An Efficiency Analysis of Nevada and Utah Counties:

Region Size Leads Regional Efficiency

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Abstract

The hypothesis that regional size increases regional efficiency is tested in this study. Data Envelopment Analysis and the Directed Acyclic Graph were used to reveal the causal relationship between regional efficiency and region size in terms of population density. Region size and the infrastructure directly cause regional efficiency, and regional efficiency affects regional income indirectly via formulation of Metropolitan area.

1. Introduction

For urban economics, one hypothesis is that regional efficiency should increase as a region's size (in terms of population density) increases, otherwise the large region would not continue to grow (Raab and Lichty, 1997). This is why densely populated regions have higher efficiency values than periphery regions. For example, Sveikauskas (1975) showed that productivity increases approximately 6% with each doubling of metropolitan area population. Segal (1976) also found that productivity was 8% higher in Standard Metropolitan Areas using an approach similar to Sveikauskas (1975). Based on these two studies, Moomaw (1981) revised productivity estimates and insisted that big cities productivity advantages are much larger, especially for the non-manufacturing sector. Henderson (1986) discovered robust evidence of increasing external economies associated with metropolitan size. Using input-output data, Raab and Lichty (1997) showed that urban core counties have greater efficiency values when compared to suburban counties. Raab and Lichty (2002) revised their previous work and showed that the greatest external economies originate in the urban core.

They found that efficiency falls along with decreasing population densities and income levels as regions moved further from the urban core.

It is natural to cast a question concerning the causal relationship between the regional efficiency and the region size; whether the region gets larger because the region is highly efficient (regional efficiency → region size) or the region is efficient because the region has enough size to keep increasing efficiency (regional efficiency ← region size). Previous studies seem to be assuming that the regional size causes regional efficiency without rigorous (statistical) test. It is worthwhile to investigate the (causal) relationship between the regional efficiency and other environmental variables such as infrastructure in the region, regional income level, unemployment rate, etc. Thus, the main objective of this paper is to attempt to investigate the causal relationships among variables and regional efficiency.

There are various approaches in measuring regional efficiency. One approach is the data envelopment analysis (DEA) which was proposed by Charnes, Cooper and Rhodes (1978, 1981). DEA is an optimization-based technique for evaluating the relative efficiency of decision making units (DMUs). It has been widely applied in performance evaluation and benchmarking of schools, hospitals, bank branches, production plants, etc. Gattoufi, Oral and Resiman (2004) have a comprehensive bibliography of DEA studies. It is expected for this paper that the larger regions have higher DEA efficiency estimates. Raab and Lichty (1997, 2002) used DEA to measure regional efficiency in Minnesota counties. Once regional efficiency is measured, Directed Acyclic Graphs (DAG) procedures can be employed to test causality. DAG is an illustration using arrows and variables to represent the causal flow among a set of variables (Pearl, 1995 and 2000; Spirtes, Glymour, and Scheines, 2000). DAG will be utilized to investigate the causal relationship among variables. The causal relationship between the region size and the regional efficiency is of particular interest in this paper.

The goals of this paper are two fold. First, regional efficiency is assessed using DEA. Input-output data is applied at the county level for the states of Nevada and Utah similar to procedures outlined by Raab and Lichty (1997 and 2002). Efficient and inefficient counties will be identified using DEA. Second, the causal relationship among associated variables, especially between the regional efficiency and the region size will be investigated. Population density will be used as a proxy variable for region size. In order to achieve these two goals, this paper is divided into three parts. First a brief discussion on the methodologies of DEA and DAG is presented. Secondly, empirical analyses are presented and finally, conclusions and policy implications from the DEA and DAG analysis are presented.

2. Methodologies

2.1. Data Envelopment Analysis (DEA)

DEA has been developed in the management science tradition with a focus on computing the relative efficiency of different decision making units (DMUs), for example, firms, hospitals or counties. To define DEA efficiency estimates the following notation is established; let $\mathbf{x}_j \in \Re_+^p$ denote a vector of p inputs and $\mathbf{y}_j \in \Re_+^q$ denote a vector of q outputs for DMU j, where $j = 1,\ldots, n$. The production possibility set is defined by $P = \{(\mathbf{x}, \mathbf{y})|$ outputs $\mathbf{y}$ can be produced from inputs $\mathbf{x}\}$. The boundary of P is referred to as the production frontier. Technically inefficient DMUs operate at points that are inferior to the production frontier, while technically efficient DMUs operate somewhere along the frontier. Define an efficiency measure θ for DMU j, $(\mathbf{x}_j, \mathbf{y}_j) \in \Re_+^{p+q}$ such that

(1) $\theta_j \equiv \sup\{\theta \mid (\mathbf{x}_j, \theta\mathbf{y}_j) \in P, \theta > 0\}$.

This is the Farrell (1957) measure of output technical efficiency, which is the reciprocal of the Shephard (1970) output distance function. The DEA estimator θ defined in equation (1) at a specific point (DMU j) can be written in terms of the linear programming (LP) model which is initially proposed by Charnes, Cooper and Rhodes (1978, 1981) and extended by Banker, Charnes, and Cooper (1984).

(2) $\hat{\theta}_j = \max\{\theta > 0 \mid \theta\mathbf{y}_j \leq \mathbf{Y}\boldsymbol{\lambda}, \mathbf{x}_j \geq \mathbf{X}\boldsymbol{\lambda}, \boldsymbol{\lambda} \in \Re^n_+\}$,

where $\mathbf{Y} = [\mathbf{y}_1, \mathbf{y}_2, \ldots, \mathbf{y}_n]$, $\mathbf{X} = [\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_n]$ and $\boldsymbol{\lambda}$ is $n \times 1$ intensity variables. It is noteworthy that the DEA formulation differs slightly along with the assumption of returns to scale. Under the constant returns to scale (CRS), the LP formulation is given by equation (2) which is called the CCR model (Charnes, Cooper, and Rhodes, 1978). The DEA estimator under the assumption of variable returns to scale (VRS) is found by solving the same LP problem in (2) with additional constraint, $\mathbf{i}'\boldsymbol{\lambda} = 1$, where $\mathbf{i}$ denotes an $n \times 1$ vector of ones. This model is called BCC model (Banker, Charnes, and Cooper, 1984) after authors. (The additional constraint imposes a convexity condition on allowable ways in which the observations for the n DMUs may be combined (Cooper, Seiford and Tone, 2007). When the above constraint is replaced by $\mathbf{i}'\boldsymbol{\lambda} \leq 1$, the production set exhibits the non-increasing returns to scale (NIRS).

The LP models in equation (2) along with additional constraint are run n times in identifying the relative efficiencies of all the DMUs. The DEA efficiency estimates are less than equal to 1 by construction. The DMU is said to be efficient if it obtains the DEA estimate of 1. The DEA estimate of less than 1 implies that it is inefficient. Also, $\theta_j^{crs} \leq \theta_j^{nirs} \leq \theta_j^{vrs}$ by construction. This is easily understood using Figure 1. Figure 1 shows a typical production possibility set in two dimensions for the single input and single output case. Panel A in Figure 1 has the production frontiers under CRS assumption and Panel B has that of under the VRS. Under the CRS assumption, DMU C is efficient and other DMUs would be inefficient (Panel A). However, under the VRS assumption, DMUs A, C, and F are efficient and DMUs B, D, and E are inefficient (Panel B). Obviously, the DEA estimator under VRS assumption is larger than those under CRS assumption.

The existence of increasing or decreasing returns to scale is of importance to many policy decisions. Unfortunately, the statistical test for returns to scale might not be appropriate because the DEA approach is non-parametric. Banker (1996) provides the test statistics of return to scale assuming that the DEA efficiency estimator follows specific distributions such as the exponential distribution or the half-normally distribution (chi-square distribution with degrees of freedom 1). Simar and Wilson (2002) point out that there is no reason to assume a specific distribution for the test and propose a bootstrap procedure avoiding the *ad hoc* assumptions of Banker (1996). Regional returns to scale (external economies scale) will be tested using the Simar and Wilson (2002) procedure.

The statistical test for the returns to scale begins with CRS. The null hypothesis is the production set exhibits CRS and the alternative hypothesis is that it shows VRS. Various test statistics are possible; however, the mean of ratios $\hat{\theta}_j^{crs} \big/ \hat{\theta}_j^{vrs}$, that is $t_{crs} = n^{-1}\sum_{j=1}^{n} \hat{\theta}_j^{crs} \big/ \hat{\theta}_j^{vrs}$ will be used as in Simar and Wilson (2002). By construction $t_{crs} \le 1$, the null hypothesis is rejected when t_{crs} is significantly less than 1. The critical value for deciding if the test statistic is significantly less than 1 can be derived from bootstrapping (Simar and Wilson, 2002). For more information about bootstrapping refer to Simar and Wilson (1998, 2000). When the null hypothesis of CRS is rejected, another test is preformed with a less restrictive, NIRS versus VRS. The test statistic is similar and decision is made based on the critical value from the bootstrapping.

Related to further statistical analysis with DEA efficiency estimates, for example regression or causal relationship investigation, Simar and Wilson (2007) insist that the statistical analyses may not be consistent unless the DEA estimates are corrected. They showed the inconsistency using Monde Carlo experiment, especially the second-stage regression. According to Simar and Wilson (2007) this inconsistency existed because the DEA estimates are complicated, serially correlated and biased downward by construction. Simar and Wilson (2007) propose bootstrap procedures to improve statistical properties of DEA estimates such that $\hat{\hat{\theta}}_j = \hat{\theta}_j - bias(\hat{\theta}_j)$. The bias term is constructed using the bootstrap. The empirical DEA estimates and bias corrected DEA estimates are reported in the following section.

2.2. Directed Acyclic Graph (DAG)[1]

A DAG approach attempts to identify the causal relationship among a set of observational or non-experimental data. The DAG is a picture representing causal flow using arrows among a set of variables (Pearl, 1995, 2000; Spirtes, Glymour, and Scheines, 2000) based on a conditional independence relationship as given by the recursive decomposition

(3) $$\Pr(x_1, x_2, x_3, \cdots, x_n) = \prod_{i=1}^{n} \Pr(x_i \mid pa_i),$$

where Pr(.) is the joint probability of variables $x_1, x_2, x_3, \cdots, x_n$ and pa_i are parents (direct causes) of x_i, the minimal set of x_i's predecessors (the variables that come before in a causal

[1] This section is heavily dependent upon Lee and Kim (2008)

sense) that renders x_i independent of all its other predecessors (Pearl, 2000, p.14-15). Geiger, Verma, and Pearl (1990) have shown that there is a one-to-one correspondence between the set of conditional independencies among variables implied by equation (3) and the graphical expression of variables in a directed acyclic graph. For example, consider four variables, x_1, x_2, x_3 and x_4. If there is causal relationship such as x_1, x_2 cause x_3 and x_3 causes x_4, then the directed graphs that represents in this causal relationship is represented in Figure 2. This directed graph is expressed as the probability distribution product by

(4) $$\Pr(x_1, x_2, x_3, x_4) = \Pr(x_1)\Pr(x_2)\Pr(x_3 \mid x_{1,} x_2)\Pr(x_4 \mid x_3) .$$

A Greedy Equivalence Search algorithm (GES) suggested by Meek (1997) and discussed by Chickering (2002, 2003) is used for identifying the causal flow among the variables. The GES algorithm starts from a graphical representation with no edges, which implies that all variables are independent, and it proceeds stepwise searching over causal flow based on equation (2) using the Bayesian scoring criterion. After score comparison among all possible equivalence classes[1], the equivalence class with the maximum score is chosen for the next step. Once a local maximum is attained in the first phase, the second phase proceeds by single edge deletions and compares the scores of DAG in equivalence classes repeatedly until a local maximum is again reached. When the algorithm reaches a local maximum, it obtains the optimal solution and DAG (Chickering, 2003). The GES algorithm and more refined extensions are marketed as the software TETRAD project (www.phil.cmu.edu/projects/tetrad/index.html). The DAG analysis for DEA efficiency scores and environmental variables are reported in the following section.

3. Empirical Results of the DEA and DAG

Using the DEA and DAG, the causal relationship between the regional efficiency and the region size (population density) is investigated. For the analyses 46 counties in states of Nevada and Utah are selected. Multiple years, 2001, 2004 and 2006 are analyzed and this allows the capture of the variation of efficiencies over time. Charnes *et al*. (1984) propose a technique called "window analysis" in the DEA. Window analysis assesses the performance of DMUs over time by treating them as different entities in each time period. For this paper there are 46 counties and 3 years, a total of 46 x 3 = 138 units need to be assessed simultaneously. This is also beneficial because the larger data set facilitates further statistical investigations.

To use the DEA, inputs and outputs are identified. Some of DEA applications in measuring the regional efficiency use county input-output data from the IMPLAN database (e.g., Raab and Lichty, 1997, 2002). The IMPLAN database provides information about a regions' structure and industry interrelationships (MIG, inc., 2004). Specifically, value added terms including employee compensation, proprietor income, other property income, and indirect business taxes can be categorized as inputs. Total import can be grouped as inputs. Final demands such as household consumption, business investment, government spending and export can be grouped as outputs. This approach is attractive because it is easy to collect data and to compare them.

However, it is questionable to use input-output data in the DEA analysis mainly because they are well-balanced itself, i.e., the sum of inputs equals the sum of outputs. Raab and Lichty (1997) include transfer payments (from other source) instead of indirect business taxes so they don't have perfectly balanced data set for the investigation but still they have a closely balanced data set. Raab and Lichty (2002) use intermediate imports instead of total imports because some of imports are consumed as the final demand. In this case, we expect data are closely balanced, too.

When inputs and outputs are perfectly balanced, the DEA efficient score would be 1. This is self-evident because it is not possible to improve any input or output without worsening some other input or output (Pareto efficiency). If data set are closely balanced DEA efficiency estimates are expected to be high. Recall Figure 1 and suppose that all of input-output pairs are arranged on the straight line or close to the line. Most of DEA efficiency estimates would be high in this case. This is why Raab and Lichty (1997, 2001) have high efficiency estimates. Sixty-five (65) Minnesota counties out of eighty-seven (87) had efficiency values of 1 and 22 counties had values less than 1 but larger than 0.93 (Raab and Lichty, 1997). The factor which makes unbalanced data set might be an important source of inefficiency. As Raab and Lichty (1997) mention in their paper, the transfer payments can be the inefficiency source. Thus, the use of input-output data for DEA analysis may not be appropriate. In this paper, the number of employees is used instead of employee compensation and proprietor income. The number of employees is not in monetary terms but in quantity. This allows the analysis to overcome the well-balanced data problem.

Once all the data from the IMPLAN database is collected, DEA efficiency for each county for each year was estimated. The FEAR software (Wilson, 2006) was used to estimate DEA efficiency. The FEAR software allows the computation of DEA estimates, implement the homogenous bootstrap algorithm described by Simar and Wilson (1998, 2000) and correct biased DEA estimates proposed by Simar and Wilson (2007).

3.1. Return to scale

It has been believed amongst regional economists that increasing returns to scale are necessary to explain the economic activity and population. However, there is no consensus in the empirical results if returns to scales are constant or increasing at the firm of other levels of aggregation (McCombie and Roberts, 2007). In regional growth analyses, constant returns to scale assumption is widely used. Returns to scale is tested using the DEA efficiency estimates and bootstrapping (Simar and Wilson, 2002). As discussed section 2.1, the test begins with the null hypothesis of CRS. The test static is $t_{crs} = n^{-1}\sum_{j=1}^{n}\hat{\theta}_j^{crs} \big/ \hat{\theta}_j^{vrs}$ which is 0.9782. If this static is significantly less than 1 (or critical value) the null hypothesis is rejected. From bootstrapping, the critical value at 5% significance level is 0.9676; therefore, the null hypothesis is not rejected. This implies that our county data over 3 years exhibit CRS.

3.2. Efficiencies of Counties

The DEA efficiencies are computed for forty six counties in Nevada and Utah over the years 2001, 2004 and 2006 assuming CRS. Table 1 contains the DEA efficiency estimates. The DEA estimates column reports the conventional DEA estimates. The corrected DEA estimates column includes the DEA estimates after correcting biased DEA estimates using the procedure proposed by Simar and Wilson (2007). Figure 3 shows the geographical pattern of DEA estimates. Note that efficiency values in Figure 3 are the three-year average of the corrected DEA estimates. For discussion, Figure 3 contains population density information. The red area indicates highly populated areas such that the population density is more than 5,000 persons per square mile. These regions consist of Metro Statistical Area (MSA). The brown and yellow areas represent the area which has population density with more than 250 persons per square mile.

From Table 1 and Figure 3, the larger region or highly populated areas tend to have higher efficiency. Especially counties close to MSA have higher DEA efficiency estimates and periphery regions have lower DEA efficiencies. As a result, the larger regions have the higher efficiency estimates. The correlation between the region size (population density) and DEA efficiency scores is positive (0.03) but not statistically significant but the correlation between the population and efficiency scores is positive (0.23) and statistically significant. The correlation between MSA and DEA efficiency scores is also positive (0.27) and statistically significant.

3.3. Causal relationship

After estimation of county efficiencies, the causal relationship between the regional efficiency and the set of environmental variables such as region size, infrastructure, unemployment rate, regional income, per capita government expenditure etc. are investigated. DAG analysis was employed (Pearl, 1995, 2000; Spirtes, Glymour, and Scheines, 2000) which was discussed in section 2.2. To perform DAG analysis eight variables are selected; DEA estimates, population density, highway, income per households, unemployment rate, per capita government expenditure and two dummy variables.

One dummy variable was used to derive state effects. Nevada counties were found to have consistently higher DEA estimates when compared to Utah counties. Another dummy variable is existence of MSA. The MSA county has a value of 3, if the county has more than 1 million population, for example Las Vegas-Paradise, Clark County, NV. The MSA county has a value of 2, if the county has less than 1 million population, for example Reno-Sparks, Washoe County, NV. The county has a value of 1, if the county is included in a micropolitan statistical area. Statistical area list is obtained from the Office of Management and Budget (OMB, 2006). A highway variable as the proxy for infrastructure in the region is developed. Highway variable is constructed as the number of highways in the county including interstate highways and state highways. The highway map from the US Department of Transportation (2007) was used to construct highway variable. The maximum value of highway was four for Salt Lake County, UT.

Regional income per households is another variable of interest and the data is collected from the IMPLAN database. Unemployment rate can be a good candidate when we discuss regional efficiency. Unemployment rate is collected from Nevada Department of Employment, Training and Rehabilitation (2007) and Utah Department of Workforce Services (2007), respectively. Per capita government expenditure is also included to complete regional economy. Per capita government expenditure (federal government expenditure + state government expenditure) for each year is collected from IMPLAN database. Per capital government expenditure is expected to affect unemployment rate and regional income per household.

Once all the variables are collected, the directed acyclic graph is specified by the GES algorithm in TETRAD IV (version 4.3.9-0) (www.phil.cmu.edu/projects/tetrad/index.html) and is shown in Figure 4. A plus (+) indicates the positive correlation and a negative (–) indicates the negative correlation between variables.

The population density (popdnst) and highway directly cause the regional efficiency (dea). This implies that the region size leads to regional efficiency and region infrastructure is another direct cause of regional efficiency. The GES algorithm cannot direct the edge between population density and highway. If the causal flow is directed to highway, population density indirectly causes regional efficiency via highway. This is plausible because highly populated regions require a high level of infrastructure and this infrastructure facilitates the regional efficiency. Results of this paper are in agreement with results by Shirley and Winston (2004), which show that highway investments increase firm efficiency by lowering firm inventories.

Regional efficiency indirectly causes regional income (yperhh) via formulation of MSA. The efficient region has the metropolitan area and increased regional income. Regional income reduces unemployment rate. Thus regional efficiency affects the unemployment rate indirectly via MSA and regional income. State variable causes regional efficiency, regional income and unemployment rate directly and this explains the effects of state-specific factors, for example, law or tax rate. Per capita government expenditure (pc_govE) affects MSA, regional income and unemployment rate, directly. Per capita government expenditure might be larger in rural area than MSA, which is consistent with Hu, Harris and Kim (2008). Also, per capital government expenditure decreases regional income (more tax) and unemployment (job education). Unemployment rate is the information sink, and all information eventually flows to it. The region size, state and per capita government expenditure variables are information roots in this sense.

4. Conclusion and policy implications

Regional economists have been interested in the causal relationship between region size and regional efficiency. DEA and DAG methodologies attempt to investigate the causal relationship between them. From the empirical analysis for the states of Nevada and Utah, region size in terms of population density directly and possibly indirectly causes the regional efficiency via infrastructure (highway variable). Regional efficiency affects the formulation of MSA directly and affects indirectly the regional income and unemployment via MSA variable. Per capital government expenditure affects MSA formulation, the regional income and unemployment rate directly. Also, highways were shown to positively impact regional efficiency. Given the current public debate on transportation costs, the efficiency that highways add to local economies is often ignored.

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End Note

1. Two directed acyclic graphs (DAGs) are in the same equivalence class when they are equivalent. Both DAGs are equivalent when both are distributionally equivalent and independence equivalent (Chickering, 2003, p.510). Ditributionally equivalent DAGs have the same Bayesian networks (that is, equation 2). Consider the following DAGs:

$$\begin{array}{ccc} \text{DAG}_1 & \qquad & \text{DAG}_2 \\ \begin{array}{l} x_1 \rightarrow x_2 \\ \downarrow \\ x_3 \end{array} & & \begin{array}{l} x_1 \leftarrow x_2 \\ \downarrow \\ x_3 \end{array} \end{array}$$

Based on equation (2) we can construct the joint probability distributions such that

DAG$_1$: $\Pr(x_1,x_2,x_3) = \Pr(x_1)\Pr(x_2|x_1)\Pr(x_3|x_1)$, and
DAG$_2$: $\Pr(x_1,x_2,x_3) = \Pr(x_2)\Pr(x_1|x_2)\Pr(x_3|x_1)$.

Because $\Pr(x_2|x_1) = \Pr(x_2 \cap x_1)/\Pr(x_1)$, DAG$_1$ can be rewritten as following

$$\Pr(x_1,x_2,x_3) = \Pr(x_1)\Pr(x_2|x_1)\Pr(x_3|x_1) = \Pr(x_1 \cap x_2) \Pr(x_3|x_1).$$

With the same logic, DAG$_2$ is

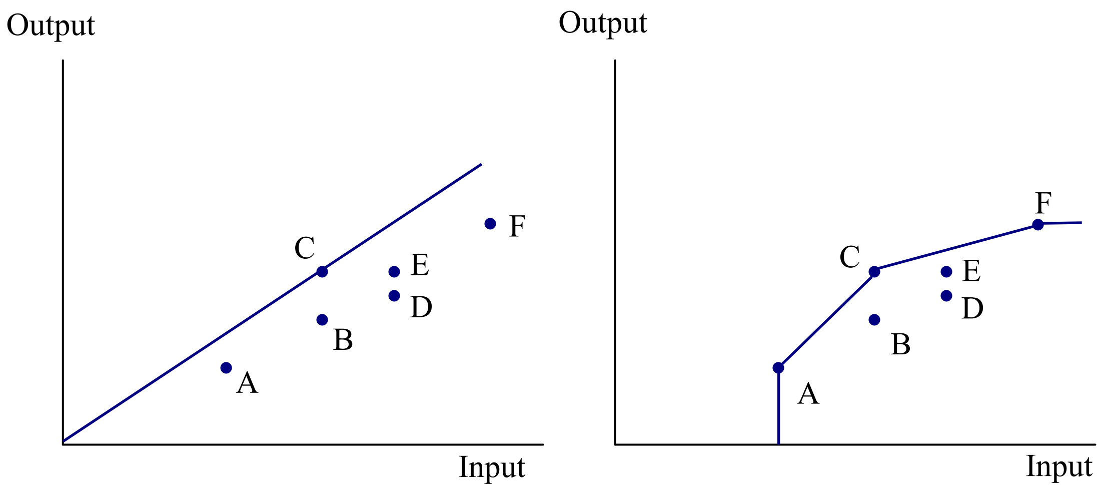
$$\Pr(x_1,x_2,x_3) = \Pr(x_2)\Pr(x_1|x_2)\Pr(x_3|x_1) = \Pr(x_1 \cap x_2) \Pr(x_3|x_1).$$

As a results, both joint probability distributions are identical (distributionally equivalent).

Two DAGs are indepnendence equivalent if the independence constraints are identical (Chicekring, 2003, p. 510). The independence constraint for DAG_1 is $x_2 \perp x_3 | x_1$ (the symbol $\perp$ indicates independence and | denotes conditioning on). The independence constraint for DAG_2 is $x_2 \perp x_3 | x_1$. Thus two DAGs have the same independent constraints, and in turn, two DAGs are equivalent and in an equivalent class. The GES algorithm computes the score of both DAGs, compare them and pick the DAG whose score is larger systematically.

Table 1. DEA scores; Output orientation with CRS assumption

	DEA estimates			Corrected DEA estimates		
	2001	2004	2006	2001	2004	2006
Carson, NV	0.875	0.880	0.865	0.848	0.858	0.841
Churchill, NV	1.000	0.942	0.923	0.919	0.908	0.902
Clark, NV	1.000	1.000	1.000	0.947	0.954	0.957
Douglas, NV	1.000	0.925	1.000	0.935	0.885	0.965
Elko, NV	0.972	1.000	0.970	0.947	0.948	0.942
Esmeralda, NV	1.000	1.000	1.000	0.961	0.958	0.926
Eureka, NV	1.000	1.000	1.000	0.918	0.918	0.918
Humboldt, NV	0.921	1.000	0.937	0.896	0.954	0.904
Lander, NV	0.952	0.935	1.000	0.925	0.895	0.965
Lincoln, NV	0.777	1.000	1.000	0.750	0.938	0.925
Lyon, NV	0.950	0.982	1.000	0.925	0.947	0.955
Mineral, NV	1.000	1.000	1.000	0.925	0.952	0.915
Nye, NV	1.000	1.000	1.000	0.956	0.961	0.945
Pershing, NV	0.852	0.915	0.966	0.820	0.877	0.934
Storey, NV	0.907	1.000	1.000	0.874	0.920	0.915
Washoe, NV	1.000	0.982	0.977	0.962	0.960	0.955
White Pine, NV	0.999	0.882	1.000	0.957	0.846	0.946
Beaver, UT	0.984	0.793	0.843	0.944	0.768	0.812
Box Elder, UT	1.000	1.000	0.929	0.928	0.914	0.889
Cache, UT	0.910	0.924	0.800	0.883	0.884	0.769
Carbon, UT	0.955	0.925	0.920	0.931	0.904	0.899
Daggett, UT	0.952	0.916	1.000	0.915	0.882	0.948
Davis, UT	0.865	0.922	0.890	0.839	0.886	0.849
Duchesne, UT	0.837	0.903	1.000	0.815	0.873	0.949
Emery, UT	0.920	0.959	1.000	0.892	0.936	0.970
Garfield, UT	0.823	0.760	0.842	0.805	0.738	0.821
Grand, UT	0.868	0.877	0.901	0.850	0.855	0.882
Iron, UT	0.842	0.821	0.830	0.816	0.797	0.801
Juab, UT	0.920	0.997	1.000	0.891	0.954	0.919
Kane, UT	0.792	0.819	0.858	0.757	0.798	0.834
Millard, UT	0.890	0.932	0.963	0.873	0.902	0.937
Morgan, UT	0.902	0.947	0.864	0.873	0.920	0.836
Piute, UT	1.000	0.825	0.974	0.916	0.790	0.933
Rich, UT	0.897	0.811	0.922	0.858	0.782	0.884
Salt Lake, UT	1.000	0.962	0.948	0.956	0.932	0.920
San Juan, UT	0.826	0.880	1.000	0.788	0.847	0.921
Sanpete, UT	0.821	0.852	0.890	0.787	0.818	0.850
Sevier, UT	1.000	0.772	0.858	0.916	0.748	0.830
Summit, UT	1.000	0.963	0.966	0.925	0.928	0.942
Tooele, UT	0.947	1.000	0.916	0.905	0.939	0.878
Uintah, UT	0.867	1.000	1.000	0.838	0.926	0.914
Utah, UT	1.000	0.973	0.935	0.955	0.934	0.908
Wasatch, UT	1.000	0.981	0.934	0.930	0.942	0.905
Washington, UT	0.951	0.944	0.968	0.926	0.916	0.936
Wayne, UT	0.844	0.837	0.921	0.813	0.807	0.886
Weber, UT	0.900	0.880	0.859	0.874	0.854	0.836



Panel A. Production frontier of the CCR model

Panel B. Production frontier of the BCC model

Figure 1. Production frontiers and efficiency measure

$$
\begin{tikzcd}
x_2 \arrow[r] & x_3 \arrow[r] & x_4 \\
& x_1 \arrow[u] &
\end{tikzcd}
$$

Figure 2. Example of directed graph and causal relationship

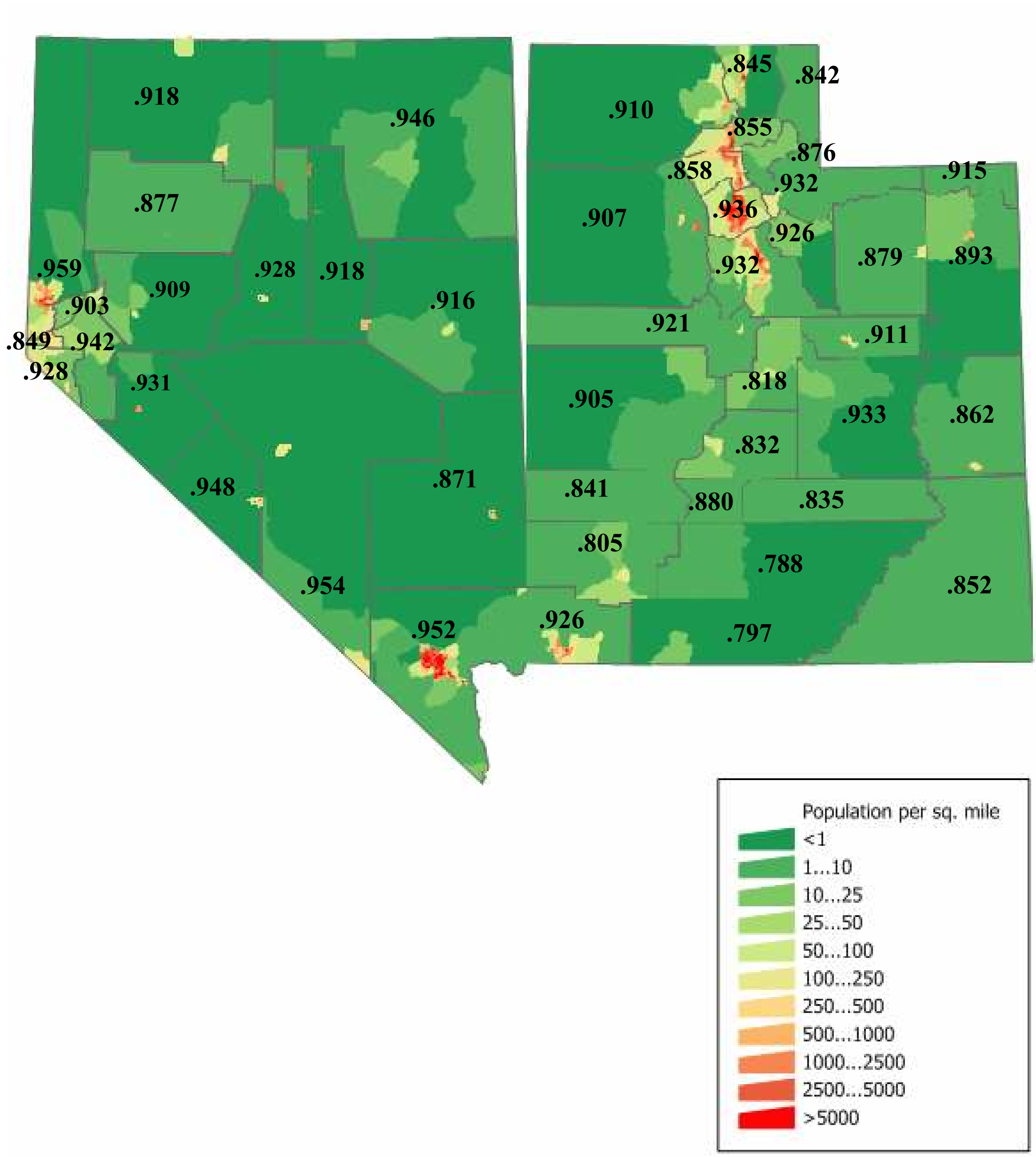


Figure 3. Geographic patterns of corrected DEA estimates with CRS (3 year average)

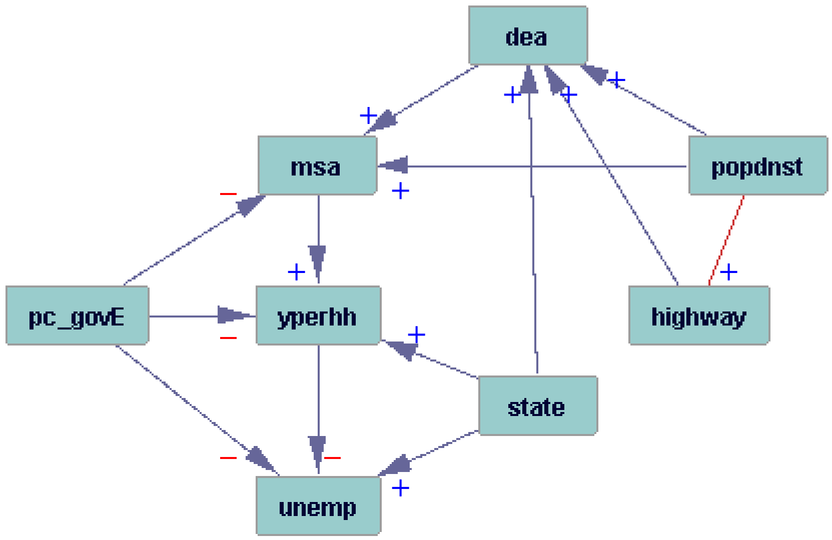


Figure 4. Directed acyclic graph specified by TETRAD IV