Measuring the Performance of the U.S. Correctional Systems at the State Level

C. Christopher Lee
Central Connecticut State University

Seong-Jong Joo
Air Force Institute of Technology

This paper attempts to measure the comparative performance of correctional facility operations at the state level in the United States of America. We apply data envelopment analysis (DEA) to the latest available data set with key performance indicators for analyzing correctional facility operations. We attempt to provide a research framework for performance measurement and benchmarking when undesirable outputs are presented in the public sector and discuss managerial implications for improving the performance of correctional facility operations.

Keywords: benchmarking, data envelopment analysis, performance measurement, prison operations

INTRODUCTION

The efficient execution of correctional facility budgets is imperative due to the fact that the United States of America maintains the highest incarceration rate in the world, which is well represented by the statistic of one in 38 adults behind bars, on probation, or on parole (Kaeble and Cowhig, 2018). In addition, cost containment is necessary to reduce the burden of this rising prison population on state budgets and, in turn, on taxpayers. On top of these efforts, the comparative analysis of correctional facility operations is necessary for finding the best practices for benchmarking and continuous improvement. Our study addresses these aspects of correctional facility operations using pertinent variables and models for instilling managerial insights. Particularly, we try to answer the following research questions. First, what is the impact of costs on the efficiency of correctional facilities? Second, can correctional facilities relate recidivism as a measure of rehabilitation quality to improving their efficiency? Third, how do they utilize their capacity? Fourth, who are efficiency frontiers that can serve as benchmarks for less efficient facilities? Accordingly, the primary objective of the current study is to examine the comparative efficiency of correctional facilities within the business perspective and provide actionable insights to managers and policy makers in this area. To achieve this objective, we employ data envelopment analysis (DEA) with the variables that can address the aforementioned research questions. DEA is good for measuring the relative performance of entities within a multivariate perspective and benchmarking peer entities for continuous improvement. DEA is also a non-parametric approach and takes less restrictive assumptions.

Our research framework can be applied to public entities with minor modifications such as variables suitable to their businesses. The major contributions of our study include demonstrating the research framework for measuring the comparative performance or efficiency of public organizations within the business perspective and providing actionable insights to managers and policy makers. In addition, our study will help fill the gap in literature and complement the results of other studies in a different perspective. The remaining parts of this study consist of Literature Review, Data and Variables, Methods, and Results and Discussion followed by Conclusion.

LITERATURE REVIEW

Literature review consists of two sections: one for general analytic studies on correctional facility operations and the other for studies on the facilities using data envelopment analysis. The general analytic studies will guide us for selecting variables. The DEA studies will also help us outline our research framework.

Studies on Correctional Facility Operations in General

We review various prison studies to understand the measures related to the performance of correctional facilities. Specifically, the variables identified in the studies will help us select inputs and outputs for our study.

Orrick and Vieraitis (2015) analyzed the relationship between costs and number of inmates using descriptive statistics in the state of Texas. They suggested that reducing inmates' time served and decriminalizing 'victimless' crimes could lessen the financial burden of prison operations. They further discussed alternatives that could impact costs of incarceration. Although they didn't use a complex method for data analysis, they clearly showed the importance of cost containment efforts on prison operations.

Pyne (2015) believed that early release of prisoners if they have showed good behavior could increase the cost efficiency of a correctional facility. The hypothesis tested in this study was that those who had a strong dislike of prison were less likely to commit another crime upon release and to end up back in prison. Savings from early released prisoners could be used to finance the full sentence for those who were not afraid of being in prison and run a high risk of recidivism. This study discussed the proper use of early release as a policy to decrease both prison cost and recidivism.

Spelman (2009) investigated factors that caused the huge increase in correctional facility populations from 1977 to 2005. This study estimated that potential victims would be saved between $4,000 and $19,000 per prisoner locked up. However, it would cost $20,000 to $40,000 to keep that individual locked up, which meant it was actually a net loss unless correctional facilities could become more efficient. Non-violent, victimless crimes could be better solved through alternative cheaper punishments such as rehabilitation. This fact would mean more savings would be achieved per prisoner as they were locked up for crimes that caused more damage.

Carver (2002) studied third party contract costs for telephone services to prison systems. The population of inmates was rising every year and more prison services were needed to keep up with the growing demand. This study showed how inefficient the phone service contracts were to the prisoners and the state because the provider was not interested in the prisoner's best interests. While under serving the interest of both the end user and the state, prison service providers were making lots of revenues each year on underperforming contracts.

Wells (2015) provided insight into the cost saving measures for correction facilities if they started using green technology. This study listed six basic cost-saving areas that could lower operating costs for correctional facilities. The six areas were lighting, HVAC systems, plug-in appliances, water, materials flow, and energy. This study outlined possible solutions for correctional facilities that had high operating costs compared to other correctional facilities that were currently using green technology.

Garland et al. (2014) investigated not only the positive effects of reducing prison populations but the negative ones as well. As prison populations shrank, the staff, who were laid off, had difficulties finding employment due to familial obligations and the inability to sell their homes. It was also risky to increase the number of parolees without increasing resources provided to the parole programs. If only the population of parolees increased, the administration of the program might fail to properly track the inmates, which would also negatively affect staff with increased caseload sizes.

Drago, Galbiati, and Vertova (2011) discussed the conditions of prisons and how it could affect criminal behavior. They observed the post-release behavior of about twenty thousand former prison inmates. They examined the relationship between recidivism and variation in prison assignment as a means of identifying the effects of prison overcrowding, deaths in prison, and isolation. According to the deterrent hypothesis, the harsher the prison conditions, the lower the propensity to re-engage in criminal activities. However, they failed to find compelling evidence that supported this hypothesis. Instead, they discovered that harsher conditions intensified recidivism. They stated the limitation of the dataset that was based on post-release recidivism of former inmates and could not rule out the possibility of the deterrent effect on criminals who didn't receive prison treatment.

Jacobson (2005) examined the overcrowding of prisons and how the penal system needed reform. The system was more concerned with incarcerating people and not reforming inmates. The United States had the highest number of inmates in the world and one of the highest incarceration rates, which contributed to the significant amount of money every state had to spend in its budget. This study found that mass incarceration had negative impact on communities, especially the minority communities. This study also described how other correction measures were not utilized to reform inmates.

Specter (2010) discussed how California's prison system was overcrowded and had more offenders than the state could house. Because expenses became too high, the state was unable to provide constitutionally acceptable healthcare both mentally and medically to the inmates. Mental health issues led to preventable deaths such as suicides and attempts to control disruptive inmates led to the overuse of lockdowns. Infectious diseases spread due to prisoners being crowded together in rooms during lockdowns. This study showed the correlation of several variables such as inmate health, lockdown incidents, and recidivism to overcrowding.

Studies on Correctional Facilities Using Data Envelopment Analysis

Cesaroni and Lamberti (2014) used multiple analyses in order to understand productivity growth in the Italian prison system during the years of 2003-2005. The most effective method found was data envelopment analysis (DEA) as it proved more effective in analyzing "complex" systems. Their DEA model showed the primary driver of productivity was technical change and better use of information technology systems. Overcrowding, on the other hand, was shown to be the biggest detriment to productivity.

Kuziemko (2013) analyzed the allocative-efficiency differences between paroles versus fixed sentence regimes using data related to quasi-experiments from the state of Georgia. If a parole board could accurately estimate an inmate's recidivism, parole could provide better allocative-efficiency benefits, i.e., costly prison space could be allocated to the highest-risk inmates and incentive benefits to prisoners to reduce their sentence.

Butler and Johnson (1997) employed DEA in order to evaluate the efficiency of prison operations and highlighted areas that needed improvement. The study assumed that prisons incapacitated a criminal from committing more crimes and rehabilitated inmates so that they did not repeat crimes later. Input variables were capacity (number of beds), expenditures per year, and the number of employees at the prison. Output variables were the total number of prisoners confined per facility and the number of prisoners participating in rehabilitation programs. DEA proved to be a useful and inexpensive tool to compare prisons and identify which were performing inefficiently.

Nyhan (2002) examined technical efficiency among the 35 juvenile justice facilities (halfway houses) in the State of Florida using DEA. This study proposed strategies for change using DEA results such as finding efficient facilities, proposing improvements for inefficient facilities, and identifying facilities for benchmarks.

To respond to the call for efficiency savings by the Government of the United Kingdom, Hall et al. (2013) used DEA to find cost saving opportunities for juvenile correction facilities in England and Wales. They included pertinent variables along with undesirable outputs such as assaults and drug uses by inmates. They also tested the relationship between facility sizes and efficiencies and found that smaller institutes were more efficient than larger ones, which contradicted the Government's preference on large institutes.

DATA AND VARIABLES

We selected data and variables from the Census of State and Federal Adult Correctional Facilities (CSFACF) in 2005, which was prepared by the Bureau of Justice Statistics (BJS) and the U.S. Department of Justice, which included the latest census of approximately 1800 prisons. Although annual prison reports on correctional populations at a state level have been published regularly up to 2016 (Kaeble and Cowhig, 2018), and the 2012 CSFACF census report with limited variables after the 2005 census report are available, some key performance indicators (KPIs) such as recidivism rates and operating expenses are missing in those reports. The BJS website states that the next wave of CSFACF will be conducted in 2019. However, we are not sure the availability of KPIs and timing as the 2005 CSFACF report was released in 2008. Accordingly, the use of the 2005 nationwide survey becomes a major limitation of our study. Nonetheless, our study can provide insights on a research framework and managerial implications for improving the performance of correctional operations.

The census data contained the various properties of prisons such as types of inmates, facility age, security level, court orders, operational information, confinement space, and staff characteristics. The scope of respondents was large and included as many correctional facilities as possible, including both private and public. However, the most recent dataset was from the census in 2005 which was relatively old. Every five to seven years, the Bureau of Justice was supposed to conduct this study but had not been able to do so due to budget restraints since 2005.

We have collected data for prisons nationwide and aggregated them at the state level. The data set contains various measures with continuous and categorical scales. Based on the literature review and the availability of data, we have chosen four total variables and tried two DEA models. We include three variables such as Capacity (input), Recidivism (undesirable output), and Number of Inmates (output) in the first model or Model 1. Capacity represents the number of beds in prisons. Recidivism means the percentage of inmates who committed crimes after being released from prisons. The Number of Inmates shows the number of inmates held at the time the survey was conducted in 2005. Table 1 exhibits descriptive statistics for the three variables aggregated at the state level.

TABLE 1
DESCRIPTIVE STATISTICS FOR THE VARIABLES IN MODEL 1

	Capacity	Recidivism	No of Inmates
Maximum	170,232.00	0.77	168,394.00
Minimum	324.00	0.23	228.00
Mean	19,699.78	0.41	22,468.12
SD*	29,276.86	0.10	33,916.76
Type	Input	Undesirable Output	Output

*SD: Standard Deviation

All three variables in Table 1 demonstrate the high level of variability with large values for ranges between minimum and maximum values. In the second model or Model 2, we include an additional input variable, Expenditure, that represents the expenses spent in the past year at the time the survey was conducted. Because 16 states do not reveal expenses, there are 34 states in Model 2. Table 2 illustrates the descriptive statistics of the four variables in Model 2.

TABLE 2
DESCRIPTIVE STATISTICS FOR THE VARIABLES IN MODEL 2

	Expenditure	Capacity	Recidivism	No of Inmates
Maximum	3,802,870,876.00	170,232.00	0.61	168,394.00
Minimum	843,510.00	324.00	0.26	228.00
Mean	592,976,885.15	22,259.24	0.40	26,099.06
SD*	879,225,516.59	32,335.09	0.09	38,245.36
Type	Input	Input	Undesirable Output	Output

* SD: Standard Deviation

Similar to the variables in Model 1, the four variables also show great variations in terms of minimum and maximum values.

Methods

DEA is a well-known method for comparative performance measurement and benchmarking. Some application-oriented studies have addressed various issues such as air cargo handling (Lo Storto, 2017), public school performance by unionized status (Overton et al., 2016), bank branch operations (Balfour, et al., 2015), airline efficiencies (Joo and Fowler, 2014), and department stores (Mhatre et al., 2014). We choose two DEA models that can handle undesirable outputs. Undesirable outputs are frequently in a form of byproducts produced during normal business activities. For example, electric power plants that use coal generate electricity and also emit pollutants such as carbon dioxide and other polluting materials. In DEA models, we usually try to maximize outputs by holding inputs at the same level. However, it is not applicable to the undesirable or bad outputs. These outputs should be minimized while maximizing intended outputs. In our study, recidivism is the undesirable output in two DEA models. There are two major ways to handle undesirable outputs in DEA models. The first approach is including the undesirable outputs as inputs and solving DEA models with input orientation. In this approach, decision making units (DMUs) with the smaller amount of undesirable outputs and input variables are more efficient than other DMUs. The second method is using the DEA model developed for handling undesirable outputs. The second approach is more flexible than the first approach for handling the variables and choosing weights between the intended outputs and the undesirable outputs. More weight on the undesirable outputs than that on the intended outputs will cause projection changes from increasing the intended outputs to reducing the undesirable outputs. For flexibility, we choose the DEA models for undesirable outputs. Cooper et al. (2007: pp. 367-379) defines the DEA model for undesirable outputs like following:

> "We define inputs, intended or good outputs, and undesirable or bad outputs by three vectors such as $\boldsymbol{x} \in R^m$, $\boldsymbol{y}^g \in R^{s1}$, and $\boldsymbol{y}^b = R^{s2}$. Let matrices $X = [x_1,\ldots, x_n]$, $Y^g = [y_1^g, \ldots, y_n^g]$, $Y^b = [y_1^b, \ldots, y_n^b]$. The production possibility set (P) is defined by

$$P = \{(\boldsymbol{x}, \boldsymbol{y}^g, \boldsymbol{y}^b) | \boldsymbol{x} \geq X\boldsymbol{\lambda}, \boldsymbol{y}^g \leq Y^g\boldsymbol{\lambda}, \boldsymbol{y}^b \geq Y^b\boldsymbol{\lambda}, \boldsymbol{\lambda} \geq 0\},$$

where $\boldsymbol{\lambda} \in R^n$ is the intensity vector. In addition, the constant returns to scale technology is applicable to P. The dual linear programming (LP) model of this problem can be defined using the dual variable vectors $\boldsymbol{v} \in R^m$, $\boldsymbol{u}^g \in R^{s1}$, and $\boldsymbol{u}^b \in R^{s2}$, where $s = s_1+s_2$.

[Dual LP] $\max \boldsymbol{u}^g \boldsymbol{y}^g - \boldsymbol{v}\boldsymbol{x}_0 - \boldsymbol{u}^b \boldsymbol{y}_1^b$

subject to $\boldsymbol{u}^g Y^g - \boldsymbol{v}X - \boldsymbol{u}^b Y^b \leq 0$

$$\boldsymbol{v} \geq \frac{1}{m}\left[\frac{1}{x_0}\right]$$

$$\boldsymbol{u}^g \geq \frac{1+\boldsymbol{u}^g \boldsymbol{y}_0^g - \boldsymbol{v}\boldsymbol{x}_0 - \boldsymbol{u}^b \boldsymbol{y}_0^b}{s}\left[\frac{1}{\boldsymbol{y}_0^g}\right]$$

$$\boldsymbol{u}^b \geq \frac{1+\boldsymbol{u}^g \boldsymbol{y}_0^g - \boldsymbol{v}\boldsymbol{x}_0 - \boldsymbol{u}^b \boldsymbol{y}_0^b}{s}\left[\frac{1}{\boldsymbol{y}_0^b}\right].$$

This model is a slack-based measure of efficiency with undesirable outputs." We directly quote the mathematical expression from Cooper et al. (2007) to facilitate readers' understanding of the model without spending time on different mathematical notations. Users of this model can choose constant, variable or general returns to scale. To scale, we will use a model with constant returns, which is stricter than other models (variable or general returns to scale) for measuring efficiency with an undesirable output. There are a handful of studies available which use DEA models with undesirable outputs such as power plant operations (Liu, et al., 2017; Khalili- Damghani et al., 2015), energy consumption and pollution abatement (Rashidi et al., 2015), cement and construction industries (Riccardi et al., 2012; Hu and Liu, 2015), and commercial banks (An et al., 2015). Nonetheless, our study is the first attempt to apply the DEA model with undesirable outputs to correctional facility operations in the United States of America.

RESULTS AND DISCUSSION

We tried two DEA models that were able to handle undesirable outputs. In our models, Recidivism was the undesirable output from the prison operations. To analyze the relative efficiency or performance of the prisons in all 50 states, we chose three variables in Model 1. The efficiency scores that can range from zero to one inclusively, ranks, and benchmarks are presented in Table 1.

TABLE 3
EFFICIENCY SCORES BY MODEL 1

State	Score	Rank	Benchmark
Alabama	1.0000	1	N/A
Alaska	0.3878	35	California
Arizona	0.4482	21	California
Arkansas	0.3926	34	California
California	1.0000	1	N/A
Colorado	0.4088	31	California
Connecticut	0.3616	46	Alabama
Delaware	0.4782	15	California
Florida	0.5318	9	California
Georgia	0.4588	20	California
Hawaii	0.5744	5	California
Idaho	0.4312	24	California
Illinois	0.6453	4	California

State	Score	Rank	Benchmark
Indiana	0.4989	12	California
Iowa	0.4599	19	California
Kansas	0.3728	44	California
Kentucky	0.4136	30	California
Louisiana	0.4218	27	California
Maine	0.4142	29	Alabama
Maryland	0.5278	10	California
Massachusetts	0.4600	18	California
Michigan	0.2631	50	Alabama
Minnesota	0.4032	32	California
Mississippi	0.3730	43	California
Missouri	0.4686	17	California
Montana	0.4739	16	California
Nebraska	0.5392	7	California
Nevada	0.4215	28	California
New Hampshire	0.3761	40	California
New Jersey	0.5403	6	California
New Mexico	0.3834	37	California
New York	0.5108	11	California
North Carolina	0.4231	26	California
North Dakota	0.3678	45	Alabama
Ohio	0.3053	49	California
Oklahoma	0.4394	22	California
Oregon	0.4294	25	California
Pennsylvania	0.4802	14	California
Rhode Island	0.3227	47	California
South Carolina	0.3987	33	California
South Dakota	0.4946	13	California
Tennessee	0.3862	36	California
Texas	1.0000	1	N/A
Utah	0.3823	38	California
Vermont	0.3745	42	Alabama
Virginia	0.3753	41	California
Washington	0.4333	23	California
West Virginia	0.3769	39	California
Wisconsin	0.5335	8	California
Wyoming	0.3115	48	California
Mean	0.4655		

In Model 1 with three variables, three states such as Alabama, California, and Texas show the score of one or 100 percent efficiency. Excluding these three states, eight states have achieved efficiency scores of 0.5 or higher. However, the highest score among the eight states is only 0.6453. In addition, the mean score of all 50 states is 0.4655. Accordingly, the majority of states or 39 states exhibit efficiency scores less than 0.5. The state with the lowest score in the model is Michigan. Among the three states with the score one, California most frequently appears as the benchmark for inefficient states. However, caution must be used for the interpretation of the efficiency scores. When we look at the data set, we find that the states with overcrowded prisons are efficient. For example, California prisons hold far more inmates than their capacities, measured by the number of beds, may indicate. In a sense, it is efficient. However, it is not always a good indicator of prison operations. Overcrowded prisons may cause prisoners' violent behaviors and invoke human-right issues. It may be also related to other problems such as higher recidivism rates. Indeed, California's recidivism rate (57.80%) is higher than most states in the model. It is the third highest after Delaware (77.10%) and Minnesota (61.20%). Among the three efficient states, California appears 43 times as the benchmark for inefficient states, and Alabama is the benchmark for four inefficient states. Although Texas is efficient, it does not serve as the benchmark for any inefficient state.

One DEA feature is showing projections on the variables in the model. Table 4 shows how inefficient states can be efficient by cutting excessive capacities and decreasing recidivism rates in comparison with the efficient states.

TABLE 4
EXCESSIVE CAPACITY AND RECIDIVISM BY MODEL 1

State	Score	Excess Capacity	Excess Recidivism	Shortage Inmates
Alabama	1.0000	0	0.00	0
Alaska	0.3878	1,268	0.49	0
Arizona	0.4482	11,995	0.28	0
Arkansas	0.3926	6,013	0.40	0
California	1.0000	0	0.00	0
Colorado	0.4088	8,045	0.43	0
Connecticut	0.3616	844	0.41	0
Delaware	0.4782	1,571	0.75	0
Florida	0.5318	38,657	0.04	0
Georgia	0.4588	21,925	0.17	0
Hawaii	0.5744	383	0.51	0
Idaho	0.4312	1,960	0.32	0
Illinois	0.6453	3,280	0.37	0
Indiana	0.4989	5,681	0.30	0
Iowa	0.4599	2,841	0.30	0
Kansas	0.3728	4,469	0.40	0
Kentucky	0.4136	5,736	0.36	0
Louisiana	0.4218	7,850	0.32	0
Maine	0.4142	702	0.54	0
Maryland	0.5278	3,994	0.40	0
Massachusetts	0.4600	2,833	0.39	0
Michigan	0.2631	197	0.31	0
Minnesota	0.4032	3,729	0.58	0
Mississippi	0.3730	8,619	0.27	0
Missouri	0.4686	8,943	0.44	0
Montana	0.4739	687	0.41	0
Nebraska	0.5392	634	0.31	0
Nevada	0.4215	4,436	0.22	0
New Hampshire	0.3761	1,055	0.43	0
New Jersey	0.5403	4,389	0.34	0
New Mexico	0.3834	2,619	0.42	0

State	Score	Excess Capacity	Excess Recidivism	Shortage Inmates
New York	0.5108	21,565	0.18	0
North Carolina	0.4231	15,861	0.28	0
North Dakota	0.3678	667	0.37	0
Ohio	0.3053	1,277	0.39	0
Oklahoma	0.4394	9,040	0.18	0
Oregon	0.4294	4,897	0.18	0
Pennsylvania	0.4802	14,561	0.25	0
Rhode Island	0.3227	2,117	0.30	0
South Carolina	0.3987	10,427	0.24	0
South Dakota	0.4946	689	0.44	0
Tennessee	0.3862	7,991	0.40	0
Texas	1.0000	0	0.00	0
Utah	0.3823	2,331	0.52	0
Vermont	0.3745	632	0.42	0
Virginia	0.3753	728	0.28	0
Washington	0.4333	5,568	0.37	0
West Virginia	0.3769	1,314	0.26	0
Wisconsin	0.5335	3,968	0.39	0
Wyoming	0.3115	930	0.24	0

Again, these projections are based on the efficient states or California. California maintains highly overcrowded prisons. That is, it holds 168,394 inmates with 95,562 beds or capacities. It is around 1.76 times of its capacity. Accordingly, these projections can be unrealistic. For example, Florida needs to cut its capacity by 38,657 beds or 44 percent of the current capacity while decreasing its recidivism rate by 0.04 or four percent. Another example is Delaware that should reduce its recidivism rate by 0.75 or 75 percent. Overall, Table 4 exhibits improvements for the correctional facility operations of inefficient states. In Model 2, we include an additional variable on prison expenditures. As a result, we are unable to include 16 states in the analysis due to missing expenditures. Table 5 lists the efficiency scores, ranks, and benchmarks of 34 states.

TABLE 5
EFFICIENCY SCORES BY MODEL 2

State	Score	Rank	Benchmark
Alabama	1.0000	1	N/A
Arizona	0.2457	20	California
Arkansas	0.2526	18	California
California	1.0000	1	N/A
Connecticut	0.3730	5	California
Georgia	0.2596	13	California
Idaho	0.2543	16	California
Illinois	0.3368	6	California
Indiana	0.4559	4	California
Iowa	0.2456	21	California
Kansas	0.2135	28	California
Kentucky	0.2425	22	California

State	Score	Rank	Benchmark
Louisiana	0.2407	23	California
Michigan	0.2637	12	California
Minnesota	0.2136	27	California
Missouri	0.2595	14	California
Montana	0.2559	15	California
Nebraska	0.2843	7	California
Nevada	0.2820	8	California
New Hampshire	0.2025	32	California
New Jersey	0.2805	10	California
New York	0.2653	11	California
North Carolina	0.2320	24	California
North Dakota	0.2287	25	California
Ohio	0.1889	33	California
Oklahoma	0.2499	19	California
Pennsylvania	0.2532	17	California
Rhode Island	0.1719	34	California
Texas	1.0000	1	N/A
Utah	0.2088	30	California
Virginia	0.2077	31	California
Washington	0.2278	26	California
West Virginia	0.2093	29	California
Wisconsin	0.2807	9	California
Mean	0.3202		

Three states, Alabama, California, and Texas are still efficient in Model 2. The mean efficiency score is 0.3202, which is lower than that in Model 1. Adding Expenditure to Model 2 widens the score gap between the efficient states and the inefficient states. When we look at expenditure per inmate, California is the lowest with $1,447, which contributes to the widened gap. Although three states are efficient in Model 2, California is the only benchmark to all inefficient states. We think this is due to having the lowest expenses per inmate and higher number of inmates held or higher utilization of capacity. The sources of California's efficiency are low expenses and high capacity utilization, which are the main reasons for DEA to choose California as the benchmark to all inefficient states regardless California's relatively high recidivism rate. Rhode Island exhibits the lowest score or 0.1719 in Model 2. Indiana, ranked12th by Model 1, is fourth in Model 2, which is the highest among inefficient states. Indiana's jump is mainly due to low Expenditure. Connecticut is fifth in Model 2, which is a big jump from 46th in Model 1. Its expense per inmate is $2,520, which is the third lowest after California's ($1,447) and Indiana's ($2,511) in Model 2. By considering these results on Capacity and Expenditure, we can easily speculate that two DEA models we have employed heavily value Capacity and Expenditure compared to other variables. Based on the results of Model 2, we list potential improvements for the inefficient states.

Table 6 presents the excess of the inputs or underutilization of the inputs along with the reduction of the undesirable output or Recidivism.

TABLE 6
UNDERUTILIZATION OF RESOURCES BY MODEL 2

State	Score	Excess Expenditure	Excess Capacity	Excess Recidivism	Shortage Inmates
Alabama	1.0000	0.00	0	0.00	0
Arizona	0.2457	763,074,367.04	11,995	0.28	0
Arkansas	0.2526	103,645,965.29	6,013	0.40	0
California	1.0000	0.00	0	0.00	0
Connecticut	0.3730	1,841,583.30	829	0.43	0
Georgia	0.2596	915,257,389.85	21,925	0.17	0
Idaho	0.2543	67,347,421.51	1,960	0.32	0
Illinois	0.3368	1,506,218,320.22	3,280	0.37	0
Indiana	0.4559	24,423,276.80	5,681	0.30	0
Iowa	0.2456	305,717,878.86	2,841	0.30	0
Kansas	0.2135	158,134,210.58	4,469	0.40	0
Kentucky	0.2425	187,671,888.29	5,736	0.36	0
Louisiana	0.2407	320,832,083.24	7,850	0.32	0
Michigan	0.2637	513,681.25	195	0.31	0
Minnesota	0.2136	379,878,947.70	3,729	0.58	0
Missouri	0.2595	575,648,086.53	8,943	0.44	0
Montana	0.2559	70,105,669.01	687	0.41	0
Nebraska	0.2843	139,202,435.69	634	0.31	0
Nevada	0.2820	66,674,152.56	4,436	0.22	0
New Hampshire	0.2025	76,041,737.10	1,055	0.43	0
New Jersey	0.2805	1,172,439,081.59	4,389	0.34	0
New York	0.2653	3,710,744,498.59	21,565	0.18	0
North Carolina	0.2320	917,647,423.55	15,861	0.28	0
North Dakota	0.2287	13,313,783.96	654	0.39	0
Ohio	0.1889	22,395,934.82	1,277	0.39	0
Oklahoma	0.2499	378,465,841.50	9,040	0.18	0
Pennsylvania	0.2532	1,775,164,187.70	14,561	0.25	0
Rhode Island	0.1719	153,564,306.47	2,117	0.30	0
Texas	1.0000	0.00	0	0.00	0
Utah	0.2088	140,640,878.29	2,331	0.52	0
Virginia	0.2077	36,998,367.62	728	0.28	0
Washington	0.2278	707,720,249.75	5,568	0.37	0
West Virginia	0.2093	64,314,630.49	1,314	0.26	0
Wisconsin	0.2807	763,109,317.09	3,968	0.39	0

Three efficient states (Alabama, California, and Texas) do not show any improvements on the variables. It is natural because they are frontiers in the group. The amount of excess on three variables (Capacity, Expenditure, and Recidivism) can be viewed as too much. Because these projections are based on three efficient states, one may argue against the validity of these figures. For example, the current capacity of Rhode Island includes 4,054 beds and the projected capacity becomes 1,937 beds (4,054 minus 2,117) for holding 3,414 inmates. It will create a situation resembling California's, which is having more inmates than its capacity. It is due to the benchmark, California. For realistic benchmarks to avoid overcrowded jails, we recommend using states with moderately efficient scores, such as Indiana and Illinois. Although we have used real data from the survey conducted in 2005, our results are somewhat unusual because of states with overcrowded prisons and their insufficient prison budgets.

The limitations of our study include the availability of data and variables in the 2005 prison survey and the interpretation of the results due to the states with overcrowded prisons and insufficient funds. There are many missing values and, maybe, prisons in the survey results. We conveniently choose the survey data as a sample and have a limited number of variables in Model 1. In addition, we have only 34 states in Model 2 due to missing values on Expenditure. Regarding the states with overcrowded prisons and insufficient funds, we simply cannot throw them away from the analysis. To overcome these limitations, we must consider improved survey methods to avoid missing values and desirable performance measures for implementing a systematic method such as DEA. Finally, analysis at a prison level by treating individual prisons as DMUs can give us additional insights for efficient prison operations.

CONCLUSION

A limited state budget has brought various issues for supporting the activities of a state government in the United States of America. It is not an exception for correctional facilities in a state. Although government operations cannot be run exactly like a commercial business, it is necessary to examine the efficiency of government operations using a business analytic model. We attempted to measure the efficiency of correctional facility operations at the state level using pertinent variables and data collected in the 2005 prison survey. We selected capacity and expenditure as input variables and number of inmates and recidivism rates as output variables for data envelopment analysis or DEA models. Because a high recidivism rate was considered undesirable, we tried a DEA model with undesirable outputs for measuring the efficiency of the correctional facility operations. We found that three states - Alabama, California, and Texas - were consistently efficient in two models due to their high utilization of prison capacities and low expenses. Since their efficiencies came from overcrowded prisons, caution must be used for interpretation. Recidivism, one of several critical factors for prison operations, needs to get the same, if not more, attention that is given to resources such as expenditure and capacity. Future studies should address the limitations of our study such as the limited availability of data and variables along with analysis at a prison level and longitudinal analysis to understand performance over time.

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