

‘customize’ these quotas. That entails including these capital restrictions as ‘fixed’ rather than variable inputs, as in Brännlund *et al* (1998).

Clearly, this is a very simplified version of the common-pool resource problem. One should, of course, include dynamics in the model. In principle, this is not difficult in a network model, and has the advantages of being readily computable using discrete time data. For an example, see Chambers, Färe and Grosskopf (1996) or Färe and Whittaker (1996). A perhaps more difficult problem is the introduction of uncertainty into the problem.

5.5 Summary

The goal of this section is to specify computable models that can be used to investigate the effect of assignment of property rights on profitability in the presence of sources of market failure. The cases we consider are a simple production externality and a common-pool resource. In modeling the production externality we specifically include joint production of goods and bads and the explicit deleterious effects of the jointly produced bad on the downstream firm. One of the innovations is to show how to use a network model to solve for the efficient allocation of resources in the presence of an externality. By employing a profit maximization model, we can solve for optimal emissions as well as providing estimates of rents and bounds on transactions costs, for example.

In the common-pool resource problem, we use a network model again to model the group problem of allocating resources in the absence of property rights. By computing a network profit maximization problem for the group of firms ‘sharing’ the common-pool resource we can solve for optimal individual quotas. The model developed here is a static model with a fixed bound on the biomass involved. Clearly the next step is to generalize this to a dynamic network model.

6. An Environmental Kuznets Curve for the OECD Countries

by

Rolf Färe, Shawna Grosskopf and Osman Zaim

Since Grossman and Krueger’s (1991) path breaking study which shows that an inverted U-type relationship exists between the level of emissions and per capita income (i.e., Environmental Kuznets Curve), a large literature has emerged estimating Environmental Kuznets Curves

and their implications. To show the existence (or non-existence) of an Environmental Kuznets Curve, the typical approach has been to estimate either quadratic or polynomial functional forms to estimate the statistical relation between simple, individual measures of environmental performance, such as emissions and per capita income (together with some control variables). For example, changes in SO₂, dark matter (fine smoke) and suspended particles (SPM) in Grossman and Krueger (1991), total annual deforestation and nine different environmental indicators⁸ in Shafik and Bandyopadhyay (1992), four different air borne emissions (SO₂, NO_x, SPM and CO) in Selden and Song, (1994), the rate of deforestation in Cropper and Griffith (1994) and carbon dioxide per capita in Holtz-Eakin and Selden (1995) are all related to per capita income and various control variables. These results empirically support the existence of an environmental Kuznets curve for air pollutants such as suspended particulate matter, sulfur dioxide and NO_x. While for the water pollutants the results are mixed, for the specific air pollutant CO₂, the relationship has been found to be monotonically increasing with per capita incomes, i.e., there is no Kuznets curve for CO₂.

Common to all these studies is a reduced form approach which typically ignores the underlying production process which converts inputs into outputs and pollutants, while in fact it is the modification or transformation of the production process that may lead to improved environmental performance at higher income levels. Furthermore, the fact that these studies analyze the relationship between environmental performance and growth for each of the many pollutants individually, i.e., in a partial equilibrium framework, implies that a clear-cut policy conclusion is very unlikely.

The obvious need for a single environmental performance index and a method which implicitly recognizes the underlying production process which transforms inputs into outputs and pollutants gave rise to a number of studies which focus on production theory in measuring environmental performance. These studies, by exploiting the aggregator characteristics of distance functions, derived various indexes which measure the environmental efficiency of various producing units. For example Färe, Grosskopf and Pasurka (1989), by using radial measures of techni-

⁸The nine other indicators are lack of clean water, lack of urban sanitation, ambient levels of suspended particulate matter, ambient sulfur oxides, change in forest area between 1961 and 1986, dissolved oxygen in rivers, fecal coliforms in rivers, municipal waste per capita and carbon emissions per capita.

cal efficiency, compute the opportunity cost of transforming a technology from one where production units costlessly release environmentally hazardous substances, to one in which it is costly to release. In another study, Färe, Grosskopf, Lovell and Pasurka (1989) suggested an hyperbolic measure of efficiency (which allows for simultaneous equiproportionate reduction in the undesirable output and expansion in the desirable outputs⁹ in measuring the opportunity cost of such transformation. Finally Zaim and Taskin (2000) and Taskin and Zaim (2000) by applying these techniques to macro level data provided evidence for the existence of a Kuznets type relationship between measures of environmental efficiency and per capita income level.

In a more recent study, Färe, Grosskopf and Hernandez-Sancho (forthcoming) propose an alternative index number approach to environmental performance which measures the degree to which a plant or a firm succeeds in expanding its good outputs while simultaneously accounting for bad outputs. The proposed index consists of the ratio of the quantity index of good outputs to a quantity index of bad outputs, the implicit benchmark being the highest ratio of good to bad outputs. In this study we first explore the environmental performance of the OECD countries between 1971-1990 and then examine the existence of a Kuznets type relationship between income and environmental performance as measured by this new index. Thus we provide a means of simultaneously accounting for multiple pollutants within a production theoretic framework that is at once rigorous (based on axiomatic production theory) yet unrestrictive—our empirical technique imposes no functional form on the underlying technology. In fact we use distance functions, natural aggregator functions as our building blocks, which yield index numbers consistent with the properties laid out by Fisher (1922).

The next section will introduce the methodology followed by the presentation of the data source and discussion of results.

6.1 Methodology

In this section we describe the environmental index adopted here.¹⁰ In short, the index is defined as the ratio of a good output quantity index and a quantity index of bad or undesirable outputs. Each of the two

⁹Here various measures of environmental performance are proposed depending on whether reductions in inputs together with undesirable outputs are sought.

¹⁰For a survey of environmental performance indexes, not including the one adopted here, see Tyteca(1996).

indexes are based on distance functions, very much like the Malmquist (1953) index, but rather than scaling the full output vector, we scale good and bad outputs separately. Thus our index is developed using “sub-vector” distance functions.

To describe the environmental performance “index” some notation is needed. Assume that a vector of inputs $x = (x_1, \dots, x_N) \in R_+^N$ produces a vector $y = (y_1, \dots, y_M) \in R_+^M$ of good output and at the same time produces a vector $u = (u_1, \dots, u_J) \in R_+^J$ of bad outputs, then we define the production technology as

$$T = \{(x, y, u) : x \text{ can produce } (y, u)\}.$$

This technology producing both good and bad outputs is assumed to satisfy the following two conditions.

Weak disposability of outputs:

if $(x, y, u) \in T$ and $0 \leq \theta \leq 1$, $(x, \theta y, \theta u) \in T$

Null-jointness:

if $(x, y, u) \in T$ and $u = 0$ then $y = 0$.

Weak disposability models the following situation: reductions in outputs (y, u) are feasible, provided that they are proportional. This means proportional contraction of outputs can be made, but it may not be possible to reduce any single output by itself. In particular it may not be possible to freely dispose of a bad output.

The null-jointness condition tells us that for an input output vector (x, y, u) to be feasible with no bad output (u) produced, it is necessary that no good output (y) be produced. Put differently if good output is produced, some bad output is also produced. In addition to the above two properties on the technology T , we assume that it meets standard properties like closedness and convexity.

To formulate the good output quantity index, we define a subvector output distance function on the good outputs as

$$D_y(x, y, u) = \inf\{\theta : (x, y/\theta, u) \in T\}.$$

This distance function expands good outputs as much as is feasible, while keeping inputs and bad outputs fixed. Note that it is homogeneous of degree +1 in y . Let x^0 and u^0 be our given inputs and bad outputs, then the good output index compares two output vectors y^k and y^l .

This is done by taking the ratio of two distance functions, and hence, the good index is:

$$Q_y(x^0, u^0, y^k, y^l) = \frac{D_y(x^0, y^k, u^0)}{D_y(x^0, y^l, u^0)}.$$

This quantity index satisfies some of Fisher's (1922) important tests like homogeneity, time reversal, transitivity, and dimensionality.

The index of bad outputs is constructed using an "input" distance function approach. The argument is obvious, it is desirable to reduce such outputs. Thus the input based distance function is defined as

$$D_u(x, y, u) = \sup\{\lambda : (x, y, u/\lambda) \in T\}.$$

This distance function is homogeneous of degree +1 in bad outputs, and it is defined by finding the maximal contraction in these outputs. Given (x^0, y^0) , the quantity index of bad outputs compares u^k and u^l again using the ratios of distance functions i.e.,

$$Q_u(x^0, y^0, u^k, u^l) = \frac{D_u(x^0, y^0, u^k)}{D_u(x^0, y^0, u^l)}.$$

Like the good index $Q_u(x^0, y^0, u^k, u^l)$ satisfies the above mentioned Fisher tests.

Next, following Färe, Grosskopf and Hernandez-Sancho (2004) we define the environmental performance index as the ratio of two quantity indexes, i.e.,

$$E^{k,l}(x^0, y^0, u^0, y^k, y^l, u^k, u^l) = \frac{Q_y(x^0, u^0, y^k, y^l)}{Q_u(x^0, y^0, u^k, u^l)}.$$

This performance index follows the tradition of Hicks-Moorsteen¹¹ by evaluating how much good output is produced per bad output.

In the simple case of one good and one bad output, the index takes the following simple form due to homogeneity of the component distance functions

$$E^{k,l} = \frac{y^k/u^k}{y^l/u^l}.$$

This one bad one good index shows that the index is the ratio of average good per bad output for k and l .

¹¹See Diewert (1992) for references and terminology.

6.2 Data and Results

In computing the environmental performance indicators for each of the OECD countries in our sample, we chose aggregate output measured by Gross Domestic Product (GDP) expressed in international prices (1985 U.S. dollars) as the desirable output and carbon dioxide emissions (in metric tons) and solid particulate matter (in kilograms) as the two undesirable outputs. The two inputs considered are aggregate labor input as measured by total employment and total capital stock. The input and the desirable output data are compiled from the Penn World Tables (PWT 5,6) initially derived from the International Comparison Program benchmark where cross-country and over time comparisons are possible in real values.¹² Pollution related data are obtained from Monitoring Environmental Progress.¹³

In developing the environmental performance index, we used time series data for the years 1971-1990 for each of the OECD countries and constructed our index so that it compares each year in the sample with the initial year 1971 which then takes a value of unity.

In computing the distance functions, we chose the data envelopment analysis (DEA) (or activity analysis) methodology among competing alternatives, so as to take advantage of the fact that the distance functions are reciprocals of Farrell efficiency measures.

In this particular application, we chose the initial year 1971 as our reference. Thus we are assuming that $l = 0$ which then refers to the associated quantities for 1971. We let $k = 1, \dots, K$ index the years in the sample. Thus for each year $k' = 1, \dots, K$, we may estimate for each country

¹²The "Geary-Khamis" method that is used to obtain Purchasing Power Parities in the Penn World Tables has been questioned by Diewert (see for example Diewert (1999)) on grounds that this method may increase the relative share of a small country with respect to a larger one in multilateral comparisons. The computation of the environmental index that we will be discussing in the subsequent paragraphs in fact does not require an internationally comparable data (however, our analysis on Kuznets curve does). All it requires is GDP and capital stock expressed in domestic real currency (in addition to other physical inputs and bad outputs). Our trial runs of "good index" with OECD data where GDP is expressed in real currency units produced virtually identical results with those obtained from using Penn World Tables and hence proving the robustness of our indexes to the data set used. We thank Kevin Fox for bringing this point to our attention and simulating us to check or results with an alternative data set.

¹³The data can be reached from <http://www.ciesin.org>.

$$\begin{aligned}
 (D_y(x^0, y^{k'}, u^0))^{-1} &= \max \theta & (2.53) \\
 &st \\
 \sum_{k=1}^K z_k y_m^k &\geq \theta y_m^{k'}, m = 1, \dots, M, \\
 \sum_{k=1}^K z_k u_j^k &= u_j^0, j = 1, \dots, J, \\
 \sum_{k=1}^K z_k x_n^k &\leq x_n^0, n = 1, \dots, N, \\
 z_k &\geq 0, k = 1, \dots, K,
 \end{aligned}$$

which is the numerator for $Q_y(x^0, u^0, y^k, y^l)$. The denominator is computed by replacing $y^{k'}$ on the right hand side of the good output constraint with the observed output for the year 1971, i.e., y^0 . This problem, using the observed data on desirable outputs, undesirable outputs and inputs between 1971 and 1990, constructs the best practice frontier for a particular country, and computes the scaling factor on good outputs required for each observation to attain best practice. The strict equality on the bad output constraints serves to impose weak disposability. Null-jointness holds provided that

$$\begin{aligned}
 \sum_{k=1}^K u_j^k &> 0, j = 1, \dots, J \\
 \sum_{j=1}^J u_j^k &> 0, k = 1, \dots, K.
 \end{aligned}$$

The first condition states that each bad is produced at least once, and the last condition tells us that at each k some bad output is produced. All conditions are met for each country in our sample.

For the bad index, for a particular country, for each year $k' = 1, \dots, K$ we compute

$$(D_u(x^0, y^0, u^{k'}))^{-1} = \min \lambda$$

$$\begin{aligned}
 & st \\
 & \sum_{k=1}^K z_k y_m^k \geq y_m^0, \quad m = 1, \dots, M, \\
 & \sum_{k=1}^K z_k u_j^k = \lambda u_j^{k'}, \quad j = 1, \dots, J, \\
 & \sum_{k=1}^K z_k x_n^k \leq x_n^0, \quad n = 1, \dots, N, \\
 & z_k \geq 0, \quad k = 1, \dots, K,
 \end{aligned}$$

which is the numerator for $Q_u(x^0, y^0, u^k, u^t)$. The denominator is computed by replacing $u^{k'}$ on the right hand side of the bad output constraint with the observed bad outputs for the year 1971, i.e., u^0 . As above, this problem constructs the best practice frontier from the observed data and computes the scaling factor on bad outputs required for each country to attain best practice.¹⁴

Leaving aside the disaggregated outcomes obtained using the methodology described above, in Table 1 below we provide the average values. In Table 1, for each index, the first columns show the geometric mean of the index between 1971 and 1990 and measure the average performance of an individual country with respect to the base year 1971. The second columns are reserved for the average annual growth rate of each index. Our comparative analysis will be based on the average performance indicators evaluated with respect to the base year. Starting from the bottom of the table, the mean environmental performance index (overall index), averaged over all the countries in the sample, indicates that over the years 1971-1990 OECD countries could have successfully expanded their desirable output to undesirable output ratio by 11%. The good output quantity index averages 34.9% and the bad output quantity index averages 21.5%. Individual country performances indicate that, while Iceland, Sweden and France were the leaders in expanding their good output over the bad outputs, Mexico, Turkey and Greece were the worst

¹⁴Note that this index measures the environmental performance of each country relative to itself in 1971. Its advantage is that it does not require any assumptions about cross country technology. However, if the interest is in the cross-country comparisons of environmental efficiency levels, one can assume the same technology for all the countries and let $k = 1, \dots, K$ index the countries in the sample. Then, a reasonable benchmark would be a hypothetical country constructed as the mean of the data, and the resultant efficiency scores will provide a cross country comparison relative to the mean. See Färe, Grosskopf and Hernandez-Sancho (2004) for an alternative approach in their application.

performers in this respect.

It is well known that during the past two decades the developed countries have made important efforts in reducing emissions of pollutants. However, as the results in Table 1 suggest, these have not been equally important for all OECD countries. In this regard, the classification of countries into those that performed better than average and those below the average with respect to the overall environmental performance indicator sheds light on the relative importance attached to environmental concerns while pursuing growth objectives.

A comparison of the average indicators reveals that relatively low income countries, as measured by average per-capita GDP between 1971-1990 expressed in international prices (1985 U.S. dollars), while trying to catch-up with relatively high income countries may have ignored environmental concerns. Note that while these countries achieved higher growth rates for the good output than high income countries, their emissions of pollutants have increased at an even faster rate, lowering their environmental performance below 1971 levels. The relatively high income countries are the ones which achieved lower than average growth in good output with rather low (and in 5 cases with negative) growth rates in bad output (again evaluated with respect to the base year 1971). This is an indication that environmental concerns are becoming a binding constraint only after a certain level of income is reached and this can be best addressed in an Environmental Kuznets Curve context using panel data, to which we turn next.

Letting E_{it} represent the environmental performance of country i in year t , the equation below specifies a possible relation between environmental performance and per-capita GDP (GDPPC):

$$E_{it} = \beta_{1i} + \beta_2 GDPPC_{it} + \beta_3 (GDPPC_{it})^2 + \beta_4 (GDPPC_{it})^3 + \epsilon_{it}$$

where: i : country index; t : time index; ϵ : disturbance term with mean zero and finite variance. The shape of the polynomial will reveal the relationship between environmental efficiency and GDP per capita. A negative sign for GDPPC coupled with a positive sign for its quadratic and a negative sign for its cubic terms will imply deteriorating environmental performance at the initial phases of growth which is followed by a phase of improvement and then a further deterioration once a critical level of per capita GDP is reached.

Table I. Average environmental performance Indicators

	<i>Good Index</i>		<i>Bad Index</i>		<i>Overall Index</i>		<i>GDP/pop</i>
	Avg.	Annl Growth	Avg.	Annl Growth	Avg.	Annl Growth	71-90 Avg. (85 \$)
High perf.							
Iceland	1.565	3.9	1.087	-0.6	1.440	4.6	10968
Sweden	1.199	1.9	0.881	-1.0	1.361	2.9	12644
France	1.281	2.4	0.977	-0.3	1.310	2.7	11650
Belgium	1.273	2.3	0.976	-1.0	1.304	3.3	10799
Canada	1.475	3.5	1.133	0.9	1.301	2.5	14181
Japan	1.497	4.1	1.154	1.7	1.297	2.3	10404
UK	1.229	2.3	0.997	0.1	1.233	2.2	10622
Neth.	1.252	2.2	1.041	0.5	1.203	1.8	11112
Italy	1.349	2.8	1.137	1.5	1.187	1.4	9963
USA	1.287	2.5	1.097	0.5	1.174	2.0	15550
Denmark	1.217	1.9	1.038	0.9	1.173	1.0	11769
Ireland	1.472	3.8	1.256	2.1	1.172	1.7	6790
Finland	1.369	3.1	1.218	1.3	1.124	1.8	10950
Switz.	1.090	1.4	0.978	0.2	1.114	1.2	14318
Average	1.319		1.064		1.239		11551
Low perf.							
Norway	1.484	3.4	1.415	2.5	1.049	0.9	11999
Austria	1.317	2.6	1.299	3.0	1.014	-0.4	10281
Germany	1.223	2.2	1.230	3.4	0.994	-1.2	11740
Australia	1.329	2.8	1.355	3.1	0.981	-0.2	12646
New Zeal.	1.230	1.7	1.270	1.8	0.968	-0.1	10858
Spain	1.356	3.0	1.424	2.8	0.952	0.2	7575
Portugal	1.479	4.2	1.559	4.2	0.949	0.0	5052
Mexico	1.608	4.0	1.713	4.0	0.939	0.0	5297
Turkey	1.566	4.6	1.808	5.8	0.866	-1.1	2992
Greece	1.381	2.8	1.673	4.9	0.825	-2.0	5790
Average	1.392		1.462		0.952		8423
Grand Mn.	1.349		1.215		1.110		10248

Notes: Annual growth is average annual percent.

Models that combine cross-section and time-series data rely on the premise that differences across units can be captured in differences in the intercept term. However estimation techniques differ with respect to the nature of assumptions made on the intercept of the equation. If the β_{1i} are assumed to be fixed parameters, then the model is known as

a fixed effects model. If on the other hand the β_{1i} are assumed to be random variables that are expressed as $\beta_{1i} = \hat{\beta}_1 + \mu_i$, where $\hat{\beta}_1$ is an unknown parameter and μ_i are independent and identically distributed random variables with mean zero and constant variance, then the model is called a random effects model. The disadvantage of the fixed effects model is that there are too many parameters to be estimated and hence loss of degrees of freedom which can be avoided if we either assume the same intercept for all the cross sectional units, or assume β_{1i} to be random variables. Nevertheless, the random effects model is not totally free from problems. In cases where μ_i and other independent variables are correlated, the random effects model is similar to an omitted variable specification which will lead to biased parameter estimates, making a fixed effects model a more appropriate choice. In examining the relationship between our environmental performance index and per-capita GDP, we will perform the relevant tests to determine the most suitable estimation form.

Table 2 below provides the parameter estimates of the regressions for the E index under alternative specifications where column one and two provide the parameter estimates of the fixed effects model with a common intercept and fixed effects model with country specific intercepts respectively. The third column is reserved for the parameter estimates of the random effects model. An F test performed on the alternative specifications of the fixed effects model rejects the null hypothesis of a common intercept in favor of the model with country specific intercept terms. Furthermore, the choice between the fixed effects model and the random effects model can be made using the Hausman test. The Hausman test has an asymptotic $\chi^2_{(k-1)}$ distribution and in this particular case we fail to reject the null hypothesis which suggests that the random effects model is the appropriate specification.¹⁵ So our preferred model is the random effects model.

The most apparent outcome in all the specifications of the model is that GDP per capita, its quadratic and cubic terms are always statistically significant and their respective signs imply deteriorating environmental performance at the initial phases of growth (up to an income

¹⁵Hausman test statistics test for the orthogonality of the random effects and the regressors, i.e., $H_0 : E(\mu_i|x_{it}) = 0$. Failure to reject this null, is failure to reject no correlation between μ_i and regressors. In this case the preferred specification is the random effects model since the random effects estimator is a best linear unbiased estimator once H_0 is satisfied. Our test statistic $\chi^2_{(3)} = 2.665$ is less than the critical value 7.82 at 5% significance level and fails to reject the null hypothesis.

level of approximately \$6000 according to both the fixed effect model and the random effects model) which is followed by a phase of improvement and then a further deterioration once a critical level of per capita GDP (approximately \$21000) is reached. This is actually another representation of the environmental Kuznets curve relationship where the initial deterioration of environmental conditions and its improvement in latter stages of economic growth manifest itself as an initial decline and then an improvement of environmental efficiency as measured by our index. The upper turning point is slightly beyond the sample range indicating that there may be negative repercussions on environmental performance after this level of income is reached¹⁶

How do these results compare to those obtained in other studies? Direct comparisons are difficult since our index is a composite one which includes both carbon dioxide and solid particulate matter, while other studies reported results for each pollutant individually. Studies almost unanimously agree that carbon dioxide emissions are monotonically increasing with income. For solid particulate matter, results reported vary from steadily declining emissions in Grossman and Krueger (1995) to improving environmental conditions after \$11217 per capita GDP in Selden and Song (1994) and \$4500 in Panayotou (1993). Our results, which simultaneously account for carbon dioxide and solid particulate matter, suggest that environmental performance deteriorates until per capita income reaches approximately \$6000, i.e., our turning point falls between the Selden and Song (1994) and Panayotou (1993) estimates.

6.3 Concluding Remarks

In this section we employed an index number approach to measure environmental performance in OECD countries between 1971 and 1990. This approach, which relies on the construction of a quantity index of good outputs and a quantity index of bad outputs by putting due emphasis on the distinctive characteristics of production with negative externalities, provides a means of simultaneously accounting for multiple

¹⁶When a Kuznets curve is sought over an alternative environmental performance index for which the computation strategy is described in footnote 7, this provides additional insight on the robustness of the results. A pooled regression of type $E_{ti} = \beta_{t1} + \beta_2 GDPPC_{ti} + \beta_3 (GDPPC)_{ti}^2 + \beta_4 (GDPPC)_{ti}^3 + \epsilon_{ti}$ where the constant term now captures any year specific effects on this alternative environmental performance index, yields the same 'sign ordering' as in regressions in Table 1 for the (quite significant) parameter estimates. The relevant hypothesis test, by rejecting any year specific effects, favors a common intercept model. The turning points with this new specification are \$7439 and \$15925.

Table 2 Parameter estimates for alternative models
Environmental Performance Index

	<i>Constant Intercept</i>	<i>Fixed Effects^a</i>	<i>Random Effects</i>
Constant	0.9726 (14.201)	1.5088	1.436 (6.896)
GDPPC	-3.96E-05 (-1.514)	-0.000232 (-7.231)	-0.000203 (-3.349)
(GDPPC) ²	7.29E-09 (2.445)	2.45E-08 (7.687)	2.18E-08 (3.810)
(GDPPC) ³	-2.05E-13 (-1.950)	-6.01E-13 (-5.959)	-5.30E-13 (-3.074)
R ^{2b}	0.275	0.687	0.684
R ^{2c}	0.938	0.968	0.661
Homogeneity test (DF)		25.39 (23, 453)	
Hausman test stat. (DF)			2.665 (3)
Turning Points	\$3129	\$6107	\$5998
	\$20578	\$21069	\$20925
N	480	480	480

^a Constant terms include the mean of the estimated country effects.
^b R² of the unweighted regression.
^c R² of the weighted regression.

pollutants within a production theoretic framework.

Our results suggest that efforts in reducing emissions of pollutants have not been equally important for all OECD countries; relatively low income countries are generally lagging behind high income countries in this regard. While lower income countries achieved higher growth rates on average for the good output than high income countries, their emissions of pollutants have increased at an even faster rate, lowering their environmental performance below 1971 levels.

A formal analysis that establishes the link between economic growth and environmental performance reveals that there exists a critical level of per capita income of approximately \$6000 above which environmental

performance increases. This result provides further evidence for the existence of an environmental Kuznets type relationship between per capita GDP and our environmental index which simultaneously accounts for multiple pollutants.

7. Remarks on the Literature

The notions of weak disposability and null-jointness may be traced back to Shephard and Färe (1974). See also Färe and Grosskopf (1983a,b) for early efforts at measuring congestion and modeling output sets with byproducts; these early efforts typically employed Shephard type distance functions. Färe, Grosskopf, Lovell and Pasurka (1989) struggled with alternate nonparametric specifications of performance measures in the presence of undesirable outputs, including a hyperbolic measure that is very close to the directional distance function which was not employed in this literature until later. Similarly, Färe, Grosskopf, Lovell and Yaisawarng (1993) used Shephard type distance functions as a basis for shadow pricing undesirable outputs.

The directional distance function approach to modeling and measuring performance in the presence of undesirable outputs may be traced back to a series of theoretical and empirical papers and a dissertation by Y.H. Chung. See Chambers, Chung and Färe (1998) and Chung, Färe, and Grosskopf (1997). The shadow price model based on directional distance functions is discussed in Färe and Grosskopf (1998) and has been applied in Ball, Färe, Grosskopf and Nehring (2001) and Färe, Grosskopf and Weber (2001a,b).

Although not discussed in detail in this essay, some work has been done on modeling the effects of regulation on profitability, particularly in the nonparametric, DEA framework, see Brännlund, Färe and Grosskopf (1995). Brännlund, Chung, Färe and Grosskopf (1998) extend this model to simulate introduction of emissions trading in the Swedish paper and pulp industry.

The network model approach includes the early paper included here by Färe, Grosskopf and Lee. See Färe and Grosskopf (1996) for a general discussion of network models.

8. Appendix: Proofs

Proof of (2.21)

Assume that