Obamacare and environmental production efficiency rankings for the 50 U.S. state governments: A Data Envelopment Analysis of health outcomes from environmental factors and state health care expenditures

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Abstract

This paper examines the health performance rankings of the 50 U.S. state governments (SGs), and addresses the relationship between SG performance rankings and SG environmental health, economic prosperity, and state healthcare policy. We use the data envelopment analysis (DEA) to estimate and compare the relative performance of the 50 SGs in a single measure. Our analyses indicate that new federal mandates, such as, universal or nearly universal health care coverage, and timely resources or lack of them from the federal government, may lead to very different state health performance outcomes. Our analyses also highlight the tradeoffs between given inputs and desired outputs involved in attaining a certain level of health performance efficiency. In particular, they show that limiting harmful exposures by timely investments in prevention is far more cost-effective than subsequent incurrence of health care expenditures in treatment of the affected population. Finally, our findings indicate that a fixed amount of federal funding per capita could lead to different health performance outcomes in different states, depending on the level of efficiency with which the SG operates during the funding period.

Keywords: Environment, Health Care, Obamacare, Efficiency ranking, DEA, U.S. State governments

1. Introduction

President Barak Obama signed the Affordable Care Act on March 26, 2010 which has the potential to significantly impact the health care delivery in America. Oftentimes, in the Congressional debates scientific evidence was missing or overwhelmed by partisan propaganda. According to the current health care mandate (sometimes, euphemistically referred to as the Obamacare), state governments will play a vital role in health care delivery in America. This paper analyzes the 50 U.S state governments' (SG) track record, and considers which environmental conditions and policies affect health outcomes most.

We identify the health performance rankings of the 50 U.S SGs, based on healthy outcomes on the one hand, and pollution levels and state health-care policy on the other hand. We use data envelopment analysis (DEA) in order to compare the relative performance of the 50 SGs in producing healthy outcomes. We benchmark the best SG's health performance record in a single measure, and then compare health performance records to each other. Our analyses indicate that new federal mandates, such as, universal or nearly universal health care coverage, and timely resources or lack of them from the federal government, may lead to very different state health performance outcomes. Our analyses also highlight the tradeoffs between given inputs and desired outputs involved in attaining a certain level of health performance efficiency. In particular, they show that limiting harmful exposures by timely investments in prevention is far more cost-effective than subsequent incurrence of health care expenditures in treatment of the affected population. Finally, our empirical results indicate that a fixed amount of federal funding per capita could lead to different health performance outcomes in different states, depending on the level of efficiency with which the SG operates during the funding period.

The rest of the paper is as follows. Section 2 provides a brief overview of the known links between environmental effluxents and health outcomes. Section 3 explains the methodological procedures for the DEA rankings, and then specifies the DEA model, with details on selection of individual inputs and outputs. Section 4 discusses the efficiency status and ranking of the SGs. Section 5 provides additional comparison of our analysis to another non-DEA based ranking of healthy lives between states. Section 6 summarizes the conclusions and provides important policy recommendations.

2. Review of the link between environmental toxins and poor health outcomes

Environmental toxins (heavy metals, solvents and pesticides) from hazardous waste-disposal facilities and manufacturing, mining and agricultural activities along with ambient air and water pollutants cause various health problems, such as, cancer, respiratory morbidity, coronary heart disease, brain damage, neurotoxicological difficulties, and in utero teratological effects (Holgate et al [1]; Johnson [2]; Lippman [3]; Scott [4]; National Research Council [5]). Many of these toxins, even in low doses, are particularly dangerous during fetal development (Riley and Vorhees [6]; Burnett et al. [7]). In a recent working paper, Currie, et. al., [8] investigate the effect of Superfund cleanups on infant health by analyzing births to mothers residing within 5km of a Superfund site. They use a "difference in differences" approach comparing birth outcomes before and after a site clean-up for mothers who live within 2,000 meters of the site, and those who live between 2,000- 5,000 meters of a site. They find that geographic proximity to a Superfund site prior to cleanup is associated with a 20 to 25% increase in the risk of congenital anomalies.

The World Health Organization [9] identified ambient air pollution as responsible for 1.4% of all deaths and 0.8% of disability -adjusted life years globally. Studies have demonstrated increased mortality with increased ambient particulate levels in urban areas, including 90 of the largest U.S. cities, and European and Canadian cities as well (Dominici et al., [10]; Katsouyanni et al., [11]; Burnett et al., [12]; Katsouyanni et al., [13]). Long-term exposure to air pollution has also been linked to mortality and increased risk of lung cancer mortality (Dockery et al. [14]; Pope et al. [15, 16]; Krewski et al. [17, 18]). Low levels of air pollution affect early stages of human development as well. Liu et al. [19] found low ambient air pollution concentrations associated with adverse pregnancy outcomes (low birth weight, preterm birth, and intrauterine growth retardation). Not only is air pollution associated with increased mortality and morbidity, it is also linked to an increase in the number of hospital admissions (Burnett et al., [12, 20]; Linn et al., [21]; Peters et al. [22]; Oftedal et al. [23]). According to the U.S. Environmental Protection Agency (EPA) [24], the monetized benefits of the Clean Air Act are $22,171 billion while the estimated costs are $523 billion, both in 1990 dollars. More than four-fifths of these benefits are from avoided mortality, valued at $4.6 million per life.

In addition to air pollution, environmental toxins pollute drinking water. The EPA [25] reports that 74% of the hazardous waste sites are associated with ground water contamination. Griffith et al. [26] studied the link between hazardous waste sites (HWS) in U.S. counties and cancer mortality rates. They found a significant association between excess deaths and all HWS counties for cancers of the lung, bladder, esophagus, stomach, and large intestine compared to non-HWS counties. Wright, Schwartz and Dockery [27] studied the effect of disinfection by-products (DBPs) in the water supply of 109 towns in Massachusetts on birth weight and gestational duration. They observed reduced mean birth weights and increased risk for being small for gestational age with increased maternal toxin exposures. The association of DBPs and the risk of low birth weight have been found by other studies as well (Bove et al., [28]; Savitz et al., [29]; Gallagher et al., [30]). Thus, there seems to be sufficient evidence linking environmental toxins to poor health outcomes, such as, increased mortality and morbidity.

3. A DEA approach to state health outcomes efficiency

Data envelopment analysis (DEA) is a multi-criteria linear-programming tool for comparing relative performance of a set of entities called, decision making units or DMUs (See, for example, Feroz, et. al., [31]; Premchandra, et. al., [32]; Chang, et. al., [33]). Comparisons of SGs are made by employing a common set of outputs (outcomes or goals) and inputs (resources or impediments to achieving goals). Frontier efficiency measurement is used extensively to evaluate health service delivery, particularly, technical efficiency within hospitals and nursing homes (Chang, et. al., [34]; Jacobs, et. al., [35]). Most of this research focuses on intermediate outputs, such as, numbers of patients treated, inpatient days or discharges rather than final outputs like, health gains of individual patients, mortality or quality of care. Input variables typically include measures of staff and capital used. Hollingsworth [36] reviewed over 300 articles using frontier efficiency (DEA and stochastic frontier analysis) in health care. Frontier efficiency methods are used to analyze general health as well. For instance, general health was analyzed in India using infant mortality rates as a function of literacy, income, water availability and health care (Kathuria & Sankar [37]).

A variant of the DEA model is the additive DEA model. It employs a criterion of maximizing several indicators of a state's health outcomes, while simultaneously minimizing pollutants and health care resources. The most efficient SG produces a maximum of good health outcomes by controlling the release of hazardous compounds, and by controlling health care and health insurance expenditures, and state environmental regulation costs. This approach allows a DEA evaluation to support the proposition that SGs which employ the least hazardous production technologies in its agricultural, chemical and industrial sectors, and at the same time maintain the most efficient use of public and private health care resources will likely result in more healthy outcomes.

A well-managed health program produces the maximum of good health outcomes while minimizing both emission of environmental pollutants or clean-up and health care resources. Our model incorporates commonly discussed and interrelated environmental and economic components, and systematically incorporates them into an operational definition of SG health-care effectiveness. Variables considered for inclusion in this analysis include measures of toxic chemicals released into the environment by industrial pollution, health expenditures which appear to be responsive to the effects of toxic chemicals, and variables which may contribute either to the level of toxic chemicals produced and released as well as contributing to the level of exposure of the population to these chemicals.

3. a. Model Specification

The particular variables selected in the DEA analysis were based on correlations primarily between inputs and outputs, while autocorrelations were also considered. Table 1 illustrates the Pearson correlations between the variables used in this paper. Correlations with other inputs and outputs considered, but not included in this table, are available by request. Of central importance to the environmental efficiency argument, correlations of outputs bear the appropriate negative signs with inputs. For example, higher average infant birth weights (Y1) or lower premature cancer deaths (Y2) are associated with less pollution (X1 or X2). Alternatively, lower average birth weights (original or untransformed Y1) also are associated with fewer public health care expenditures (X3 or X4) and pollution abatement costs (X5), indicating states with cleaner industries and cleaner environments have fewer public health policy expenditures. The model is specified as follows:

Maximize:
Y_1 = Healthy Birth Weight
Y_2 = DISTYLPDCANCER

Minimize:
X_1 = RCRA Total
X_2 = TRI Total
X_3 = Heath Care Expenditures
X_4 = Percent of Health Care Uninsured
X_5 =Pollution Abatement Operating Costs (PAOC)

Variables are defined as follows (including the sources of data):

Y_1= HEALTHY BIRTH WEIGHT is 100 % minus the percent of low birth weights (below 5lb. 8oz or 2500 grams) and represents a healthy outcome to be maximized [38].

Y_2= DISTYLPDCANCER is a distance transformation defined as the difference between the SG with the highest premature death from cancer before age 75 (SG max) and the ith SG under consideration (SGmax - SG_i). This distance is maximised. The transformed variable is interpreted as low premature death rate from cancer [39].

X_1= RCRA Total is the quantity of hazardous waste generated, per square mile of land area by SG, as defined in the Resource Conservation and Recovery Act and reported in the National Biennial RCRA Hazardous Waste Report based on 2005 data [40].

X_2= TRI Total is defined as the sum of the quantities of point-source and fugitive air emissions and surface water discharges per square mile of land area of those chemicals listed in the Toxic Release Inventory or TRI [40, 41].

X_3= Health Care Expenditures is defined as SG funded direct and population based health care expenditures including treatment, prescription drugs, and hospitalizations paid for by the SG, as a percent of gross state product [42].

X_4= Health Care Uninsured is defined as the percent of a state's population without health insurance coverage [43].

X_5= Pollution Abatement Operating Costs (PAOC) is defined as the pollution abatement operating costs for all industries as a per cent of gross state product, including treatment, prevention, recycling and disposal costs [44, 45].

Table 1 : Correlations

		Healthy Birth Weight	DIST YLPD CANCER	RCRA Total	TRI Total	Health Care Expenditures	Health Care Uninsured	PAOC
		Y_1	Y_2	X_1	X_2	X_3	X_4	X_5
Healthy Birth Weight	Y_1	1.000						
DIST YLPD CANCER	Y_2	0.700[a]	1.000					
RCRA Total	X_1	-0.397[a]	-0.336[b]	1.000				
TRI Total	X_2	-0.336[b]	-0.359[a]	0.197[b]	1.000			
Health Care Expenditures	X_3	-0.311[b]	-0.420[a]	0.153	-0.096[c]	1.000		
Health Care Uninsured	X_4	-0.310[b]	-0.135	0.186	-0.133	-0.032	1.000	
PAOC	X_5	-0.502[a]	-0.583[a]	0.442[a]	0.287[b]	0.272[b]	0.175	1.000

a Significant at the 0.01 level
b Significant at the 0.05 level
c Significant at the 0.10 level

3. b. A brief description of the additive DEA model and stability index formulation of efficiency indexes

The DEA approach objectively determines a set of weights or coefficients for inputs and output variables that allow the SG to achieve its highest efficiency ranking among its peers. One linear program is computed for each SG. For a given SG, the best set of weights are chosen for a particular combination of outputs and inputs which allows that SG to achieve its highest efficiency score. The remaining SGs are constrained to employ that SG's "best practice" set of weights. This approach allows an SG to choose its best balance between health care outcomes and toxic releases, health care resources, and pollution abatement stringency.

Unlike the CCR model [46] and the BCC model [47], the additive model is neither strictly input-oriented nor output-oriented. These models measure radial inefficiency by either an input or an output distance to the frontier. Since the additive model is neither input nor output oriented, DEA can construct a stability index that simultaneously maximizes "good" indicators and minimizes "bad" indicators, even without assuming a specific production function or transformation relationship. Although our model does specify a loose production relationship, as indicated by the signs of the correlation coefficients in Table 1, it is primarily a health performance index. Other health performance indexes do not distinguish between inputs (resources) and outputs (goals) and utilize fixed or subjective weights.

As we have already mentioned, DEA is an analytical tool for evaluating the relative efficiency of an SG that employ the same multiple inputs and multiple outputs. As a linear programming notion of technical efficiency (Farrell [48]), DEA constructs an efficient frontier composed of those SGs that consume as few inputs, such as, toxic compounds and health care resources as possible, while producing as many good health outcomes (outputs) as possible. The SGs that comprise the efficient frontier are classified as efficient, while those not on the efficient frontier are inefficient (enveloped or dominated by the efficient SG's reference set). The additive model of Charnes et al. [49] utilizes the convex hull of input consumption and output production for all the 50 U.S. SGs. These 50 SGs form the production possibility set (PE):

$$PE = \left\{(Y^T, X^T) = \sum_{i=1}^{50} \mu_i (Y_i^T, X_i^T); \sum_{i=1}^{50} \mu_i = 1, \mu_i \geq 0\right\}.$$

where, *i* represents the general index of 50 SGs and (Y^T_j, X^T_j) is the transposed vector of outputs and inputs for a particular SG under evaluation, denoted as SG_i. The health efficiency status (efficient or inefficient) for each SG is determined by comparing its inputs and outputs to PE. If no other SG's components, observed or hypothetical, in PE consumes the same or less input while simultaneously producing more or the same output, with at least one strict inequality, then SG_i is deemed technically health efficient. Those SGs which do not meet the above criteria are deemed health inefficient, relative to the benchmark, and are considered enveloped or dominated by the frontier. This linear program yields only a classification of efficient and inefficient SGs, and the program does not yield a rank ordering of SGs from most robustly efficient to most robustly inefficient. To develop this rank ordering from a single number, one additional linear program must be executed for each SG to determine an SG's stability index value.

Charnes et. al. [50, 51], Sieford and Zhu [52], and Cooper et .al. [53] developed a sensitivity technique for the additive DEA model. It defines the necessary and simultaneous input/output perturbations of a given SG to cause it to move to a condition of "virtual" efficiency. Virtual efficiency is defined as a point on the efficient frontier where any minuscule detrimental perturbation (increase in inputs and/or decreases in outputs) will cause an efficient SG to become inefficient. Virtual efficiency is also defined by any minuscule favourable perturbation (decrease in inputs and/or increase in outputs) which will cause an inefficient SG to become efficient.

3. c. The data

The additive DEA model simultaneously maximizes both the infant birth weight (Y_1) and avoidance of premature cancer deaths (Y_2), while minimizing RCRA hazardous waste (X_1), toxic releases TRI (X_2), health care expenditures as a percent of the gross state product of each variable (X_3), percent of population without insurance coverage (X_4), and pollution abatement operating costs (X_5). The transformed variables or components (Y_1, Y_2; X_1... X_5) were scaled by dividing by the standard deviation of each variable. This scaling is required to make the additive model both unit invariant and translation invariant (Lovell and Pastor [54]). See Table 2 below.

Table 2: Scaled Outputs and Inputs for Comparison

	OUTPUTS		INPUTS				
State	Healthy Birth Weight	DIST YLPD CANCER	RCRA Total	TRI Total	Health Care Expenditures	Health Care Uninsured	PAOC
	Y_1	Y_2	X_1	X_2	X_3	X_4	X_5
Alabama	65.94	0.85	0.62	1.16	4.22	3.88	2.24
Alaska	69.26	3.58	0.00	0.57	4.34	4.59	0.27
Arizona	68.67	2.92	0.01	0.42	3.34	5.22	0.40
Arkansas	67.19	0.93	0.03	0.47	4.56	4.81	2.26
California	68.67	2.89	0.17	0.13	3.00	5.09	0.72
Colorado	66.97	3.86	0.03	0.12	2.00	4.56	0.24
Connecticut	67.86	2.87	0.33	0.49	3.34	2.86	0.36
Delaware	66.75	1.60	0.27	3.93	3.00	3.44	0.56
Florida	67.34	1.72	0.02	1.07	3.11	5.58	0.37
Georgia	66.75	1.45	0.30	0.00	3.67	4.84	0.98
Hawaii	67.71	3.24	0.01	0.23	5.00	2.36	0.10
Idaho	68.82	1.78	0.01	0.39	3.11	4.10	1.38
Illinois	67.49	1.78	0.08	0.10	3.00	3.74	0.99
Indiana	67.64	1.21	0.10	3.20	2.89	3.60	2.14
Iowa	68.45	2.66	0.03	0.41	3.00	2.56	1.27
Kansas	68.45	2.42	0.10	0.16	3.34	3.05	0.90
Kentucky	67.05	0.10	1.05	1.19	4.34	3.79	2.21
Louisiana	65.28	0.00	4.54	1.46	4.89	5.09	6.22
Maine	68.74	2.00	0.00	0.17	5.78	2.61	1.25
Maryland	67.05	1.88	0.15	1.97	3.56	3.71	0.42
Massachusetts	67.93	2.33	1.72	0.43	2.89	2.83	0.40
Michigan	67.64	1.88	0.19	0.74	3.56	2.91	1.27
Minnesota	68.96	3.29	0.11	0.16	3.67	2.34	0.96
Mississippi	65.05	0.06	1.23	0.63	6.56	4.98	1.43
Missouri	67.78	1.19	0.05	0.77	4.45	3.38	1.12
Montana	68.89	3.18	0.00	0.14	4.11	4.67	0.96
Nebraska	68.59	2.91	0.01	0.22	3.67	3.05	1.04
Nevada	67.64	2.38	0.00	0.96	2.00	5.03	0.39
New Hampshire	68.67	2.80	0.02	0.23	3.22	2.86	0.31
New Jersey	67.71	2.12	4.85	1.42	3.56	4.01	0.60
New Mexico	67.49	3.41	0.28	0.09	4.78	5.77	0.22
New York	67.64	2.33	0.86	0.36	5.89	3.63	0.34
North Carolina	66.97	1.45	0.29	1.34	3.78	4.40	1.38
North Dakota	69.04	2.74	0.29	0.16	4.00	3.05	1.01
Ohio	67.34	1.54	1.90	3.45	3.67	2.94	1.67
Oklahoma	67.86	1.09	0.11	0.21	3.78	5.14	0.97
Oregon	69.26	2.43	0.02	0.12	3.56	4.56	1.03
Pennsylvania	67.64	1.75	0.29	1.67	4.78	2.80	1.15
Rhode Island	68.00	1.79	0.22	0.23	5.34	2.80	0.41
South Carolina	66.23	1.14	0.21	1.21	4.78	4.40	2.65
South Dakota	68.89	2.83	0.00	0.05	3.11	3.19	0.49
Tennessee	66.75	0.74	0.68	1.55	4.45	3.68	1.29
Texas	67.64	2.20	2.10	0.44	3.45	6.63	1.68
Utah	68.74	4.69	0.03	0.87	2.22	4.32	1.33
Vermont	69.18	2.60	0.01	0.03	4.56	2.97	0.93
Virginia	67.71	1.93	0.12	0.87	2.00	3.63	0.70
Washington	69.26	2.85	0.00	0.21	3.56	3.44	0.80
West Virginia	66.68	0.76	0.11	2.05	5.34	4.26	3.20
Wisconsin	68.59	2.56	0.00	4.06	3.00	2.58	1.53
Wyoming	67.41	3.04	0.00	0.08	3.56	3.85	1.89

4. Ranking of the 50 U.S. state governments

To rank SGs from most "robustly" efficient to most inefficient, the stability indexes for inefficient SGs are first negated. The SGs then can be ordered from highest positive to lowest negative value. Cooper et. al. [53] supports the appropriateness of this approach for efficiency rankings. These formulations provide a correct way of ranking the efficiency of SGs by reference to their stability index values.

Using the additive model, Table 3 displays the stability rankings for the 50 U.S. SGs in the early 2000s. The SGs' Performance Ranks appear in descending order from most robustly efficient to the least robustly efficient. The frontier contains the first 20 SG ranks appearing in bold and having positive Stability Index ranks, thus forming the efficient frontier. The five most environmentally efficient SGs are Utah, Colorado, Minnesota, Alaska and Hawaii, while the five least environmentally efficient SGs include Mississippi, Alabama, Tennessee, Kentucky and Louisiana. Referring to the data in Table 4, a comparison between Utah, the most environmentally efficient SG, and Louisiana, the least environmentally efficient SG, illustrates why these efficiency rankings differ. Utah has much higher scaled (raw data divided by the standard deviation of the variable) desirable health outcomes (Y1 and Y2), and correspondingly, much smaller levels of pollution (X1 and X2), smaller health care expenditures (X3 and X4) and less pollution abatement stringency and costs. Intuitively, the difference between the groups of rankings seem obvious, namely, less densely populated, higher income states have less pollution to deal with and, therefore, have less health care regulatory enforcement and costs.

4.a. Comparison of the results of the Additive and CCR models.

The additive model, as a variable returns to scale model, allows an efficiency comparison between SGs of different sizes using a singular, technical efficiency criteria, but ignores scale efficiency. The additive model frontier is comprised of the most technically efficient SGs for a particular size range. Smaller, less efficient SGs are compared to that portion of the frontier comprised of the smaller states forming its particular reference set. Similarly, larger, less efficient SGs are compared to that portion of the frontier comprised of the larger SGs forming its reference set. In constant returns to scale models like the CCR, the frontier is comprised of the most technically efficient SGs across all of the size ranges, and less efficient SGs in other size ranges are compared without regard to their scale of operation. Thus, different sized states will be ranked differently when the additional scale criterion is imposed by the CCR model. A comparison of the frontiers for the additive, variable returns to scale (VRS) model, and the CCR or constant returns to scale (CRS) model provides a type of scale analysis. SGs comprising the frontier in the CRS model are both technically efficient and scale efficient, while the frontier SGs identified in the VRS model are only technically efficient and therefore may not appear in the CRS envelope. In Table 3 the additive model's frontier (shaded in the table) contains 20 technically efficient SGs (with positive stability index values); the CCR's frontier (also shaded in the table) contains only 17 technically efficient and scale efficient SGs. In Table 3, these three technically but not scale efficient SGs (Washington, Montana and Oregon) fell well below the CCR's frontier and exhibited increasing returns to scale (denoted by I's in the Table 3). [A detailed explanation of the CCR model used in this paper can be found in Feroz, et .al. [31 an 55].

Table 3: Stability Rankings

INPUTS:

RCRA total lbs per sq mile of land area

TRI total lbs per sq mi of land area

State govt health expenditures as % of GSP

Percent without health insurance

Pollution abatement operational costs as % of GSP

OUTPUTS:

BIRTHS above 5lb 8 oz as a % of births

DISTYLPDCANCER

	Model: Additive			Model: CCR		Model: BCC		
Nd Efficiency Rank	State	Efficiency Score	Stability Value	State	Efficiency Score	State	Efficiency Score	Returns to Scale
1	**Utah**	1	**0.9292**	Utah	1.00	Alaska	1.00	I
2	**Colorado**	1	**0.4993**	Colorado	1.00	Colorado	1.00	D
3	**Minnesota**	1	**0.4112**	Minnesota	1.00	Georgia	1.00	D
4	**Alaska**	1	**0.3908**	Alaska	1.00	Hawaii	1.00	D
5	**Hawaii**	1	**0.3689**	Hawaii	1.00	Iowa	1.00	D
6	**Virginia**	1	**0.311**	Virginia	1.00	Maine	1.00	I
7	**Iowa**	1	**0.1563**	Iowa	1.00	Massachusetts	1.00	D
8	**South Dakota**	1	**0.146**	South Dakota	1.00	Minnesota	1.00	D
9	**Washington**	1	**0.1308**	New Hampshire	1.00	Montana	1.00	I
10	**New Hampshire**	1	**0.1301**	Vermont	1.00	Nevada	1.00	I
11	**Vermont**	1	**0.116**	Massachusetts	1.00	New Hampshire	1.00	D
12	**Massachusetts**	1	**0.1083**	Nevada	1.00	New Mexico	1.00	I
13	**Nevada**	1	**0.107**	Wisconsin	1.00	Oregon	1.00	I
14	**Oregon**	1	**0.0536**	Georgia	1.00	South Dakota	1.00	D
15	**Wisconsin**	1	**0.0511**	New Mexico	1.00	Utah	1.00	D
16	**Georgia**	1	**0.0384**	Maine	1.00	Vermont	1.00	I
17	**New Mexico**	1	**0.0329**	Wyoming	1.00	Virginia	1.00	D
18	**Maine**	1	**0.0308**	Connecticut	0.98	Washington	1.00	I
19	**Montana**	1	**0.0243**	Kansas	0.95	Wisconsin	1.00	I
20	**Wyoming**	1	**0.0043**	Nebraska	0.94	Wyoming	1.00	I
21	Arizona	0.9698	-0.0067	Illinois	0.92	Connecticut	0.99	D
22	Idaho	0.9598	-0.0109	Washington	0.91	California	0.97	I
23	Nebraska	0.9835	-0.0125	Arizona	0.90	Arizona	0.95	I
24	Florida	0.9303	-0.0139	Delaware	0.89	Kansas	0.95	D

25	Connecticut	0.9817	-0.0169	Idaho	0.89	Nebraska	0.94	I
26	Arkansas	0.8982	-0.0308	Michigan	0.86	Illinois	0.94	D
27	California	0.9705	-0.0376	North Dakota	0.86	Delaware	0.91	D
28	Illinois	0.9579	-0.0434	Rhode Island	0.86	Idaho	0.91	I
29	Missouri	0.9322	-0.0469	Indiana	0.86	North Dakota	0.91	I
30	North Dakota	0.982	-0.0656	Ohio	0.84	Michigan	0.88	D
31	Kansas	0.9799	-0.0765	Montana	0.83	Indiana	0.86	D
32	Rhode Island	0.9508	-0.0873	Pennsylvania	0.82	Rhode Island	0.86	D
33	Indiana	0.9093	-0.101	Maryland	0.82	Ohio	0.85	D
34	West Virginia	0.8638	-0.1091	California	0.81	Maryland	0.83	D
35	Oklahoma	0.9269	-0.1114	Florida	0.80	Pennsylvania	0.83	D
36	Maryland	0.9317	-0.1401	Oregon	0.79	Florida	0.80	D
37	Michigan	0.9504	-0.1732	Missouri	0.76	Missouri	0.76	D
38	New York	0.9293	-0.178	New Jersey	0.75	New Jersey	0.76	D
39	Delaware	0.9113	-0.1859	New York	0.70	New York	0.71	D
40	South Carolina	0.8795	-0.2136	Oklahoma	0.70	Tennessee	0.71	D
41	North Carolina	0.911	-0.2851	Tennessee	0.69	Oklahoma	0.70	D
42	Pennsylvania	0.9264	-0.2865	North Carolina	0.68	Alabama	0.69	D
43	New Jersey	0.8921	-0.3502	Kentucky	0.67	North Carolina	0.69	D
44	Texas	0.8936	-0.3943	Alabama	0.66	Kentucky	0.68	D
45	Ohio	0.8906	-0.4549	Arkansas	0.63	Texas	0.64	I
46	Mississippi	0.8437	-0.6117	Texas	0.63	Arkansas	0.64	D
47	Alabama	0.8849	-0.6232	South Carolina	0.59	South Carolina	0.61	D
48	Tennessee	0.8965	-0.6801	West Virginia	0.57	West Virginia	0.59	D
49	Kentucky	0.884	-1.0129	Louisiana	0.53	Louisiana	0.56	D
50	Louisiana	0.7838	-1.4339	Mississippi	0.49	Mississippi	0.51	D

4. b. Required input adjustments of inefficient SGs to move toward the efficient frontier using the CCR model

Table 4 contains inefficient SGs arranged by CCR model efficiency scores. The thirty-three SGs whose efficiency scores are not on the efficient frontier are ranked from the most to the least robustly inefficient. The latter columns show the input reductions and output augmentations necessary to reach the efficient frontier. The quantity of hazardous waste generated per square mile of land area by SG (RCRA releases) require the most prominent input reductions with 20 of the 33 inefficient SGs requiring adjustments. The Toxic Release Inventory (TRI Total) releases (17 out of 33 SGs) and Pollution Abatement Operating Costs (PAOC) (19 out of 33 SGs) also appear as the main input excesses that are necessary to minimize in achieving the frontier. Health Expenditures (X_3) and Health Insurance Coverage (X_4) have little influence on moving an SG toward the efficient frontier. Apparently, preventing exposure is much more important than improving heath outcomes after the exposure has occurred.

Augmentations in outputs, especially premature death by cancer, are required for nearly all of the inefficient SGs, and these levels in units of standard deviations must be increased as the degree of inefficiency increases. Louisiana and Mississippi show the largest deficiencies in premature years lost to cancer death.

Table 4: CCR Output Augmentations and Input Reductions

State	Efficiency Score E_j	Healthy Birth Weight	DIST YLPD CANCER	RCRA Total	TRI Total	Health Care Expenditures	Health Care Uninsured	PAOC
		Y_1	Y_2	X_1	X_2	X_3	X_4	X_5
Connecticut	0.98	0.00	0.00	0.62	0.32	0.00	0.00	0.00
Kansas	0.95	0.00	0.20	0.15	0.00	0.00	0.00	0.08
Nebraska	0.94	0.00	0.00	0.00	0.00	0.00	0.00	0.27
Illinois	0.92	0.00	0.60	0.12	0.00	0.00	0.00	0.38
Washington	0.91	0.00	0.00	0.00	0.00	0.00	0.00	0.16
Arizona	0.90	0.00	0.00	0.00	0.00	0.00	0.22	0.00
Delaware	0.89	0.00	0.36	0.00	3.55	0.00	0.00	0.00
Idaho	0.89	0.00	0.47	0.00	0.00	0.00	0.00	0.53
Michigan	0.86	0.00	0.39	0.00	0.34	0.00	0.00	0.00
North Dakota	0.86	0.00	0.17	0.38	0.00	0.00	0.00	0.04
Rhode Island	0.86	0.00	0.67	0.32	0.00	0.00	0.00	0.00
Indiana	0.86	0.00	0.50	0.02	2.48	0.00	0.00	0.74
Ohio	0.84	0.00	0.57	3.27	3.00	0.00	0.00	0.18
Montana	0.83	0.12	0.00	0.00	0.00	0.00	0.04	0.20
Pennsylvania	0.82	0.00	0.70	0.27	1.42	0.08	0.00	0.00
Maryland	0.82	0.00	0.40	0.00	1.56	0.00	0.00	0.00
California	0.81	0.00	0.31	0.25	0.00	0.00	0.00	0.19
Florida	0.80	0.00	0.56	0.00	0.30	0.00	0.00	0.00
Oregon	0.79	0.00	0.34	0.00	0.00	0.00	0.00	0.30
Missouri	0.76	0.00	0.76	0.00	0.32	0.00	0.00	0.00
New Jersey	0.75	0.00	0.07	4.88	0.66	0.00	0.00	0.00
New York	0.70	0.00	0.30	0.66	0.00	0.00	0.00	0.00
Oklahoma	0.70	0.00	0.99	0.12	0.00	0.00	0.00	0.11
Tennessee	0.69	0.00	0.91	0.00	0.86	0.00	0.00	0.00
North Carolina	0.68	0.00	0.40	0.00	0.38	0.00	0.00	0.00
Kentucky	0.67	0.00	1.17	1.41	0.45	0.00	0.00	0.22
Alabama	0.66	0.00	0.77	0.79	0.39	0.00	0.00	0.27
Arkansas	0.63	0.00	0.84	0.00	0.00	0.00	0.00	0.49
Texas	0.63	0.00	0.57	2.69	0.00	0.00	0.00	0.50
South Carolina	0.59	0.00	0.64	0.18	0.32	0.00	0.00	0.33
West Virginia	0.57	0.00	0.93	0.03	0.98	0.00	0.00	0.56
Louisiana	0.53	0.00	1.11	5.03	0.33	0.00	0.00	1.93
Mississippi	0.49	0.00	1.28	0.00	0.07	0.00	0.00	0.00

5. Comparison of health rankings from DEA analysis and from the Commonwealth Fund

We compared the SG rankings from the DEA analysis to the rankings of states according to a study conducted by the Commonwealth Fund (Cantor et al., [56]). Both the overall ranking and the rankings on the healthy lives dimension of the study are compared. Healthy lives were measured using mortality related to health care, infant mortality, deaths due to breast cancer, deaths due to colorectal cancer, and percent of adults under age 65 limited in any activities because of physical or emotional problems. Table 5 compares the rankings. Overall, the Commonwealth Fund rankings [56] are again significantly and positively correlated (significance at the 0.01 level) with the rankings from our DEA analysis (0.463). Rankings from our DEA analysis compared with rankings of the Commonwealth Fund healthy lives dimension subset are even more strongly correlated with the DEA analysis rankings (0.758 significance at the 0.001 level) according to the Spearman's rank correlation test. The comparison to these studies emphasizes the difference between the two approaches. Our environmental efficiency approach considers the effective use of policy initiatives by highlighting outcomes relative to the resource base and environmental conditions, and focuses on the effectiveness of these inputs. The Commonwealth Fund [56] uses primarily fixed weights and does not distinguish between inputs and outputs in defining healthy lives.

Table 5: Comparisons of DEA and Commonwealth Fund Rankings

State	DEA	Commonwealth Fund		State	DEA	Commonwealth Fund	
		Overall	Healthy Lives			Overall	Healthy Lives
Alabama	47	41	38	Montana	19	17	28
Alaska	4	26	4	Nebraska	23	12	23
Arizona	21	26	9	Nevada	13	46	31
Arkansas	26	48	44	New Hampshire	10	3	6
California	27	39	2	New Jersey	43	26	28
Colorado	2	22	2	New Mexico	17	35	14
Connecticut	25	7	17	New York	38	22	30
Delaware	39	14	26	North Carolina	41	30	34
Florida	24	43	25	North Dakota	30	13	17
Georgia	16	42	35	Ohio	45	24	41
Hawaii	5	1	8	Oklahoma	35	50	47
Idaho	22	30	12	Oregon	14	34	19
Illinois	28	36	36	Pennsylvania	42	15	39
Indiana	33	38	33	Rhode Island	32	6	22
Iowa	7	2	9	South Carolina	40	33	43
Kansas	31	20	27	South Dakota	8	10	11
Kentucky	49	45	49	Tennessee	48	40	42
Louisiana	50	46	51	Texas	44	49	24
Maine	18	5	20	Utah	1	24	1
Maryland	36	19	39	Vermont	11	3	14

Massachusetts	12	8	20	Virginia	6	29	32
Michigan	37	16	37	Washington	9	17	13
Minnesota	3	11	7	West Virginia	34	44	45
Mississippi	46	50	51	Wisconsin	15	9	16
Missouri	29	37	45	Wyoming	20	21	5

6. Summary and policy implications

This paper hopes to facilitate the current health care debate in America by providing some timely findings about the health care efficiencies of the 50 U.S. state governments. We were interested only in a cross sectional comparison of the 50 SGs. However, a similar analysis could also be conducted for individual SGs or programs over a period of time. For example, if annual data were available, a time series analysis could compare the improvement or deterioration of the Commonwealth of Massachusetts' environmental health track-record before and after the state moved in the direction of nearly universal health care coverage. In this sense, the approach suggested here might be of interest to agencies like the EPA, Medicaid, Medicare, or the Government Accountability Office (GAO). These agencies could compare the relative efficiency of individual SGs or the relative efficiency of the Medicaid or Medicare programs over a period of time.

Analysis of this type is clearly important in determining the level of efficiency with which a particular state or governmental program operates (See, for example, Chang et. al., [57]). New health care mandates, such as, the universal or nearly universal coverage, and resources or lack of them from the federal government, may lead to very different outcomes, both in terms of quality and quantity, depending on the track record of a particular SG or the federal government agency. It is also important to highlight the trade-offs between given inputs and desired outputs involved in attaining a certain level of efficiency. While objectives, such as, reducing infant mortality by ensuring a healthy infant birth weight or minimizing premature cancer death before the age of 75, are laudable policy goals, our findings of differential SG efficiencies suggest the importance of weighing environmental efficiency as a factor in allocating federal dollars to states. The same (fixed rate) federal funding per capita as input, is likely to lead to differential health outcomes across states, depending on the mix of resources and the level of efficiency with which the SG operates during the funding period. Health care policy makers should take into consideration the cost-efficiency of individual SGs before distributing additional resources with the hope of attaining certain health care outcomes nationally both in terms of quality and quantity.

Prevention of environmental degradation and the consequent harm to the affected population appears more critical than fixing the adverse health effects after the harm has actually been inflicted upon the population with or without their consent. If state governors and legislators are not performing well in terms of delivering desired health outcomes within a certain specified period of time, perhaps, they need to go back to the drawing board and ask some fundamental questions about the environmental quality of their state, and the allocation of their scarce health care dollars between prevention versus cure.

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