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Methods

Measuring environmental performance of state manufacturing through changes in pollution intensities: a DEA framework

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Abstract

In decomposing the total emissions into scale and pollution intensity, the conventional approach uses the total output as a measure of scale, and hence ignores the fact that pollution is mainly a byproduct of the manufacturing activity. This study recognizing that air pollution is mainly a byproduct of manufacturing activity proposes a new definition of pollution intensity—pollution per unit of manufacturing output—, and a new technique to measure the aggregate pollution intensity. The index used is a variant of Malmquist quantity index and satisfies well-established axiomatic properties. One other focal point of this study is the overtime comparisons of pollution intensities, i.e., change in pollution intensity, using indexes that are firmly established in productivity growth literature.

Keywords: Pollution intensity; Malmquist quantity index; Data envelopment analysis; Distance functions

1. Introduction

A large number of studies have now suggested that a correct assessment of economic performance should also incorporate costs resulting from environmental degradation or benefits of environmental improvements. Consequently, economic measures ranging from national accounts to social indicators of development had to be adjusted.

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 within a Data Envelopment Analysis (DEA) framework, derived various indexes, which measure the environmental efficiency of various producing units. For example, Färe et al. (1989b), by using radial measures of technical 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 et al. (1989a) suggested a hyperbolic measure of efficiency (which allows for simultaneous equiproportionate reduction in the undesirable output and expansion in the desirable outputs) in measuring the opportunity cost of such transformation. Finally, Zaim

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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. However, in none of these studies briefly introduced here pollution intensity has been a focal point of interest.

Recently, a substantial body of work has been devoted to developing models that account for changes in pollution emissions in measuring productivity growth. In this regard, one can site models such as "Multilateral productivity comparisons with undesirable outputs" proposed by Pittmann (1983) and "Malmquist–Luenberger index of productivity growth" or "Cost Malmquist Productivity index" by Chung et al. (1997) and Ball et al. (2001) respectively. While these indexes are certainly an improvement over traditional measures of productivity growth, they still fail to establish a link between pollution intensities (i.e., pollution emission per unit of desirable output) and productivity growth. That is, a higher productivity growth after accounting for changes in pollution emissions than traditional measures of productivity growth which ignore undesirable outputs, while implying reduced emissions, do not necessarily imply reduced emissions per unit of desirable output, i.e., an improvement with respect to pollution intensities.

Although pollution intensity indexes have been used in ecological economics, most notably recently in Material (Energy) Flow Analysis (MEFA),[1] arguments about MEFA's ability to describe "rebound effect" still prevails. Furthermore, measurement of pollution intensities has gained particular importance with President Bush's "new" initiative of voluntarily reducing the greenhouse gas "intensity" by 18%. In his Presidential address at the National Oceanic and Atmospheric Administration (February 2002), the president states that

> My administration is committed to cutting our nation's greenhouse gas intensity—how much we emit per unit of economic activity—by 18 percent over the next 10 years. This will put America on a path to slow the growth of our greenhouse emissions and as science justifies, to stop and then reverse the growth of emissions.

This positive sounding proposal has also created a controversy on what really pollution intensity measures and whether reduced pollution intensity implies reduced emissions, again reviving the discussions on the rebound effect. For example greenhouse gas intensity, measured as metric tons per million dollars of GDP has been declining in the US since economic growth has outpaced the rise in pollution as the economy has experienced a structural shift from industrial to services production, and to lighter less producing industries within manufacturing. This calls for a more profound measure of pollution intensity. Since pollution is mainly a byproduct of manufacturing industry, measuring pollution intensity per unit of manufacturing output is a more meaningful alternative, which will not yield in over optimistic statements especially when the overall growth of GDP outpaces the growth of manufacturing industry. One other problem with the conventional measure of pollution intensity (including the ones derived by MEFA) is, how to aggregate them into a composite index of environmental performance when there exist multiple pollutants. While analysis over individual pollution intensity indexes prevent clear-cut policy conclusions, there seems to be no agreement on various aggregation alternatives ranging from statistical techniques such as principal components to more scientific ones that attach weights to individual indexes reflecting their toxicity levels.

The objective of this paper is measuring environmental performance through changes in pollution intensities in manufacturing industry. After defining pollution as a ratio of quantity index of undesirable outputs to quantity index of desirable outputs, changes in environmental performance is analyzed within an intertemporal setting. Since the pollution intensity index used in this study relies on computation of quantity indexes, it naturally produces a composite index. All our measures rely on computation of distance functions, which provide a valuable framework in modeling a technology with multiple outputs (i.e., desirable and undesirable). An empirical application on U.S. State manufacturing sectors further complements existing studies.

[1] MEFA applies the concepts of industrial ecology to study how materials and energy flow into, throughout, and out of a system.

The paper unfolds as follows. The following section will introduce Methodology. Section 3 is allocated to the presentation of the data source and discussion of results. Finally, Section 4 concludes.

2. Methodology

In developing a pollution intensity index, the modelling technique developed in a series of papers by Färe et al. (1999, 2000) and Zaim et al. (2001) is adopted. The computation of this index relies on the construction of a quantity index of bad outputs and a quantity index of good outputs by putting due emphasis on the distinctive characteristics of production with negative externalities. Intuitively, the quantity index of good outputs shows the relative success of an observation, say i, in expanding its good outputs while using the same level of inputs and producing the same level of pollutants as another observation say j, in an environment where the disposal of bad outputs are not free. The quantity index of bad outputs on the other hand measures the relative success of observation i in contracting its bad outputs while holding its good outputs and inputs at the same level as an other observation j. The ratio these two indexes provides an pollution intensity index. As is the standard convention in the index numbers literature, i and j can refer to observations of a given firm—for example in different time periods—or they may refer to different firms in a single time period.

To describe the theoretical underpinnings of the index used, suppose we observe a sample of K units each of which uses inputs $x=(x_1,\ldots,x_N)\in R_+^N$, to produce a vector of desirable outputs $y=(y_1,\ldots,y_M)\in R_+^M$ and undesirable outputs $b=(b_1,\ldots,b_J)\in R_+^J$. Using the notation at hand, the technology can be described as all feasible vectors (x,y,b), i.e., $T=\{(x,y,b){:}x$ can produce $(y,b)\}$. This technology, besides satisfying standard regularity conditions, should also account for distinctive characteristics of production with negative externalities such as nulljointness and weak disposability. The nulljointness can be formally expressed as

$$\text{if } (x,y,b)\in T \text{ and } b=0 \text{ then } y=0$$

to state that the production of good output without producing bad is impossible. The weak disposability of bad outputs on the other hand can be imposed with the following restriction

$$\text{if } (x,y,b)\in T \text{ and } 0\leq\theta\leq 1 (x,\theta y,\theta b)\in T$$

which requires a proportionate sacrifice from good output if a reduction is sought for bad outputs. In addition to the above two properties on the technology T, we assume that it meets standard properties like closedness and convexity. See Färe and Primont (1995) for details.

Among alternative approaches, distance functions prove to be a particularly useful tool not only to represent a technology with distinctive characteristics such as nulljointness and weak disposability, but also as being a perfect aggregator and a performance measure. Hence, output based distance function

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

for the subvector of good outputs and input based distance function

$$D_b(x,y,b)=\sup\{\lambda:(x,y,b/\lambda)\in T\}$$

for the subvector of bad outputs provide a basis for pollution intensity index.

More specifically following Färe et al. (1999), the quantity index of good outputs

$$Q_y(x^0,b^0,y^i,y^j)=\frac{D_y(x^0,y^i,b^0)}{D_y(x^0,y^j,b^0)}$$

which compares good outputs b^i and b^j given a vector of inputs x^0 and a vector of bad outputs b^0, and the quantity index of bad outputs

$$Q_b(x^0,y^0,b^i,b^j)=\frac{D_b(x^0,y^0,b^i)}{D_b(x^0,y^0,b^j)}$$

which compares bad outputs y^i and y^j given a vector of inputs x^0 and a vector of good outputs y^0, are used to define the pollution intensity index

$$\mathrm{PI}^{i,j}(x^0,y^0,b^0,y^i,y^j,b^i,b^j)=\frac{Q_b(x^0,y^0,b^i,b^j)}{Q_y(x^0,b^0,y^i,y^j)}.$$

Since both good output and bad output index satisfies all the desirable properties due to Fisher (1922)—i.e., homogeneity, time reversal, transitivity and dimensionality—pollution intensity index naturally passes the Fisher test.

One should note that, although beyond the scope of this paper, Material (Energy) Flow models, defined as models describing systems which take inputs from nature and return outputs into the nature, and the model presented above are in conformity not only with respect to their system view but also with respect to their evaluation criteria on ecological efficiency. In both the approaches, the higher the amount of desirable output produced per unit of resource or bad output, the more efficient a production unit (firm, region or country) is, in using its resources. Therefore, the modeling technique presented here, which relies explicitly on production theory (with negative externalities) and hence allows incorporation of technological progress, provides a useful alternative to those models, which rely on static input–output analysis. Because as will be demonstrated, identification of production units which face rebound effect, requires an intertemporal analysis where productivity increase (i.e., technological progress) is explicitly taken into account while measuring the changes pollution intensity over time, which we turn next.

As for the changes in pollution intensity over time, the relevant measure is the simultaneous success of a particular observation in contracting its bad outputs and expanding its good outputs from year t to year t+1 measured with respect to a common (manufacturing) benchmark technology constructed for the period t. The change in bads between two periods

$$\Delta Q_b^{t,t+1} = \frac{D_b^{k,t}(x^{k,t}, y^{k,t}, b^{k,t+1})}{D_b^{k,t}(x^{k,t}, y^{k,t}, b^{k,t})}$$

is the ratio of two distance functions where

$$D_b^{k,t}(x^{k,t}, y^{k,t}, b^{k,t+1}) = \sup\{\lambda^{k,t+1} : (x^{k,t}, y^{k,t}, b^{k,t+1}/\lambda^{k,t+1}) \in T^t\}$$

and

$$D_b^{k,t}(x^{k,t}, y^{k,t}, b^{k,t}) = \sup\{\lambda^{k,t} : (x^{k,t}, y^{k,t}, b^{k,t}/\lambda^{k,t}) \in T^t\}.$$

The first-distance function shows the success of an observation, say k, in contracting its bad outputs in year t+1 (with respect to a common frontier which represent the technology at t) while using the same level of inputs and producing the same level of good outputs goods as in year t (i.e., $x^{k,t}$ and $y^{k,t}$).[2] Similarly, the second-distance function measures the success of the same observation in contracting its bad outputs in period t with respect to a common frontier representing the technology at t. Note that, since the distances are measured with respect to the same benchmark (while holding resources and good outputs at their year t levels), the ratio provides the change in bad outputs for observation k.

Similarly after defining the change in good outputs as

$$\Delta Q_y^{t,t+1} = \frac{D_y^{k,t}(x^{k,t}, y^{k,t+1}, b^{k,t})}{D_y^{k,t}(x^{k,t}, y^{k,t}, b^{k,t})}$$

with relevant distance functions,

$$D_y^{k,t}(x^{k,t}, y^{k,t+1}, b^{k,t}) = \inf\{\theta^{k,t+1} : (x^{k,t}, y^{k,t+1}/\theta^{k,t+1}, b^{k,t}) \in T^t\}$$

and

$$D_y^{k,t}(x^{k,t}, y^{k,t}, b^{k,t}) = \inf\{\theta^{k,t} : (x^{k,t}, y^{k,t}/\theta^{k,t}, b^{k,t}) \in T^t\},$$

the change in pollution intensity between t and t+1 can be expressed as:

$$\Delta PI^{t,t+1} = \frac{\Delta Q_b^{t,t+1}}{\Delta Q_y^{t,t+1}}.$$

3. Data and results

The data used for the computation of the pollution intensity index is the same as in Färe et al. (2001)[3] which consists of state level observations on manufacturing output, inputs and emissions of pollutants.

[2] For some years, the technology constructed from observations in year t may not contain bad outputs in year t+1, i.e., $b^{k,t+1}$. In this case, linear programming problem will yield infeasible solutions.

[3] I gratefully acknowledge Carl Pasurka for providing the data used in this study.

Manufacturing output is proxied by Gross State Product (GSP) in manufacturing. The two inputs considered are the state aggregates of manufacturing employment and capital stock. The bad output data consists of emissions of SO_x, NO_x and CO by the manufacturing. The source of GSP in manufacturing and manufacturing employment is Regional Economic Information System of Bureau of Economic Analysis. Capital stock data is compiled in Munnell (1990). Data on emissions of air pollutants by the industrial sector is published by Environmental Protection Agency and allocated between manufacturing and non-manufacturing components by Färe et al. (2001). The period for which the data are compiled is 1972–1983 and 1985–1986. For the year 1984, EPA did not publish emissions of pollutants by states. For details in data construction, please see Appendix C in Färe et al. (2001).

In computing the distance functions which will form the basis of pollution intensity indexes, the data envelopment analysis (DEA) (or activity analysis) methodology is chosen among competing alternatives, so as to take advantage of the fact that the distance functions are perfect aggregator functions and reciprocals of Farrell efficiency measures. In this particular application, Alabama is chosen as the reference state.[4] Thus, we are assuming that $j=0$ which then refers to the associated quantities of Alabama. Letting $k=1,\ldots,K$ index the states in the sample, for each state $k'=1,\ldots,K$, we may compute for each year

$$(D_y(x^0,y^{k'},b^0))^{-1} = \max\theta$$

st

$$\sum_{k=1}^{K} z_k y_m^k \geq \theta y_m^{k'} \quad m=1,\ldots,M$$

$$\sum_{k=1}^{K} z_k b_j^k = b_j^0 \quad j=1,\ldots,J$$

$$\sum_{k=1}^{K} z_k x_n^k \leq x_n^0 \quad n=1,\ldots,N$$

$$z_k \geq 0 \quad k=1,\ldots,K$$

which is the numerator for $Q_y(x^0,b^0,y^i,y^j)$. The denominator is computed by replacing $y^{k'}$ on the right-hand side of the good output constraint with the observed output for Alabama, i.e., y^0. This problem, using the observed data on desirable outputs, undesirable outputs and inputs for each state, constructs the best practice frontier for the aggregate manufacturing industry for a particular year, 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. Nulljointness holds provided that

$$\sum_{k=1}^{K} b_j^k > 0 \quad j=1,\ldots,J$$

$$\sum_{j=1}^{J} b_j^k > 0, \quad k=1,\ldots,K.$$

The first condition states that each bad is produced at least once, and the second condition tells us that at each k some bad output is produced. These conditions are met for 41 states in our sample.[5]

For the bad index, for each state $k'=1,\ldots,K$, we compute for each year

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

st

$$\sum_{k=1}^{K} z_k y_m^k \geq y_m^0 \quad m=1,\ldots,M$$

$$\sum_{k=1}^{K} z_k b_j^k = \lambda b_j^{k'} \quad j=1,\ldots,J$$

$$\sum_{k=1}^{K} z_k x_n^k \leq x_n^0 \quad n=1,\ldots,N$$

$$z_k \geq 0 \quad k=1,\ldots,K$$

which is the numerator for $Q_b(x^0,y^0,b^i,b^j)$. The denominator is computed by replacing $b^{k'}$ on the right-hand side of the bad output constraint with the observed bad outputs for Alabama, i.e., b^0. As above, this problem constructs the best practice frontier from the observed data and computes the scaling factor on

[4] Alternatively, one could use a hypothetically average state as a base, in which case results would be independent of Alabama as a base.

[5] West Virginia, New York, South Dakota, Arizona, Nevada, Vermont and Oklahoma failed to satisfy nulljointness (see Färe et al., 2001) and hence are excluded from the analysis.

bad outputs required for each observation to attain best practice. Finally, the ratio of $Q_b(x^0,y^0,b^i,b^j)$ to $Q_y(x^0,b^0,y^i,y^j)$ results in a pollution intensity index with basis chosen as Alabama. Nevertheless, since this index is transitive it allows any bilateral comparison among two states.

While constructing the reference technologies in the above linear programming problems, a multiple year windows data is employed as in Färe et al. (2001). In this particular application, it is assumed that the reference technology at time period t (i.e., the left side of equalities and inequalities in the linear programming problems) is determined by observations from period t and previous two periods, i.e., $t-1$ and $t-2$. This proved to be a particularly useful exercise in reducing the number of infeasible solutions in two mixed period linear programming problems that are constructed to compute the change in pollution intensity (see footnote 1). Furthermore, the data being evaluated (i.e., the right side of equalities and inequalities in the linear programming problems) are also chosen to be 3-year moving averages (i.e., average of observations in year t and the previous 2 years $t-1$ and $t-2$) in order to smooth the data by reducing fluctuations due to chance events.

Table 1, in addition to the composite index of pollution intensity measure computed using the methodology described above, provides crude measures of pollution intensities measured with respect to Alabama for three selected years. Although the results show considerable variation in relative rankings of states with respect to the composite measure of pollution intensities across the years, Connecticut, Massachusetts, New Hampshire and Rhode Island have kept their position within the best 10 performers. Montana, New Mexico, North Dakota, Texas and Wyoming on the other hand, were persistently ranked within the 10 states with highest pollution intensity. Although by construction comparison of this composite pollution index across years does not reveal information on the growth rate of pollution intensity, comparison of the relative positions of states across years disclose some interesting results. One particularly interesting result is that, the spread between the worst and the best performer increases considerably in time. For example, the comparison of the worst and the best performers reveals that while the pollution intensity of Montana in 1974 was 43 times higher than Connecticut, this figure is 145 times between Wyoming and Rhode Island in 1980 and 338 times between Wyoming and Massachusetts in 1985. One also notes that, the differences between crude measures of pollution intensities are also in conformity with this general pattern of increased spread between the best and the worst performers. A comparison shows that, while emission of SO_x, NO_x and CO per unit of manufacturing output in Montana are respectively 258, 13 and 913 times higher than in Connecticut in 1974, corresponding figures are 148, 404 and 1698 times between Wyoming and Massachusetts in 1985.

Now we turn our attention to the intertemporal analysis of pollution intensities proposed in this study. The numerator of $\Delta\mathrm{PI}^{t,t+1}$ shows the annual change in a composite measure of pollution emissions (i.e., from period t to t+1) measured with respect to the reference technology of the base period t. This requires for each k', solution of two linear programming problems:

$$\begin{aligned}
&(D_b^{k't}(x^{k',t}, y^{k',t}, b^{k',t+1}))^{-1} = \min \lambda^{k',t+1}\\
&\text{st}\\
&\sum_{k=1}^{K} z_k b_{kj}^t = \lambda^{k',t+1} b_{k'j}^{t+1} \quad j = 1,\ldots,J\\
&\sum_{k=1}^{K} z_k y_{km}^t \geq y_{k'm}^t \quad m = 1,\ldots,M\\
&\sum_{k=1}^{K} z_k x_{kn}^t \leq x_{k'n}^t \quad n = 1,\ldots,N\\
&z_k \geq 0 \quad k = 1,\ldots,K.
\end{aligned}$$

The second linear programming problem can be computed in a similar fashion by replacing $\lambda^{k',t+1}$ with $\lambda^{k',t}$ and $b_{k'j}^{t+1}$ on the right side of the first equality with $b_{k'j}^{t}$. The solution to these two linear programming problems yields $\Delta Q_b^{t,t+1}$ which is the numerator of $\Delta\mathrm{PI}^{t,t+1}$.

In Table 2, we provide the average annual growth rates of the three pollutants and the average annual change in a composite measure of pollution emission which is termed as $\Delta Q_b^{t,t+1}$. Following the usual index number convention, while figures greater than one show an increase (percentage increase can be calculated by subtracting 1 and multiplying by 100) figures less than one represent a decrease. The results under

Table 1
Emission per unit of manufacturing output (measured with respect to Alabama)

	1974					1980					1985				
	SO_x	NO_x	CO	Pollution intensity	Rank	SO_x	NO_x	CO	Pollution intensity	Rank	SO_x	NO_x	CO	Pollution intensity	Rank
Alabama	1.000	1.000	1.000	1.000	13	1.000	1.000	1.000	1.000	8	1.000	1.000	1.000	1.000	8
Arkansas	0.176	0.649	0.041	0.269	33	0.309	0.651	0.849	0.424	16	0.362	0.949	0.704	0.340	22
California	0.149	0.546	0.069	0.333	30	0.189	0.372	0.155	0.328	22	0.058	0.318	0.046	0.210	33
Colorado	0.360	0.180	0.471	0.236	35	0.273	0.483	0.628	0.292	27	0.034	0.422	0.032	0.141	37
Connecticut	0.055	0.219	0.002	0.129	41	0.042	0.065	0.048	0.077	40	0.032	0.032	0.004	0.046	40
Delaware	1.798	0.714	0.109	0.490	24	0.349	0.252	0.013	0.216	33	1.326	0.615	0.234	0.402	16
Florida	0.487	0.898	0.117	0.813	14	1.012	0.468	0.372	0.554	13	0.329	0.311	0.172	0.298	24
Georgia	0.333	0.830	0.266	0.482	26	0.271	0.340	0.400	0.339	21	0.339	0.493	0.487	0.378	17
Idaho	1.061	2.065	0.040	1.302	6	0.917	0.334	0.290	1.155	7	0.997	0.757	0.120	0.588	12
Illinois	0.293	0.472	0.144	0.332	31	0.257	0.240	0.261	0.229	30	0.573	0.475	0.146	0.442	15
Indiana	0.613	1.220	0.308	1.540	4	0.459	0.469	0.393	0.505	15	0.882	0.816	1.392	0.636	10
Iowa	0.375	0.646	0.105	0.484	25	0.339	0.352	0.201	0.389	17	0.497	0.474	0.037	0.249	28
Kansas	0.251	0.743	0.443	0.462	27	0.151	3.040	0.395	0.144	36	0.365	2.366	0.506	0.366	18
Kentucky	0.330	0.245	0.078	0.208	38	0.384	0.260	0.355	0.302	24	0.499	0.818	0.301	0.332	23
Louisiana	1.389	7.781	5.539	1.890	2	0.814	3.333	3.831	0.241	28	2.283	5.986	4.217	0.616	11
Maine	1.378	1.770	0.484	1.247	7	1.443	0.528	0.468	0.765	10	1.216	0.595	0.245	0.149	36
Maryland	0.492	1.034	0.226	0.578	21	0.265	0.258	0.214	0.323	23	0.378	0.468	0.107	0.360	19
Massachusetts	0.174	0.364	0.011	0.223	37	0.065	0.061	0.007	0.079	39	0.097	0.088	0.006	0.044	41
Michigan	0.200	0.638	0.107	0.563	22	0.254	0.228	0.234	0.195	35	0.164	0.264	0.149	0.257	26
Minnesota	0.321	0.604	0.219	0.453	28	0.177	0.291	0.123	0.301	25	0.148	0.232	0.199	0.215	32
Mississippi	0.248	0.920	0.154	0.550	23	0.818	1.565	0.507	1.274	5	0.554	1.090	0.527	1.040	7
Missouri	0.722	0.860	0.175	0.624	18	0.370	0.340	0.144	0.217	32	0.721	0.373	0.229	0.250	27
Montana	14.202	2.930	1.826	5.573	1	8.890	1.815	5.171	0.822	9	6.044	3.274	2.181	1.723	4
Nebraska	0.243	1.509	0.076	0.417	29	0.209	0.659	0.111	0.361	19	0.126	0.337	0.018	0.246	29
New Hampshire	0.195	0.271	0.064	0.235	36	0.233	0.089	0.063	0.091	38	0.075	0.068	0.111	0.114	38
New Jersey	0.131	0.482	0.087	0.259	34	0.237	0.277	0.109	0.294	26	0.135	0.248	0.013	0.205	34
New Mexico	17.074	2.072	0.152	1.146	8	15.493	10.249	0.597	1.890	4	8.529	8.436	0.564	4.988	2
North Carolina	0.182	0.374	0.105	0.312	32	0.283	0.220	0.190	0.237	29	0.277	0.284	0.204	0.258	25
North Dakota	1.344	1.916	0.673	1.100	10	1.730	0.939	0.095	2.088	3	8.392	4.379	0.227	2.949	3
Ohio	0.528	0.689	0.096	0.667	16	0.400	0.304	0.573	0.136	37	0.368	0.273	0.280	0.352	21
Oregon	0.106	1.403	0.030	0.188	40	0.148	0.661	0.121	0.226	31	0.190	0.327	0.161	0.172	35
Pennsylvania	0.383	0.479	0.115	1.061	11	0.677	0.298	0.541	0.198	34	0.302	0.404	0.351	0.359	20
Rhode Island	0.094	0.272	0.016	0.191	39	0.041	0.061	0.027	0.075	41	0.040	0.065	0.003	0.064	39
South Carolina	0.398	0.897	0.274	0.599	20	0.400	0.463	0.170	0.570	12	0.520	0.542	0.202	0.551	13
Tennessee	0.409	0.835	0.230	0.607	19	0.415	0.602	0.325	0.723	11	0.619	0.630	0.368	0.758	9
Texas	1.007	3.298	1.153	1.433	5	1.032	3.694	2.323	2.106	2	1.134	2.964	0.726	1.104	6
Utah	2.334	1.527	0.464	1.007	12	1.010	1.043	0.406	1.260	6	0.680	1.521	0.564	1.401	5
Virginia	0.516	1.086	0.258	0.693	15	0.440	0.475	0.226	0.511	14	0.652	0.621	0.136	0.540	14
Washington	0.664	1.760	0.326	1.116	9	0.960	0.322	0.679	0.367	18	0.435	0.455	1.411	0.217	31
Wisconsin	0.304	0.954	0.061	0.645	17	0.383	0.303	0.069	0.340	20	0.379	0.292	0.138	0.237	30
Wyoming	2.110	4.968	6.260	1.817	3	6.383	12.161	5.568	10.921	1	14.410	35.603	10.193	14.899	1

the column $\Delta Q_b^{t,t+1}$ display that five states: New Mexico, Louisiana, North Dakota, Arkansas and Kansas recorded substantially high average annual growth rates—all well beyond 10%—in the emission of pollutants and that an additional 12 states had positive growth rates. However, New Jersey, Washington and Rhode Island were depicted as being the most successful states in reducing the emission of pollutants at rates above 10% per annum. A comparison of annual growth rates of the composite measure of pollution emissions with those of crude measures also reveals the advantage of the former with respect

Table 2
Growth rates of pollutants

States	Infeasible solutions	Average annual growth rates				Rank
		SO_x	NO_x	CO	$\Delta Q_b^{t,t+1}$	
Alabama		0.963	1.032	0.930	1.025	11
Arkansas		1.094	1.076	1.100	1.154	4
California		0.950	0.951	0.922	0.922	34
Colorado	1	0.940	1.080	0.866	1.095	6
Connecticut		0.908	0.902	1.039	0.916	36
Delaware		0.901	1.012	0.974	0.948	27
Florida		0.968	0.961	0.988	0.997	18
Georgia		0.988	1.027	1.007	1.009	15
Idaho		0.937	0.965	1.090	0.959	25
Illinois		0.973	1.002	0.823	0.940	29
Indiana		0.935	0.892	0.883	0.947	28
Iowa		0.996	0.978	0.793	0.966	23
Kansas	2	0.979	1.124	0.938	1.114	5
Kentucky		0.975	1.098	0.954	1.008	16
Louisiana	6	0.977	1.057	0.872	1.346	2
Maine		0.970	0.973	0.937	1.064	8
Maryland		0.906	0.955	0.932	0.972	20
Massachusetts		0.925	0.942	0.919	0.909	37
Michigan		0.911	0.840	0.912	0.934	32
Minnesota		0.914	1.037	0.913	0.919	35
Mississippi		1.081	1.076	1.023	1.081	7
Missouri		0.922	0.960	0.943	0.938	30
Montana		0.841	0.922	0.909	0.907	38
Nebraska	1	0.946	0.940	0.859	0.965	24
New Hampshire		0.954	0.991	1.044	0.970	22
New Jersey		0.940	0.967	0.777	0.834	41
New Mexico	1	0.962	1.173	1.096	1.401	1
North Carolina		1.006	1.002	0.994	1.005	17
North Dakota	1	1.127	1.166	1.028	1.248	3
Ohio		0.893	0.933	0.893	0.937	31
Oregon		0.989	0.953	1.138	1.015	13
Pennsylvania		0.893	0.845	0.963	0.933	33
Rhode Island		0.877	0.918	0.854	0.878	39
South Carolina		0.994	1.009	0.936	1.015	14
Tennessee		0.995	1.030	0.957	1.021	12
Texas		0.997	1.057	0.898	0.972	21
Utah		0.912	1.076	0.963	1.051	9
Virginia		0.967	0.995	0.929	0.982	19
Washington	1	0.915	0.924	1.008	0.836	40
Wisconsin		0.964	0.932	0.983	0.950	26
Wyoming	5	1.068	1.183	0.883	1.026	10

to the crude measures. Note for example that a comparison of the crude measures of emission growth would lead one to falsely claim that environmental performance in North Dakota deteriorated more than in Louisiana since growth rate for each pollutant is higher in North Dakota than the corresponding figures in Louisiana. But one should also note that the crude measures of pollution growth do not account for neither the change in resource use nor the change in desirable output production. Nevertheless, changes in resource use and desirable output production are accounted for in computing the growth of pollution emissions by the $\Delta Q_b^{t,t+1}$ measure.

The denominator of the change in pollution intensity $\Delta \mathrm{PI}^{t,t+1}$, requires solution to additional two linear programming problems which would yield the change in desirable outputs (i.e., $\Delta Q_y^{t,t+1}$) between period t and t+1. The solution to

$$(D_y^{k't}(x^{k'.t}, y^{k',t+1}, b^{k',t}))^{-1} \quad = \max \theta^{k',t+1}$$

st

$$\sum_{k=1}^{K} z_k b_{kj}^t = b_{k'j}^t \quad j = 1, \ldots, J$$

$$\sum_{k=1}^{K} z_k y_{km}^t \geq \theta^{k',t+1} y_{k'm}^{t+1} \quad m = 1, \ldots, M$$

$$\sum_{k=1}^{K} z_k x_{kn}^t \leq x_{k'n}^t \quad n = 1, \ldots, N$$

$$z_k \geq 0 \quad k = 1, \ldots, K.$$

problem yields the success of an observation, say k, in expanding its manufacturing output in year t+1 (with respect to a common frontier which represent the technology at t) while using the same level of inputs and emitting the same level of pollutants as in year t (i.e., $x^{k,t}$ and $b^{k,t}$). The second problem, which measures the expansion of manufacturing output in year t, can be formulated by replacing $\theta^{k',t+1}$ with $\theta^{k',t}$ and $y_{k'm}^{t+1}$ on the right side of the second inequality with $y_{k'm}^t$.

Table 3 provides average annual growth rates for composite index of pollution emissions, manufacturing output and pollution intensity. Starting from the last row of this table which shows the weighted geometric mean of corresponding columns (where weights are the share of each state in total manufacturing output), we observe that between 1974 and 1986 emissions of pollutants have been decreasing at the rate of 4.3% per annum. This, coupled with a 2.4% average annual increase in manufacturing output, led to an average annual reduction of 6.5% in pollution intensity. Note however that, in 10 states (Louisiana, New Mexico, North Dakota, Arkansas, Kansas, Wyoming, Colorado, Mississippi, Maine and

Table 3
Growth rate of pollution intensity and its components

States	Infeasible solutions	Average annual growth rates			Rank
		$\Delta Q_b^{t,t+1}$	$\Delta Q_y^{t,t+1}$	$\Delta PI^{t,t+1}$	
Alabama		1.025	1.030	0.995	12
Arkansas		1.154	1.040	1.109	4
California		0.922	1.046	0.881	36
Colorado	1	1.095	1.049	1.043	7
Connecticut		0.916	1.024	0.894	35
Delaware		0.948	1.015	0.934	28
Florida		0.997	1.057	0.943	22
Georgia		1.009	1.046	0.965	17
Idaho		0.959	1.038	0.924	31
Illinois		0.940	0.995	0.945	21
Indiana		0.947	0.999	0.949	20
Iowa		0.966	1.025	0.943	23
Kansas	2	1.114	1.021	1.091	5
Kentucky		1.008	1.005	1.003	10
Louisiana	6	1.346	1.009	1.333	1
Maine		1.064	1.038	1.026	9
Maryland		0.972	1.010	0.962	18
Massachusetts		0.909	1.038	0.876	38
Michigan		0.934	1.000	0.935	27
Minnesota		0.919	1.045	0.879	37
Mississippi		1.081	1.042	1.037	8
Missouri		0.938	1.022	0.919	33
Montana		0.907	0.982	0.923	32
Nebraska	1	0.965	1.032	0.936	25
New Hampshire		0.970	1.078	0.899	34
New Jersey		0.834	1.008	0.827	40
New Mexico	1	1.401	1.075	1.303	2
North Carolina		1.005	1.033	0.973	15
North Dakota	1	1.248	1.049	1.189	3
Ohio		0.937	1.002	0.935	26
Oregon		1.015	1.016	0.999	11
Pennsylvania		0.933	0.994	0.938	24
Rhode Island		0.878	1.017	0.863	39
South Carolina		1.015	1.044	0.972	16
Tennessee		1.021	1.032	0.990	14
Texas		0.972	1.043	0.931	29
Utah		1.051	1.058	0.994	13
Virginia		0.982	1.031	0.953	19
Washington	1	0.836	1.015	0.824	41
Wisconsin		0.950	1.026	0.926	30
Wyoming	5	1.026	0.951	1.079	6
Weighted geo. Mean		0.957	1.024	0.935	

Kentucky) pollution emissions have increased at faster rates than manufacturing output and hence leading to increased pollution intensities over time. In five states (Alabama, North Carolina, Oregon, Tennessee and Utah), we simultaneously observe decreasing pollution intensities with increased pollution emissions which constitute an example to the criticism that reduced pollution intensity does not necessarily imply reduced emissions. This is the rebound effect as commonly referred to in studies within the framework of MEFA. In all other states, reduced pollution emissions coupled with increased manufacturing output, led to the reduction in pollution intensities.

In studies on MEFA, the changes in resource use efficiency are mostly attributed to structural changes, i.e., a shift from industrial to services production, and to lighter less producing industries within manufacturing. Hence, in a final analysis, the likely effects of structural changes on the change in pollution intensities are analyzed within a pooled regression framework. The dependent variable $\Delta PI^{t,t+1}$ is regressed on explanatory variables: Share of manufacturing in State Gross Product (MANSHARE), share of polluting industries in Gross State Product in manufacturing (POLSHARE) and the level of pollution, i.e., PI. The square of MANSHARE and POLSHARE are also included in order to depict any quadratic relationship between change in pollution intensities and these variables. The source of explanatory variables is BEA, which provides disaggregated data on Gross State Product from 1977 onwards. In computing the share of polluting industries in Gross State Product in manufacturing, paper and allied products (SIC 26), chemicals and allied products (SIC28), petroleum and coal products (SIC29), stone clay and glass products (SIC32) and primary metal industries (SIC 33) are considered as polluting industries as in Färe et al. (2001). Our pooled sample consists of all feasible solutions for 41 states and 7 years. Since our data set do not include year 1984, the change in pollution intensity between 1983 and 1985 has been discarded to be consistent with annual observations for explanatory variables.

Table 4 shows the parameter estimates of the pooled regression with a common intercept estimated using OLS technique. An F test performed on the alternative specifications of the fixed effects model failed to reject the null hypothesis of a common intercept, against the model with state-specific intercept terms. This is as expected due to difficulties in capturing state specific effects with only seven observations over time. In addition, various specification tests performed reveals that residuals are homoskedastic and are not autocorrelated.

Table 4
Pooled regression estimation explaining change in pollution intensity

	Parameter estimate	*t*-statistics
CONSTANT	1.7862	7.194
MANSHARE	−9.5781	−5.053
$(\text{MANSHARE})^2$	18.8824	4.572
POLSHARE	2.6713	2.218
$(\text{POLSHARE})^2$	−3.9897	−2.117
PI	−0.1199	−3.434
Adj. R^2	0.095	
F statistics	6.5	

The parameter estimates, which are all significant at 5% significance level, suggest a quadratic relationship between change in pollution intensity and the two explanatory variables MANSHARE and POLSHARE. The quadratic relationship between change in pollution intensity and MANSHARE is of U type with turning point of 0.25. This indicates that increased share of manufacturing in gross state product over 25% puts an upward pressure on the growth of pollution intensities. The quadratic relationship between change in pollution intensity and POLSHARE variable is of inverse U type with a turning point of 0.34. This suggests that, increased share of polluting industries in the manufacturing industry puts an upward pressure on the growth of pollution intensities until the share of polluting industries in manufacturing industry reach to 34%. As the share of polluting industries increase beyond this turning point, there is a downward pressure on the change in pollution intensities, which may be due to regulatory constraints which are binding especially when some threshold level of emission levels are reached. The negative and significant coefficient of the pollution intensity variable PI indicates that there is a downward pressure on the growth of pollution intensities as the level pollution intensity increase and hence supports the view that regulatory constraints become increasingly more binding for states which reach certain emission levels.

4. Conclusions

In decomposing the total emissions into scale and pollution intensity, the conventional approach uses the total output as a measure of scale, and hence ignores the fact that pollution is mainly a byproduct of the manufacturing activity. This study recognizing that air pollution is mainly a byproduct of manufacturing activity proposes a new definition of pollution intensity—pollution per unit of manufacturing output—, and a new technique to measure the aggregate pollution intensity. The index used is a variant of Malmquist quantity index and satisfies well-established axiomatic properties. One other focal point of this study is the overtime comparisons of pollution intensities, i.e., change in pollution intensity, using indexes that are firmly established in productivity growth literature.

An empirical application on U.S. State manufacturing sectors (by using a new data set on state level manufacturing production and emission of pollutants) the study provides both cross sectional and overtime comparisons of environmental performance for individual states between 1974 and 1986. In a final analysis, the likely effects of structural changes on the growth of pollution intensities are analyzed within a pooled regression framework. The results suggest that, share of manufacturing in total state product and share of polluting industries in total manufacturing activity are two important factors determining change in pollution intensities overtime.

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