\Gamma}_m) m_{t-1}^* - \hat{\Gamma}_m m_{t-2}^* + \hat{\Theta}^{1/2} \varepsilon_t^*, \quad t = 1975, ..., T_S, \tag{A2}$$

where ε_t^* is a vector with random drawings from the univariate standard normal distribution, *I* is the identity matrix and T_S denotes the last year in the simulated sample (which may differ from the last year in the estimation sample). The initial conditions are given by

$$m_{1973}^* = m_{1973}; m_{1974}^* = m_{1974}.$$

In the conditional model (that is the emission equation) we will also need the two first powers of the log of GDP per capita. Thus

$$x_t^{p*} = (x_t^*)^p, \ \ p = 2, 3, t = 1973, 1974, 1975, ..., T_S. \tag{A3}$$

[7] The actual data are reported in Table B1 in Appendix B.

Next let us consider (4) as the conditional model for y_t (which is the log of monoxide emission per capita).

We estimate an equation corresponding to (4) (including also a linear time trend) by ordinary least squares using actual data for t=1974 to 2003. The results are reported in Table B3 in Appendix B. To replicate data for y we apply the following equation

$$\begin{aligned} y_t^* &= \hat{\lambda} + \hat{\eta}\tau_t + (1+\hat{\kappa})y_{t-1}^* + \hat{\xi}_{x^1}x_t^* + \hat{\xi}_v v_t^* + \hat{\xi}_w w_t^* + \left(\hat{\theta}_{x^1} - \hat{\xi}_{x^1}\right)x_{t-1}^* + \left(\hat{\theta}_v - \hat{\xi}_v\right)v_{t-1}^* + \\ &\left(\hat{\theta}_w - \hat{\xi}_w\right)w_{t-1}^* + \hat{\xi}_{x^2}x_t^{2*} + \left(\hat{\theta}_{x^2} - \hat{\xi}_{x^2}\right)x_{t-1}^{2*} + \hat{\xi}_{x^3}x_t^{3*} + \left(\hat{\theta}_{x^3} - \hat{\xi}_{x^3}\right)x_{t-1}^{3*} + \hat{\phi}\varphi_t^*;\ t = 1975,\ldots,T_S. \end{aligned} \tag{A4}$$

In (A4) (^) denotes an ordinary least squares estimate. $\hat{\phi}$ denotes the estimated standard error of the regression and φ_t^* represents a random drawing from the standard normal distribution. Further, we define $\tau_t = t - 1974$ and apply the initial condition $y_{1974}^* = y_{1974}$. Based on the simulated data we can now for each replication estimate the following equation by ordinary least squares

$$\begin{aligned} y_t^* &= \lambda + \eta\tau_t + (1+\kappa)y_{t-1}^* + \xi_{x^1}x_t^* + \xi_v v_t^* + \xi_w w_t^* + \left(\theta_{x^1} - \xi_{x^1}\right)x_{t-1}^* + \left(\theta_v - \xi_v\right)v_{t-1}^* + \\ &\left(\theta_w - \xi_w\right)w_{t-1}^* + \xi_{x^2}x_t^{2*} + \left(\theta_{x^2} - \xi_{x^2}\right)x_{t-1}^{2*} + \xi_{x^3}x_t^{3*} + \left(\theta_{x^3} - \xi_{x^3}\right)x_{t-1}^{3*} + \zeta_t^*;\ t = 1975,\ldots,T_S, \end{aligned} \tag{A5}$$

where ζ_t^* is an error term. The estimates of the long-run parameters related to the variables x, x^2, x^3 and the variables in q in an arbitrary replication are given by

$$\hat{\Xi}_{x^j}^* = -\hat{\theta}_{x^j}^* / \hat{\kappa}^*;\ j = 1,\ldots,3\left(\text{for } x, x^2 \text{ and } x^3\right),$$

$$\hat{\Xi}_v^* = -\hat{\theta}_v^* / \hat{\kappa}^* \text{ (for } v\text{), and}$$

$$\hat{\Xi}_w^* = -\hat{\theta}_w^* / \hat{\kappa}^* \text{ (for } w\text{)}.$$

Actual data and estimation results related to the actual data

Table B1. The actual time series

Year	y^a	x^b	v^c	w^d
1973	2.901033572	2.693334664	-0.97613559	-0.89425416
1974	2.837633032	2.728151418	-0.76102594	-0.79986853
1975	2.907110081	2.772952944	-0.53866633	-0.85174729
1976	2.959975469	2.825044011	-0.52664701	-0.92049787
1977	3.013490482	2.862337738	-0.29218876	-0.95202303
1978	3.040572637	2.8926614	-0.02162776	-0.94582462
1979	3.080761756	2.932821329	-0.03387391	-0.93248455
1980	3.068778472	2.977995177	-0.12950296	-0.91932209
1981	3.057825133	2.984319363	-0.10263823	-0.86584771
1982	3.063832869	2.982812011	0.139728762	-0.84512584
1983	3.050824035	3.014240063	-0.58142956	-0.80651406
1984	3.078365481	3.06876043	-0.61661048	-0.80371167
1985	3.078700372	3.116668348	-0.72483922	-0.80024276
1986	3.10253746	3.14882109	-0.71562614	-0.8106051
1987	3.055456892	3.165245154	-0.6926981	-0.80745212
1988	3.083518111	3.159376564	-0.49812631	-0.78657721
1989	3.024760358	3.163574235	-0.41920613	-0.75758283
1990	3.019169438	3.181273375	-0.35410108	-0.76296186
1991	2.934647527	3.212857038	-0.32135538	-0.70660588
1992	2.902319379	3.23973896	-0.21231667	-0.69956497
1993	2.899824823	3.26067027	-0.1935873	-0.71750928
1994	2.87461928	3.305949939	-0.36256624	-0.73506611
1995	2.825841158	3.343159964	-0.34357915	-0.73593181
1996	2.783126473	3.389424886	-0.10734815	-0.77081695
1997	2.72474536	3.434816431	-0.38673139	-0.77978011
1998	2.663709784	3.455122804	-0.56974079	-0.76682319
1999	2.602990555	3.469973448	-0.55685734	-0.77309906
2000	2.545866819	3.490515638	-0.61060024	-0.74566507
2001	2.519796489	3.511860863	-0.63132595	-0.77650529
2002	2.460125765	3.520964681	-0.75790196	-0.77180885
2003	2.385137758	3.517743602	-0.80454751	-0.80692423

Data Source: Statistics Norway

[a] The log of CO per capita (10 kg per capita).

[b] The log of income per capita (10 000 kr per capita).

[c] The log of the percent of overall government expenditures devoted to environmental purposes.

[d] The log of the share of electricity consumption relative to total energy consumption.

Table B2. OLS estimates and standard errors of the parameters in the DVAR(1) model[a]

Para-meter	Interpretation	Estimate	Standard error
$\mu_{m,1}$	Intercept in the first equation of the DVAR(1) model	0.0082	0.0058
$\Gamma_{m,11}$	The coefficient related to Δx_{t-1} in the first equation in the DVAR(1) model	0.6585	0.1765
$\Gamma_{m,12}$	The coefficient related to Δv_{t-1} in the first equation in the DVAR(1) model	0.0103	0.0137
$\Gamma_{m,13}$	The coefficient related to Δw_{t-1} in the first equation in the DVAR(1) model	0.0473	0.0875
$\mu_{m,2}$	Intercept in the second equation of the DVAR(1) model	-0.0871	0.0775
$\Gamma_{m,21}$	The coefficient related to Δx_{t-1} in the second equation in the DVAR(1) model	2.8122	2.3485
$\Gamma_{m,22}$	The coefficient related to Δv_{t-1} in the second equation in the DVAR(1) model	0.0568	0.1827
$\Gamma_{m,23}$	The coefficient related to Δw_{t-1} in the second equation in the DVAR(1) model	1.1749	1.1649
$\mu_{m,3}$	Intercept in the third equation of the DVAR(1) model	0.0161	0.0112
$\Gamma_{m,31}$	The coefficient related to Δx_{t-1} in the third equation in the DVAR(1) model	-0.5674	0.3401
$\Gamma_{m,32}$	The coefficient related to Δv_{t-1} in the third equation in the DVAR(1) model	-0.0168	0.0265
$\Gamma_{m,33}$	The coefficient related to Δw_{t-1} in the third equation in the DVAR(1) model	-0.0106	0.1687
Θ_{11}	The variance of the first element of u_t	0.000194	
Θ_{21}	The covariance of the second and first element of u_t	-0.000878	
Θ_{31}	The covariance of the third and first element of u_t	0.000088	
Θ_{22}	The variance of the second element of u_t	0.034436	
Θ_{32}	The covariance of the third and second element of u_t	-0.001039	
Θ_{33}	The variance of third element of u_t	0.000722	

[a] Cf. (A1). The sample period is 1974-2003.

Table B3. OLS estimates and standard errors of the parameters in the emission equation[a]

Parameter	Interpretation	Estimate	Standard error
λ	Intercept	-29.9533	25.2592
η	Trend coefficient	-0.0148	0.0093
κ	The coefficient related to y_{t-1}	-0.7774	0.2574
ξ_{x^1}	The coefficient related to Δx_t	165.2430	87.9887
θ_{x^1}	The coefficient related to x_{t-1}	23.4937	24.8042
ξ_{x^2}	The coefficient related to Δx_t^2	-52.2242	27.7917
θ_{x^2}	The coefficient related to x_{t-1}^2	-5.1140	8.1984
ξ_{x^3}	The coefficient related to Δx_{t-1}^3	5.4846	2.9225
θ_{x^3}	The coefficient related to x_{t-1}^3	0.2924	0.9039
ξ_v	The coefficient related to Δv_t	-0.0234	0.0328
θ_v	The coefficient related to v_{t-1}	-0.0518	0.0341
ξ_w	The coefficient related to Δw_t	-0.2858	0.1974
θ_w	The coefficient related to w_{t-1}	-0.1722	0.2562
ϕ	Standard error of regression	0.0187	

[a] Cf. (A4). The sample period is 1974-2003.

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