Shadow Prices for Undesirables in Swedish Industry: Indication of Environmental Kuznets Curves?*

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Abstract

In this note, we estimate time series of shadow prices for Swedish emissions of CO_2, SO_2, and VOC for the period 1918 - 1994. The shadow prices are in the second step related to income to explain the environmental Kuznets curves previously found for Swedish data on the three emissions. A Shephard distance function approach is used to estimate a structural model of the industry's production process in order to calculate the opportunity costs of a reduction in the emissions. We conclude that the times series of the shadow prices obtained using this approach do not show support for EKCs for Swedish industry.

Key Words: Emissions, Historical time series, Distance function.

JEL Classification: O11, O13, Q51, Q53, Q56

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1 Introduction

In this note, a Shephard distance function approach is used to estimate time series of shadow prices for emissions of carbon dioxide (CO_2), sulphur dioxide (SO_2), and volatile organic compounds (VOC) for the Swedish industrial sector. In a second step, the shadow prices are regressed on the per capita GDP to explain the Swedish pattern of emissions: first increasing and then, after a turning point, decreasing as the GDP per capita increases. This relationship is generally known as the environmental Kuznets curve (EKC)[1], and observing the shadow prices enables the EKC pattern of the emissions to be explained via the industries' abatement costs.

One view put forward by Meadows et al. (1972) among others, is that economic growth requires greater use of energy and material and will, thus, generate larger quantities of emissions and waste as by-products. A substantial extraction of natural resources and an increased concentration of pollutants will then lead to a degradation of the environment. Another view originates from The World Bank's *World Development Report 1992* (IBRD, 1992). This argues that the traditional way of relating growth to environmental damage is based on assumptions that are too static with regard to technology, consumer preferences and environmental investments. It is suggested, instead, that growth may improve environmental quality via technological progress and a rising demand for a clean environment. If the second view is correct, then one would expect emissions to grow when a country with low economic activity increases its production. As the level of economic activity increases, there will eventually be a turning point after which pollution decreases.

Theoretical studies (Selden and Song, 1995; Stokey, 1998; among others) use structural models to explain how changes in technology and preferences are related to changes in the environment, but, as noted by Panayotou (2003), these theoretical models have not yet been empirically tested. The empirical literature originates from the study of Grossman and Kreuger (1991) in which they estimate EKCs for SO_2, dark matter (fine smoke) and suspended particles. A common approach for many of these studies (see Stern, 1998, for an overview) is to estimate the relationship between an environmental index and per capita income, controlling for various other factors such as trade, energy prices, public R&D expenditures and measures of democracy. For Sweden, Brännlund and Kriström (1998) find support for an EKC for SO_2 using data for the period 1900-1993, and Kriström and Lundgren (2005) find indications of an EKC for CO_2 using data for the period 1900-1999. Both studies plot the emissions against GDP per capita and use data on a national level.

The method used in this study originates from Färe et al. (1993), who develop a distance

[1] The EKC is named after Kuznets (1955) who originally proposed a similar relationship between inequality in the distribution of income and economic growth.

function approach to obtain shadow prices for undesirables in the absence of market prices. By using this approach, this note is a first step towards narrowing the gap between the underlying theory and the empirical assessment of the EKC.

The rest of the note is organized as follows; in the next section we present the theory underlying our approach and derive the theoretical shadow prices. The empirical model is specified in Section 3 and the data and estimation procedure are discussed in Section 4. In Section 5, we present the results and finally, some conclusions are drawn in Section 6.

2 The Model

The theoretical framework is analogous to Brännlund and Kriström (1998) and Kriström and Lundgren (2005). Here, we estimate the shadow prices as the slope of the equilibrium condition that the marginal willingness-to-pay (MWTP) for environmental quality should be equal to its supply cost in terms of reduced production of the desirable good. The EKC is then interpreted as the expansion path of this equilibrium over different income levels.

As we only have data on the production side of the economy, we simplify the problem to a "partial analysis", in the sense that we disregard the consumer's utility function and estimate only the production possibilities for society. The shadow price is then calculated as the marginal rate of transformation between the good product and pollution.

Pollution is viewed as a by-product of the production of the desirable good and it is, therefore, natural to model the desirable and undesirable goods as joint-products of a multi-output production technology. We assume a vector of N inputs $\mathbf{x} = (x_1, ..., x_N)$ used in the production of a vector of M outputs $\mathbf{y} = (y_1, ..., y_M)$, where some can be considered undesirable or bad outputs. The prices of the undesirables are expected to be non-positive, thus we define $\mathbf{p} = (\mathbf{p}_g', \mathbf{p}_b')'$ where $\mathbf{p}_g > \mathbf{0}$, for desirable outputs and $\mathbf{p}_b \leqslant \mathbf{0}$ for undesirable outputs.

The origins of the distance function approach to modelling outputs of desirables and undesirables can be found in Färe et al. (1993) who use the distance function as defined by Shephard (1970). The function is defined to measure the ratio of the observed output bundle to the maximum potential output bundle conditional on the input bundle

$$D_o(\mathbf{x}, \mathbf{y}) = \min\{\theta : (\mathbf{x}, \mathbf{y}/\theta) \in T\},$$

where the notation o separates it from an input distance function, and the θ is the minimum multiplier that projects the observed output bundle along a ray from the origin to the greatest potential output bundle, given the input bundle. The technology is given by $T = \{(\mathbf{x}, \mathbf{y}) : \mathbf{x}$ can produce $\mathbf{y}\}$. We assume weak disposability, which basically means that the reduction of a bad output comes at the cost of a proportional reduction of the good output. The assumption of weak disposability is formally written; $(\mathbf{x}, \mathbf{y}) \in T$ and $\theta \in [0,1] \Rightarrow (\mathbf{x}, \theta\mathbf{y}) \in T$. For the representative firm, we may then write the following maximization problem:

$$R(\mathbf{x}, \mathbf{p}) = \max_{\mathbf{y}} \ \mathbf{p}'\mathbf{y} \quad \text{s.t.} \ \ D_o(\mathbf{x}, \mathbf{y}) \leq 1.$$

The distance function will take a value that is less than or equal to one if the output vector is an element of the feasible production set. In the following, we assume that all observed output bundles are efficient, i.e., lie on the production frontier, and the distance function will therefore take value one. The associated Lagrangean can therefore be written as $\mathfrak{L}(\mathbf{y}, \lambda) = \mathbf{p}'\mathbf{y} + \lambda(1 - D_o(\mathbf{x}, \mathbf{y}))$, and the first order necessary condition, with respect to output, becomes $\mathbf{p} = \lambda \boldsymbol{\nabla}_y D_o(\mathbf{x}, \mathbf{y})$. Here we are interested in the shadow price of a bad output, denoted p_b, in terms of the price of a good output, p_g:

$$\frac{p_b}{p_g} = \frac{\partial D_o(\mathbf{x}, \mathbf{y})/\partial y_b}{\partial D_o(\mathbf{x}, \mathbf{y})/\partial y_g}, \tag{1}$$

where $g =$ value added, and $b = CO_2$, SO_2, and VOC, respectively. Computing these prices for each year gives a series that makes it possible to: first, study how the prices develop over the sample period and, second, regress the prices on income to see how they change as the economy grows larger.

3 Empirical Specification

To calculate the empirical shadow prices of eq. (1), we must first estimate the parameters of the distance function. Accordingly we specify the following estimating equation (suppressing time subscripts):

$$1 = D_o(\mathbf{x}_k, \mathbf{y}_k) \cdot \exp(\varepsilon_k) \ , \tag{2}$$

where $\mathbf{x}$ is a vector of N inputs and $\mathbf{y}$ is a vector of M outputs in the industrial sector $k = 1, ..., K$. As we want to allow the technology parameters to change over time, we do not wish to estimate the equation for the full sample at the same time. Instead, we estimate the equation for a series of sub-samples, or *windows*, of length T. One shadow price per undesirable and window is calculated using the window means of the variables in the equation. Ascribing the price to a year within the window, and repeating this procedure for all windows, gives a series of "year specific" shadow price observations.

However, before estimation is possible, we must pay attention to two problems with the specification in eq. (2). First, we assume that the firms are efficient, i.e. they operate on the production possibility frontier. The left hand side of the equation will, therefore, take the value one as it represents the function without an error term. The right hand side of the equation is the observed value; $D_o(\mathbf{x}_k, \mathbf{y}_k)$ and an error term, $\exp(\varepsilon_k)$. Often in frontier estimation, one seeks the estimates of firm efficiency and, when this is the case, the error term is modelled to represent inefficiency. In this note, the focus lies on the slope of the production possibility frontier, and the deviation from the frontier is viewed as due to variables that are unknown to the researcher, and that influence the production process. The error term is assumed to be normally distributed with a zero mean and variance σ^2. Second, we wish to ensure that the assumption of weak disposability is fulfilled. It turns out that by solving the second problem, we also solve the first. To ensure weak disposability, we impose the restriction that the distance function be linearly homogeneous of degree one in all outputs. Imposing this restriction is equivalent to normalizing the left hand side and the output vector on the right hand side by one of the outputs (Lovell et al., 1994). Choosing the M:th output, we can define $\phi_k = 1 / y_{Mk}$, and rewrite eq. (2) as

$$\phi_k = D_o(\mathbf{x}_k, \phi\widetilde{\mathbf{y}}_k) \cdot \exp(\varepsilon_k) \ , \tag{3}$$

where $\widetilde{\mathbf{y}}_k$ includes $M-1$ output ratios. Unfortunately, this normalization introduces a new problem in the estimation. Since one variable now appears on both sides of the equation, the estimated parameters will suffer from simultaneity bias. The severity of this problem will depend on the variance of y_M in relation to the other variables.

When estimating eq. (3), a translog specification is chosen as a flexible approximation to the true underlying distance function:

$$\begin{aligned} \ln \phi_k \quad = \quad & \alpha_0 + \sum_{n=1}^{N} \beta_n \ln x_{nk} + \sum_{m=1}^{M-1} \alpha_m \ln \phi_k y_{mk} + \frac{1}{2} \sum_{n=1}^{N} \sum_{n'=1}^{N} \beta_{nn'} (\ln x_{nk})(\ln x_{n'k}) \\ & + \frac{1}{2} \sum_{m=1}^{M-1} \sum_{m'=1}^{M-1} \alpha_{mm'} (\ln \phi_k y_{mk})(\ln \phi_k y_{m'k}) + \sum_{n=1}^{N} \sum_{m=1}^{M-1} \gamma_{nm} (\ln x_{nk})(\ln \phi_k y_{mk}) + \varepsilon_k \ . \end{aligned} \tag{4}$$

The set of inputs with $N = 2$ has x_{1k} denoting the input of labor, and x_{2k} is the input of capital. The set of outputs with $M = 4$ has the desirable output per capita production (value-added) denoted by y_{1k}, and the undesirable outputs CO_2, VOC, and SO_2 denoted by y_{2k}, y_{3k} and y_{4k}, respectively. The chosen normalizing variable is SO_2 which implies that the left hand side variable becomes $1/SO_2$, thus resolving the problem of no variation in the variable. Finally, symmetry restrictions are imposed, i.e.

$$\begin{aligned} \alpha_{mm'} &= \alpha_{m'm}, \qquad m = 1, ..., M, \quad m' = 1, ..., M \\ \beta_{nn'} &= \beta_{n'n}, \qquad n = 1, ..., N, \quad n' = 1, ..., N \ . \end{aligned}$$

Once eq. (4) is estimated and the empirical shadow prices are calculated, we estimate the possible relationship between the prices and the per capita GDP with a simple polynomial regression:

$$\widetilde{p}_{i,t} = \delta_{0i} + \delta_{1i} z_t + \delta_{2i} (z_t - \overline{z})^2 + \delta_{3i} (z_t - \overline{z})^3 + \eta_{i,t} \ , \tag{5}$$

Table 1: Descriptive Statistics. The full sample for the time period 1913-1999: 87 years and 8 sectors yields 696 observations.

Variable	Unit	Mean	St. Dev.	Minimum	Maximum
Labor	K. hours	17370	20683	2156	100744
Capital Stock	M. SEK	2368	4376	29	26469
Value-Added	M. SEK	13770	22397	191	135655
CO_2	K. tons	3197	4436	2	27252
SO_2	10 tons	1603	2533	3	12239
VOC	K. tons	1219	1849	3	9243
GDP/capita	SEK	86036	46499	27195	166266

Notes: The sample size for GDP equals the number of calculated shadow prices: 77 observations. The Capital Stock, Value-Added and GDP are expressed at the 1990 price level.

where i = CO_2, SO_2, VOC, and the z is the window mean of the GDP per capita, obtained for the same windows as used in the calculation of the shadow prices. Ascribing the window mean to a year within the window, and repeating this procedure for all windows gives a series of smoothed per capita GDP. The t denotes time for the constructed series of the shadow prices and the smoothed per capita GDP, and for this estimation, the sample size is defined by the length of the obtained shadow price series. To reduce multicollinearity, the deviation from the mean of the smoothed GDP series, denoted $\overline{z}$, is used for the quadratic and cubic terms. The error term η is assumed to have a zero mean and constant variance.

4 Data and Estimation

We use historical data for Swedish industry, divided into eight industrial sectors (Lindmark, 2003)[2]. The balanced panel of annual data series covers the period 1913 - 1999. Labor input is expressed in working hours, and the capital stock, the value-added and the per capita GDP are all expressed in SEK at the 1990 year's price level. Further, the emissions are all expressed in metric tons. Descriptive statistics of the data set is displayed in Table 1.

The estimation of the model is structured as follows; we choose the window so that is consists of eleven years, or 88 panel observations, and the calculated shadow prices are attributed to the sixth year (the center) in each period. The first window ranges from 1913 to 1923 and we let

[2]The industries are: 1) Mining and metal, 2) Stone, clay and glass, 3) Wood products, 4) Paper and printing, 5) Food processing, 6) Textile and clothing, 7) Leather and rubber, and 8) Chemicals.

the window shift one year for every estimation so that the final window ranges from 1989 to 1999. In the estimation for each sub-sample, we apply a number of specification tests and model diagnostics to ensure the econometric reliability of the estimation results[3].

Sector specific fixed effects are assumed to be present, representing, e.g., differences in technology between the sectors. These are modelled by adding seven sector dummies to the restricted equation. Results from an F-test of the fixed effect regression versus a restricted pooled regression, support the former specification. Dummy variables are also used for the period 1914 - 1919 and 1939 - 1945 to account for the effects that World Wars I and II have on the data. We also use a dummy variable for the years 1930 - 1936 to account for the unusually large emissions of SO_2 made by the major Swedish metal melting plant, Rönnskär, during its initial years of operation.

The equation is estimated using OLS. Before calculating the shadow prices, we re-specify the estimated equation as eq. (2) and proceed by calculating the ratio of the derivatives as in eq. (1). The confidence interval is obtained using the delta-method.

In the next step, each price is regressed on a smoothed (the window mean) per capita GDP as in eq. (5). The series of shadow prices calculated range from 1918-1994, giving a sample size of 77 observations. The equation is first estimated using OLS and a Durbin-Watson test is applied, rejecting the null of no first order serial correlation. The partial autocorrelation function indicates no higher order serial correlation for the CO_2 and the SO_2 equations, but the lag five autocorrelation is significant for the VOC equation. When an LM-test is used for testing against heteroskedasticity we can reject the null of homoskedasticity for all three equations. The equation is, therefore, re-estimated using the Newey-West estimator, including a lag one autocorrelation for the first two equations and a lag five autocorrelation for the last equation.

5 Results

The shadow prices and their confidence intervals for the 77 sub-samples are shown in Figures 1a-c. All three price series seem to fluctuate around zero throughout most of the period. In general, they are not significantly different from zero, and when there are significantly positive or negative values, this only occurs for a few short periods. There is no sign of the prices turning negative for the latter years of the period.

In Figure 1a, we see the sequence of shadow prices for CO_2 evaluated at corresponding window data means. Prices are significantly negative only for one year in the early 1950s.

[3]The output file for the test results is large and not well suited for presentation. It is available from the author on request.

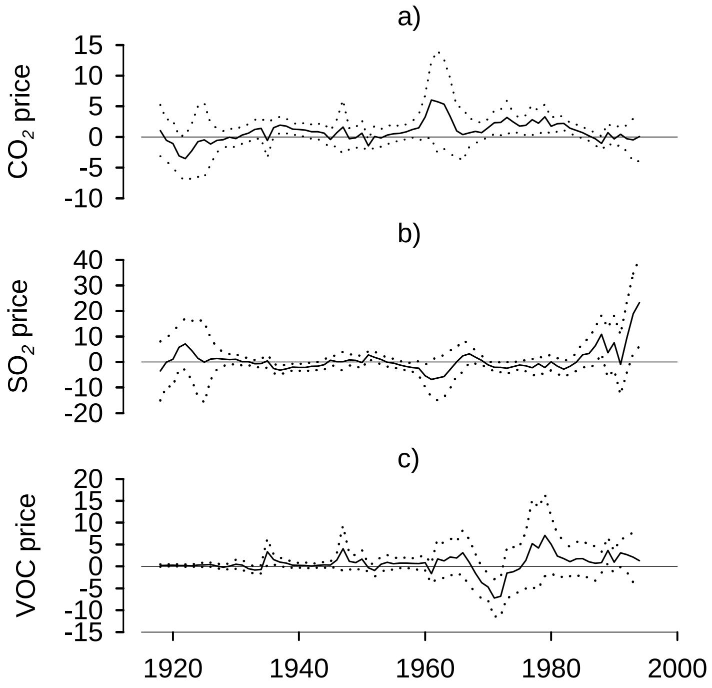

Figure 1: The Figures a to c show the shadow prices for CO_2, SO_2 and VOC, respectively, plotted against time. The dotted lines mark the endpoints of individual 95 percent confidence intervals.

Prices are significantly positive for a number of years in the late 1930s and early 1940s and for a longer period stretching from 1970 to the middle of the 1980s. Overall, the pattern does not indicate a particular sign or any marked deviation from zero.

In Figure 1b, the shadow prices for SO_2 are evaluated at the data mean for each window. From the figure, we can see that the price is significantly negative from the late 1930s to the beginning of the 1940s, from the late 1950s to the early 1960s and for a few years in the early 1970s. It is significantly positive for one year in the early 1950s. The price series has a positive mean during the last ten years of the sample. However, the observations are accompanied by wider confidence intervals, accordingly they are not significantly positive except for a short period in the late 1980s. The overall impression is that, even though prices sometimes deviate from zero, they still fluctuate around zero and there is no indication of prices turning negative during the latter period of the sample.

Turning to the final shadow price, the series for VOC is plotted in Figure 1c. The price shows significantly negative values for a few years in the early 1970s. Significantly positive values are shown for a short period in the mid 1930s and for one year in the late 1980s. From the figure, one can see that the fluctuations tend to increase in magnitude after 1970, and that these are in turn accompanied by a wider confidence interval. Once again, the total impression is that the price series fluctuates around zero and that there is no indication of the price turning negative in the latter period.

The reliability of these results is tested by means of the following diagnostics of the underlying model: the condition number of the data matrix is calculated and there is a clear indication of multicollinearity. We examine the severeness of the multicollinearity by comparing the model with a Cobb-Douglas specification, which shows less problems with multicollinearity, and may then conclude that the regression results seem robust with respect to the choice between the two models. The parameter estimates from the Cobb-Douglas are, of course, different but the evolutions of the shadow prices do not give rise to interpretations other than those given by the translog specification. Durbin-Watson tests of no first order serial correlation in the residuals give inconclusive results, although the reliability of the test is lessened by the short time series for each sector in the subsamples. The same reasoning applies when we test for homoskedasticity, however, one can argue that heteroskedasticity is likely to exist between the sectors in the Swedish industry. When applying an LM-test, the null of homoskedasticity cannot be rejected, possibly due to the normalization of the output variables.

Furthermore, the robustness of these results is examined with respect to the size of the window. To identify the parameters, we need at least four years of observations. The efficiency of the parameter estimates increases as we include more years in the window, but it comes at the cost of losing shadow price observations at the end of the full sample. The upper bound is thus given by the number of shadow price observations we are willing to sacrifice. The model is re-estimated with less, and with more, than eleven years in the window. The results seem robust with respect to the number of years included. However, when six years or less are used, problems arise with spikes in the confidence interval, possibly due to too small variation in the dependent variable for the number of observations in the short time period.

Next, we explore the relationship between each shadow price and the GDP per capita. The results from the regressions are reported in Table 2. In Figure 2, we see the three shadow prices plotted against the per capita GDP, stretching from 27000-167000 SEK. Generally, the production is increasing over time so low per capita GDP levels appear early, and higher levels appear later in the time period. The point estimates of the CO_2 price show a tendency to be negative for low production levels and to increase as production increases, with the highest estimates at production levels between 85000-95000 SEK, after which the price decreases. For the CO_2 polynomial approximation, the level and the quadratic terms are significant at the five percent level. The level term is positive, the quadratic term is negative, and the predicted values (solid circles) show a turning point[4] at approximately 110000 SEK.

The pattern for the SO_2 price is almost the opposite. A positive price at low production levels becomes negative as production increases, with the lowest estimates at production levels of between 85000-90000 SEK. As production increases even more, the estimates become positive again. All terms, except for the constant, are significant. The level term is negative and the quadratic and cubic terms are both positive, and the predicted values show a turning point at 105000 SEK. Turning to the final shadow price, the estimates for VOC show a more spread pattern with negative and positive estimates throughout all production levels. No term is significant in this regression and the R^2 is as low as 0.066. Although close to zero for some periods, the predicted values never become negative. The price is first increasing as production increases, then decreasing and then increasing again.

Some of the calculated shadow prices are significantly positive, which is not expected from theory. Disaggregating the model to generate sector specific shadow prices, makes it possible to study whether the positive prices may be overrepresented in one or a few sectors. When doing so, however, there is no clear indication that such prices would be prevailent in a specific sector. Nevertheless, spikes of extreme variance do arise in some sectors[5], and these spikes are also transmitted when aggregating these prices to manufacturing industry level (i.e., taking the mean of the sector specific prices for each year). Further, when regressing the mean of the sector specific prices on income, very few parameters are significant, making a formal presentation of the results redundant.

Accordingly, we return once more to the aggregate prices from the "main model" and examine how sensitive the estimates for the shown price equations are to the positive prices. First, the equations are re-estimated with the significantly positive prices excluded. The samples are reduced by 20 observations for the CO_2 equation and by 3 observations for the SO_2 and the VOC equation, respectively. The first term in the CO_2 equation, and the level and the cubic terms in the SO_2 equation become insignificant, but there are no major changes in the predicted values from these estimations. Next, the equations are estimated as Tobit models. We set the threshold to zero, which implies that *all* positive prices are set to zero, not only those that are significantly so. The fraction of negative prices is 0.3 for the CO_2 equation, 0.53 and 0.19 for the SO_2 and VOC equations, respectively. As in the former estimation, the level term for the SO_2 equation, and the level and the cubic terms in the SO_2 equation become insignificant, but also, all the parameters except for the quadratic term become significant for the VOC equation.

[4] Note that these turning points concern the shadow prices and not the actual emissions, as are usually referred to.

[5] For the shadow prices of all three emissions, spikes arise in the sectors: 1) mining, basic metal industries, and 6) textile and wearing apparel. For CO_2 , spikes also appear in sector 7) leather and rubber.

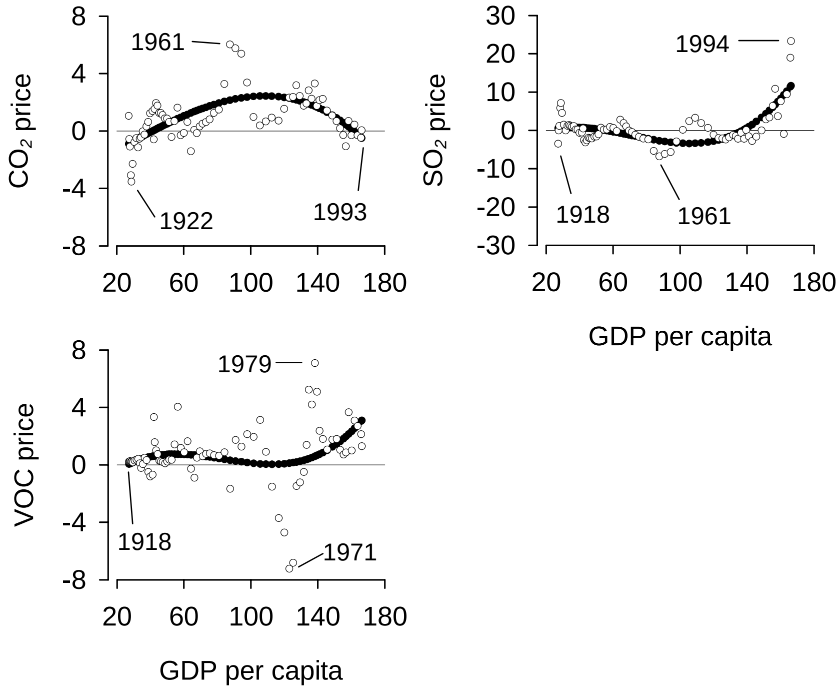

Figure 2: The point estimate of the shadow prices for CO_2, SO_2 and VOC, plotted against GDP (in 1000 SEK) per capita. The solid circles mark the predicted values from the polynomial approximations in Table 2.

There are no major changes in the predicted values from the Tobit estimation, and the overall impression is still that the results from the first estimation are fairly robust with regard to the exclusion or censoring of positive prices.[6]

In the end, when interpreting these regression results, one should keep in mind that most of the observed prices are not significantly different from zero so these price fluctuations are still quite small.

6 Concluding Comments

In this note we have used a Shephard distance function to obtain the shadow prices for Swedish emissions of carbon dioxide, sulphur dioxide and volatile organic compounds. In a second step,

[6]The predictions from the latter two estimations are plotted and compared with the predictions from the first, and there does not seem to be much difference between the predictions from the three estimations. Only the predictions from the first estimation are reported. We also regress the prices on the non-smoothed GDP per capita and the significance level of the parameter estimates are then generally lessened, leaving only the significance levels of the CO_2 regression fairly unchanged.

Table 2: Parameter estimates for the price equations.

	CO_2 price		SO_2 price		VOC price	
Variable	Coeff	s.e.	Coeff	s.e.	Coeff	s.e.
z	0.284	0.085 *	-0.734	0.307 *	-0.186	0.352
$(z-\overline{z})^2$	-0.054	0.018 *	0.112	0.034 *	0.005	0.013
$(z-\overline{z})^3$	-0.003	0.003	0.025	0.011 *	0.008	0.008
Constant	-0.357	0.869	3.701	2.447	1.944	2.533
R^2_{Adj}	0.395		0.506		0.066	
LM	21.373 *		39.068 *		29.037 *	
DW	0.596 *		0.656 *		0.563 *	
AR	1		1		5	

Notes: The z is the GDP per capita, scaled to 10000 SEK for this estimation. The * indicates significance at the 5 percent level. LM is the Lagrange-multiplier test against heteroskedasticity. DW is the Durbin-Watson test against serial corellation of lag one and the AR denotes the number of lags finally used in the regression.

these prices have been used to evaluate the hypothesis of an environmental Kuznets curve. An advantage of observing shadow prices rather than observing the actual emission levels is that, as the shadow prices reflect the firm's abatement costs for reducing emissions, they may be used to explain the evolution path of the actual emissions. The more the firm reduces its emissions, the greater the abatement costs are and, hence, the shadow prices become "more negative". In the results, all three price series seem to fluctuate around zero throughout most of the period. They show significantly negative or positive values for some periods, but in general they do not deviate significantly from zero. There is no sign of the prices steadily turning negative for higher production/consumption levels. However, the results from the CO_2 regression do reveal a pattern that can be interpreted as an indication of an EKC for the emissions, although, since the price is generally not significantly different from zero, we chose to interpret these indications cautiously.

Altogether, we do not, therefore, find support in this model for the EKC patterns found in the previous studies made by Brännlund and Kriström (1998) and Kriström and Lundgren (2005). Both studies use data at a national level and they find indications of EKCs for Swedish emissions of CO_2 and SO_2 with turning points in the early 1970s, which in our data is equivalent to a per capita GDP of approximately 120000 SEK.

The reason our observations do not predict an EKC pattern may lie in the estimation technique, or rather, in how the distance function is specified. The specification of the Shephard distance function allows for the ray to aim at the production frontier in a way that generates positive shadow prices. The advantage of using this specification is that it does not impose a restriction that the observed shadow prices must be non-positive as is suggested by the theory. An alternative specification that can be defined to assure negative shadow prices is the directional distance function (see, e.g., Färe and Grosskopf, 2004). With this approach, one can arbitrarily specify in what direction the output vector is scaled so as to reach an economically feasible part of the production function, ensuring non-positive shadow prices. The drawback is, of course, that restrictions are imposed on the estimation and the question is raised concerning how to choose the direction of the distance function. We cannot a priori say that the results from using a directional distance function would lead us to come to conclusions other than those we reach in this note.

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