USING DATA ENVELOPMENT ANALYSIS TO EXPLORE STATE-BY-STATE TRANSPORTATION PERFORMANCE INDICES

by

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ABSTRACT

The Transportation Performance Index (TPI), developed by the U.S. Chamber of Commerce, captures the relationship between transportation infrastructure performance and the U.S. economy, specifically in terms of GDP growth. Both a national TPI and state-by-state indices were developed. Although the TPI serves as a useful quantitative tool that connects economic prosperity to transportation infrastructure, this relationship is complex and the TPI does not capture the nuances, particularly at the state-by-state level.

The TPI is assembled from a variety of indicators capturing supply, quality of service and utilization for each mode of transportation, but it does not fully consider environmental influences that exert pressure on the TPI. Using the data envelopment analysis (DEA) method, the relationship between TPI and GDP can be clearly defined for the state-by-state data, while taking into account the effects of environmental factors, such as population growth and annual vehicle miles traveled. Similar to TPI, DEA yields a single measure of performance, where it produces a ratio of the aggregated, weighted outputs to the aggregated, weighted inputs by state and year. The main output is GDP per capita and the main input is TPI, along with other inputs, including debt and life expectancy. Overall, the research presented in this thesis focuses on how much influence environmental factors have on the relationship between transportation infrastructure and economic growth.

Chapter 1

INTRODUCTION

In recent years, the debate regarding the effects of transportation policy and infrastructure on U.S. economic growth has become fairly heated (Goetz, 2011). With the strain of the recent economic challenges, both the public and the government call for increased investment into transportation as a way to provide more jobs and improve the economy. On June 20th, 2011, Representative Peter DeFazio, a Democrat from Oregon, sent a letter to President Obama urging him to consider a plan to invest in critical transportation and infrastructure projects, which he believes will put millions of Americans back to work. In the letter, DeFazio states that during these hard economic times other countries as well as the U.S. have had to make severe budget cuts, but "even as our competitors are making austerity cuts, many have maintained investments in their transportation and infrastructure systems because they know these investments produce economic gains" (DeFazio, 2011). Moreover, DeFazio does not stand alone in his belief that investment into the country's infrastructure is an effective option on the road to economic recovery.

The American Recovery and Reinvestment Act (ARRA) of 2009 is a notable example of the belief that there is a direct connection between transportation infrastructure investment and economic growth. In the $800 billion ARRA stimulus package, about $50 billion was allocated toward transportation infrastructure (Federal Highway Administration, 2009). On the one hand, similar to DeFazio, there are those who believe that this amount is far below what is needed to make any real improvement.

While on the other hand, there are those that believe that infrastructure investment is the right approach for improving the economy, but acknowledge there are many challenges that face public investment. In a paper published by the News Democratic Network (NDN) titled, "Investing in Our Common Future: U.S. Infrastructure," Moynihan describes these different challenges (Moynihan, 2007).

One of these major challenges is the lack of public support. Even though there is an evident increase in public awareness of the importance of infrastructure investment with the 2007 collapse of the I-35W Bridge in Minnesota (Benson, 2007) and the American Society of Civil Engineers (ASCE) Infrastructure Report Card (Ritholtz, 2010), public support for infrastructure is incomparable to what is given towards issues related to social security and national safety (Moynihan, 2007). Also, related to public support, there is a void that needs to be filled in terms of political leadership. There needs to be an advocate or champion for infrastructure investment, who is able to convey effectively the significance of maintaining and upgrading America's infrastructure. Along with the increasing budget deficit, other issues related to infrastructure investment include the complex process for allocating funds from the federal to the state level, which can cause projects to be extended out for many years (Moynihan, 2007). In addition, there is the issue of conflicting goals at the federal and the state level on to how to address specific infrastructure problems (Moynihan, 2007).

Overall, the debate about the economic effects of infrastructure investment is ongoing, where there are several institutions and organizations that have examined this issue in detail. For example, the Research and Development (RAND) Corporation released a report "Highway Infrastructure and the Economy: Implications for Federal Policy," which is a synthesis of a collection of work that investigates the relationship between highways and the economy from both a qualitative and quantitative perspective.

From the report, it was concluded that based on current research “positive effects of highway infrastructure on economic outcomes, in particular productivity and output” exist (Shatz, Kitchens, Rosenbloom, & Wachs, 2011). However, it is noted that the cases of positive effects are very context specific, and focus primarily on small geographical areas. The majority of the statistical research connects infrastructure and productivity, but fails to place a value on the economic changes that result from infrastructure investment. In addition, for other transportation infrastructure, such as freight and transit, there was a relative lack of information available related to economic growth compared to the several statistical studies found on highway infrastructure.

While the connection between infrastructure investment and the economy is a complex issue, there is, without a doubt, a fundamental need for infrastructure. The quality of life of every American is directly related to the performance of our nation’s infrastructure, from our bridges and roads to our power plants and wastewater treatment facilities. Infrastructure is what we conduct business on, what we use for recreational activities, and what we require to satisfy our everyday needs. Consequently, the need for a better understanding of the role of infrastructure preservation as well as the relationship between transportation infrastructure and the economy is paramount. This need is even more significant with the national transportation bill having expired in 2009 (Davis, 2009) and the slowly depleting Federal Highway Trust Fund (Farkas, 2011). Reshaping U.S. transportation policy and committing to the goal of improving the nation’s infrastructure is quickly becoming an imperative, and research and analysis are needed in preparation for this opportunity.

Through the U.S. Chamber of Commerce’s “Let’s Rebuild America” project, more insight into the relationship between infrastructure and the economy is developed. The “Let’s Rebuild America” project is an initiative to develop an infrastructure performance index, which can communicate the importance of infrastructure investment as a way for America to remain globally competitive (Gallis M. , et al., 2010) More specifically, the infrastructure performance index serves as a quantitative tool that measures the performance of the nation's infrastructure as it meets the needs of business and industry, which addresses some of the issues outlined in the RAND report with existing research in this area. The infrastructure performance index focuses on transportation, water and energy infrastructure as major influences on the economy; while creating a sub-index for transportation, known as the Transportation Performance Index (TPI). In addition, the indices are developed so that they are accessible and transparent, as well as easily repeatable.

This research builds on the U.S. Chamber of Commerce's work, focusing on the Transportation Performance Index (TPI) and its ability to capture the effect environmental or contextual influences have on transportation infrastructure itself. The main objectives of this research are to provide an alternative perspective to the results of the TPI and expand the growing catalog of work in the area of infrastructure and the economy.

Problem Statement

In September 2010, the U.S. Chamber of Commerce released the Transportation Performance Index (TPI) to the public as a part of the "Let's Rebuild America" project. The TPI is developed at the national level for the years 1990 – 2008 and at the state level for 1995, 2000 and 2007. The TPI is a precursor to the Let's Rebuild America Index (LRA-Index); a composite index derived from indicators capturing transportation, water and energy infrastructure performance. The motivation for the development of these indices is to be able to provide a tool for policy makers that can effectively communicate the relationship between the performance of infrastructure and economic prosperity, specifically in terms of GDP growth. TPI is defined based on weighted measures of indicators related to supply, quality of service, and utilization (Gallis M. , et al., 2010)As shown in Figure 1, state-by-state indices for 1995, 2000 and 2007 were developed.

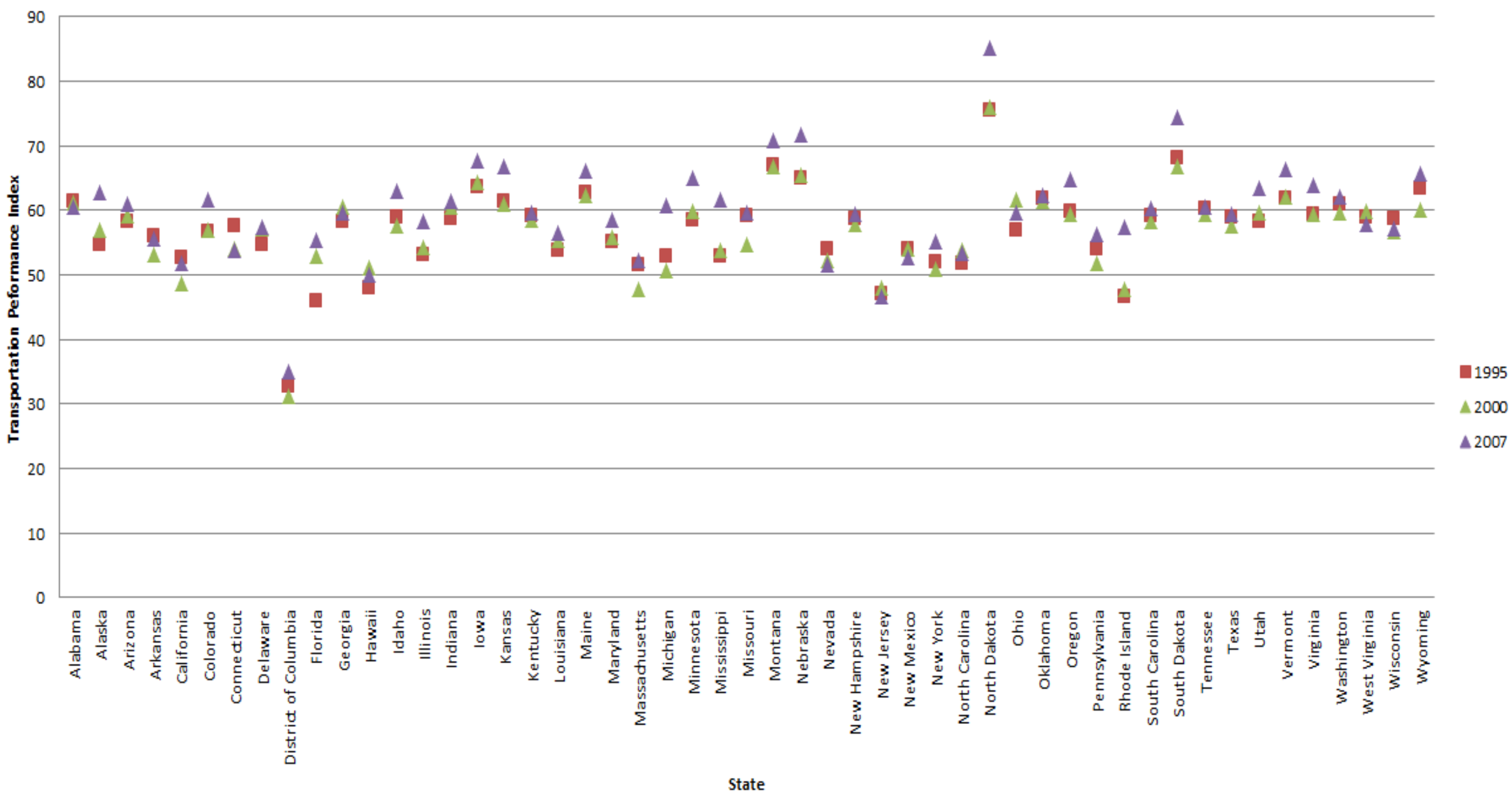

Figure 1 State-by-State Transportation Performance Index (TPI) for all years.

To date analysis of the relationship between the TPI and the economy used the annual national TPI for years 1990 to 2008 and the following relationship between GDP per capita and TPI on the national level was developed (Gallis M. , et al., 2010):

$$\mathrm{lnGDPpc}_t = 0.0037\,\mathrm{TPI}_t + 0.6210\,\mathrm{GDP}_t - 0.0025\,\mathrm{Debt}_t; \qquad (1)$$

where $t = \text{year}$

lnGDPpc = the natural log of GDP per capita by year (in 2000 dollars)

TPI = the national TPI by year (lagged by 3 years)

GDP = the national real GDP by year (in 2000 dollars)

Debt = the federal debt as a percentage of GDP by year

The dependent variable is the natural log of GDP per capita by year, where the independent variables include the national TPI, real GDP and federal debt as a percentage of GDP by year. From the coefficients of the independent variables, it can be seen that GDP per capita increases when TPI and GDP increase. On the other hand, GDP per capita decreases when debt increases. The simplest way to interpret Equation 1 is to consider a 1 point increase in TPI (with all other variables remaining constant) results in a 0.3% increase in GDP per capita (Gallis M. , et al., 2010)

The structure of Equation 1 derives from Sala-i-Martin's work with time-series growth models (Gallis M. , et al., 2010) where there are five key determinants or independent variables of economic growth, as shown below:

1. initial level of the economy
2. quality of the government
3. population health (but not related to "human capital")
4. free market institutions
5. open economies

Equation 1 includes the initial level of the economy (*GDP*) and the quality of the government (*Debt*). The TPI was added to capture the performance of the transportation infrastructure. The last three determinants are not considered since population health is fairly constant between 1990 and 2008, free market institutions are widespread in America and the U.S. is a major part of the global economy (Gallis M. , et al., 2010).

Even though TPI does well in capturing the specific indicators related to the physical transportation infrastructure, it does not necessarily capture the nuances of environmental influences on the infrastructure itself. For example, a state may receive a low index value within a particular year as compared to the other states, but it may still be functioning efficiently and experiencing economic prosperity despite its environmental constraints. Consequently, the goal of this research is to examine the effect environmental influences have on the relationship between GDP per capita and TPI at the state level. So, using the equation developed on the national level as a basis, data envelopment analysis (DEA) is used to determine the relative efficiencies of each state while examining the effects of adding and removing the influences of the environment. In addition, similar to the principles outlined for the U.S. Chamber of Commerce's "Let's Rebuild America" project, one of the central missions of this research is to ultimately influence policy change that supports economic growth through infrastructure investment using concrete findings. However, the main objectives are to provide a different perspective on the TPI results and expand the growing catalog of work in the area of infrastructure and the economy. Accordingly, this paper explores the relationship between GDP per capita and TPI on a state-by state basis using data from 1995, 2000 and 2007 and applying the data envelopment analysis (DEA) model to determine the efficiency of each state.

Outline of Thesis

The following chapter provides background information on DEA and the software used. The next section introduces the methodology, including the DEA outputs and inputs, environmental influences, the data collection process and the general DEA hypotheses. In the following chapter, results are presented and then the thesis concludes with opportunities for future work. Appendices document the following: Appendix A lists the abbreviations used throughout the thesis, Appendix B summarizes the four step process for using the DEA software, Appendix C provides additional graphs of the variables analyzed, Appendix D provides individual box-and-whiskers plots for the variables, Appendix E shows the graphs for Hypothesis 0 DEA results, Appendix F shows the graphs for Hypothesis I DEA results and lastly, Appendix G shows the graphs for Hypothesis II DEA results.

Chapter 2

BACKGROUND

Defining DEA

In order to further understand the relationship between the economy and transportation, while taking into account environmental influences, the DEA method is utilized. DEA is a nonparametric linear programming method for measuring production efficiency that is predominant in operations research and economics. Specifically, DEA is used to evaluate the activities of different organizations, from hospitals to schools, and in this case, U.S. states (Rozkovec, 2009).

With a foundation in economics, production efficiency as an area of study has a very long history. The topic of efficiency measurement for production units increased in notoriety with the 1978 paper, “Measuring the Efficiency of Decision Making Units” (Charnes, Cooper, & Rhodes, 1978). This publication, which is typically referred to as the CCR paper for its three authors, has over 700 citations and counting (Førsund & Sarafoglou, 1999). The CCR paper addresses many issues related to the application of DEA and provides the basis for production efficiency research today.

Production Efficiency

Overall, DEA is a multi-factor productivity analysis model that can be used to measure the relative efficiencies of a homogenous set of decision making units (DMUs) (Li, Xiao, McNeil, & Wang, 2011). A DMU is a unit of analysis such as a state, a section of pavement, a transit agency or business unit (Hoff, 2007). DEA produces a single comprehensive score for each DMU, which is the ratio of the weighted outputs to the weighted inputs. The specific weights for each DMU are determined to maximize the score. Consequently, each individual DMU receives the highest score possible and the argument of using different weights is not valid when comparing final scores (Tandon, McNeil, & Barnum, 2006). Also, all DMUs use the same set of non-negative weights. The final output of DEA is a ranked efficiency score for each DMU, which is determined using the following equation:

$$\text{Production Efficiency} = \frac{\text{Weighted Sum of Outputs}}{\text{Weighted Sum of Inputs}} \tag{2}$$

Production efficiency within DEA can essentially be defined as how well a specific DMU is able to function or operate based on its given constraints and characteristics. In total, there are three different production efficiency classifications examined, all of which can be seen in Figure 2.

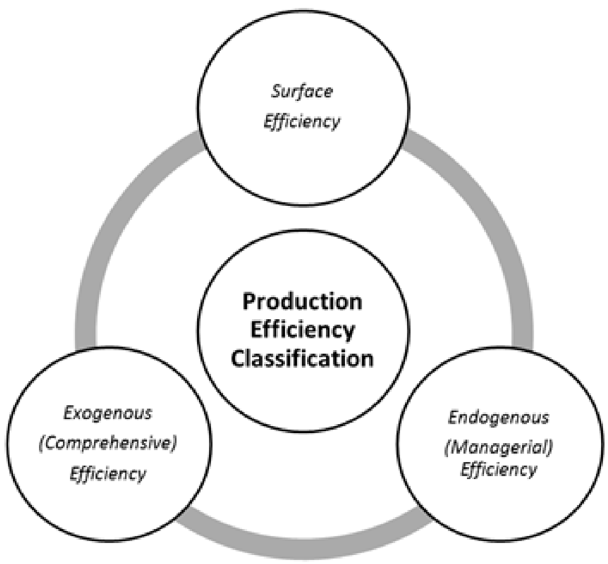

Figure 2 Production Efficiency Classification.

The first production efficiency classification is surface efficiency. Surface efficiency refers to the relative efficiency of the states in regards to transportation and the economy, without taking into account the environmental influences that are considered to be problematic to control and place the most pressure on TPI. The advantages of using this ranking are that it requires less computational effort and provides some insight into the productivity of the states. However, it is not exact since it completely disregards the role of the environment.

The second production efficiency classification is exogenous or comprehensive efficiency, which is similar to surface efficiency but adds the effects of the environment. In turn, it is more computationally intensive. Comprehensive efficiency is the productivity of the states in terms of how well their individual practices and policies overcome or succumb to the effects of the environment.

The third and final production efficiency classification is endogenous or managerial efficiency and requires the most computational effort. Managerial efficiency represents the efficiency that is under the control of the states. It only refers to the practices and policies of each state, not a specific agency or organization, and completely removes the effects of the environment. As a result, it is considered to be the true efficiency of all three.

Overall, efficiency rankings are a useful tool in terms of obtaining a better understanding of how specific entities or organizations function in relation to one another. For example, on May 17th, 2011, the International Institute for Management Development (IMD) released the 2011 World Competitiveness Rankings as well as the results of the "Government Efficiency Gap", which compares the government efficiency and the business efficiency of about 60 countries. For each country, the magnitude of the government efficiency gap determines whether the government either hinders or supports the growth and success of businesses (International Institute for Management Development, 2011). These efficiency rankings are an easy way to demonstrate the relative competitiveness of various countries. Furthermore, the same analysis can be applied to DEA, where “Managerial Efficiency Gap” results can be developed by comparing the comprehensive efficiency and the managerial efficiency of the states. In turn, the managerial efficiency gap would reflect how well states deal with environmental factors that affect their transportation infrastructure.

DEAFrontier Software

The analysis for each production efficiency classification was conducted using DEAFrontier, which is a DEA modeling software that uses Excel Solver™ as its engine (Zhu, 2009). There are a few types of DEA models that the software is able to run, but the one used was the input-oriented Envelopment Model with Constant Returns to Scale (CRS) (Zhu, 2009). DEA models can be input or output orientated, of which the former determines the minimum input for which the observed production of the i^{th} DMU is possible, while the latter determines the maximum output of the i^{th} DMU given the observed inputs (Hoff, 2007). The CRS Envelopment model is the most widely used and most basic DEA model. It is structured to minimize the inputs, while maintaining the outputs at their current levels. In addition, CRS assumes that outputs should be increased or maximized and are defined as desirable outputs, while the inputs should be decreased or minimized and are defined as desirable inputs (Li, Xiao, McNeil, & Wang, 2011).

Furthermore, the method by which the CRS model calculates efficiency is very similar to how efficiency is defined within economics, where it is typical defined as maximizing net benefits or maximizing the sum of individual utilities (Baradach, 2009).

A mathematical formulation of the CRS mode as a fractional program (FP_0), based on Equation 2, can be seen below (Ozbek, Garza, & Triantis, 2009):

$$\text{Maximize } Q_0 = \frac{\sum_{r=1}^{s} u_r y_{r0}}{\sum_{i=1}^{m} v_i x_{i0}}$$

$$\text{Subject to} \quad \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1$$

$$j = 1, \dots \dots \dots, n$$

$$r = 1, \dots \dots \dots, s$$

$$i = 1, \dots \dots \dots, m$$

$$u_r, v_i \geq 0 \tag{3}$$

Q_0 = efficiency score of individual DMU

N = number of DMUs in data set

S = number of DEA outputs

m = number of DEA inputs

y_{rj}, x_{ij} = outputs and inputs of the j-th DMU, where all are positive

u_r, v_i = weights of outputs and inputs of the j-th DMU, where all are positive

For each DEA model, Equation 3 is applied, where all models a single-output/multi-input process. The specific steps for running the DEAFrontier software can be seen in Appendix A.

With a given set of DMUs, an efficiency frontier or data envelopment curve can be formed from the production efficiency function, as shown in Figure 3. The efficiency frontier represents the DMUs that are determined to be the most efficient where, based on Equation 2, the best efficiency score that can be obtained is a ratio of 1. On the other hand, the less efficient DMUs have an efficiency score that ranges between 0 and 1. So, similar to TPI, DEA produces a single comprehensive quantitative value.

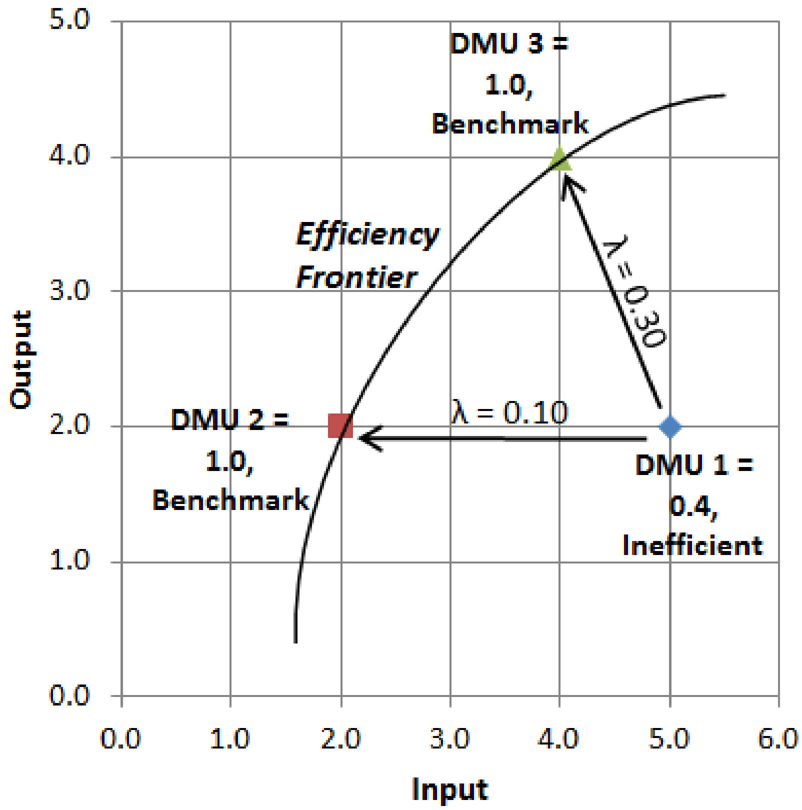

Figure 3 Example of a DEA Efficiency Frontier curve.

The efficiency frontier curve not only represents the group of the most optimally performing DMUs, but serves as the benchmarks against which the less efficient DMUs are compared. Furthermore, the most efficient DMUs are benchmarked against themselves. In terms of comparison, the inefficient DMUs may be benchmarked by one or more of the efficient DMUs, which are each given an associated λ weight. The associated λ weight represents the percentage by which the inefficient DMU must be more like the benchmarked DMUs in order to become efficient. For example, referring back to Figure 3, the results of an efficiency analysis may state that DMU 1 has an efficiency score equal to 0.40 and is benchmarked by both DMU 2 and DMU 3 with respective λ weights of 0.10 and 0.30. This means that DMU 1 will try to be more like DMU 3 rather than DMU 2, because it has a higher λ weight. In turn, for DMU 1, its efficiency can be improved or respectively its inefficiency reduced by reducing its inputs.

Alternatives to DEA

DEA is often used as a performance assessment tool due to the fact that it provides valuable information about the individual parts of a company or an organization in relation to the whole. On the other hand, regression analysis (RA) is also a common statistical technique that is used for performance assessment. After examining the advantages and disadvantages of each method, the most significant difference between DEA and RA is that the former is nonparametric and the latter is parametric (Thanassoulis, 1993). Since RA is parametric, the user must have some idea of what mathematical form the production efficiency function will take. Specifically, an initial set of parameters must be assumed. Another alternative to DEA is stochastic production frontier (SPF) analysis, which, similar to RA, is parametric in form. An additional disadvantage with SPF is that only one output can be considered at a time, which limits modeling possibilities (Hoff, 2007). So, for DEA, compared to RA and SPF, an initial hypothesis of the form of the production efficiency function is one less thing the user has to specify.

Other advantages DEA has over RA are that it measures overall performance based on relative efficiency rather than average performance using a boundary method, it is more capable of dealing with multiple inputs and outputs and it produces more accurate efficiency estimates. In addition, DEA is not affected by collinearity, where even if two or more variables are highly correlated, the results will not change drastically with small changes to the model or data. Conversely, RA is a better predictor of future performance, provides confidence limits for efficiency estimates and produces results that are transparent and thus are easier to communicate. Thanassoulis concludes that DEA may be the more appropriate option because it results in more accurate efficiency estimates (Thanassoulis, 1993). However, it was noted that both methods provide relatively accurate results and using one over the other is a matter of preference.

Understanding DEA Results

In terms of interpreting the DEA results, the comparison of scenarios involving different variables and formulations of the DEA model can be beneficial. Philosophically, this approach is similar to common methods used in data analysis, including scenario analysis, data mining, sampling sensitivity analysis, and hypothesis testing.

Scenario analysis is the evaluation of possible future events from a set of alternatives (Swart, Raskin, & Robinson, 2004). Future events or outcomes are defined based on their likelihood of occurring, ranging from least likely to most likely. For the DEA hypotheses, there is no forecasting involved, but alternative models are compared to qualitatively determine which has the highest probability of being accurate.

Data mining is large scale data analysis, using statistics, artificial intelligence and database management (Fayyad, Piatetsky-Shapiro, & Smyth, 1996). Whereas data mining focuses on discovering new or unknown patterns in large data sets, the approach used for the DEA hypotheses focuses on identifying known patterns. Furthermore, the DEA hypotheses follow an approach that is more similar to machine learning, where computer-based algorithms, like those found in the R software, are used to classify, generalize and predict patterns in data sets.

Sensitivity analysis refers to the study of how variations in the inputs of a model affect the variation or the uncertain of the outputs. In terms of sampling sensitivity analysis, it is the process of repetitively running different combinations of a model using values sampled from the distribution of the inputs. In turn, sensitivity factors are obtained for each of the inputs (Helton & Davis, 2001). Similarly, for the DEA hypotheses, models are run repeatedly but with whole data sets rather than samples. Also, sensitivity factors are not produced.

Hypothesis testing, which is also known as confirmatory data analysis, is the method of making decisions based on the statistical properties of data. Moreover, in terms of frequency probability, null-hypothesis testing is used to decide whether to accept or reject a specific hypothesis using statistical significance (Voelz, 2006). Hypothesis testing is the most like the approach used for the DEA hypotheses, where accepting or rejecting a specific variable or model type is based on what is observed in the DEA results.

In summary, the approach used for the DEA hypotheses has similarities with all the previous data analysis methods presented. However, it is designed to fit the relatively small data used, consisting of only 153 data points. Also, the previous methods are primarily used for predicting future values, where that is not the objective for using DEA. In addition, the approach is more qualitative than quantitative, where the effects of varying certain factors can be interpreted in different ways.

Transportation Performance Index

The Transportation Performance Index (TPI), developed by the U.S. Chamber of Commerce, captures the relationship between transportation infrastructure performance and the U.S. economy, specifically in terms of GDP growth. The

Infrastructure Index focuses on three sectors: transportation, energy and water. In September 2010, the first of the indices, the TPI, was released. Both a national TPI and state-by-state indices were developed. The parallel between the national TPI and the state-by-state TPI is that both are developed using weighted measures of a variety of indicators related to supply, quality of service and utilization for each mode of transportation. However, the former is based on a representative sample of 36 metropolitan statistical areas (MSAs), whereas the latter is directly based on available state data. Thus, the national TPI is developed using sampling and the state-by-state TPI is developed without sampling. Furthermore, due to data availability, the state-by-state TPI is assembled only using a subset of the indicators used for the national TPI. For example, highway congestion as a quality of service indicator was removed due to the lack of travel time index data for each state (see Table 2).

Overall, the state-by-state TPI is not as robust as the national TPI, being based on only 17 of the 21 initial indicators, but it nonetheless provides detailed information about the states (Gallis M. , et al., 2011). The indicators of supply, quality of service and utilization for the national TPI and the state-by-state TPI are compared in Table 1, Table 2 and Table 3 respectively, where each table denotes the mode and user related to the indicator, a description of the indicator, possible data sources, whether the indicator is included in the stat-by-state analysis, and for which years data for the indicator is available.

Table 1 Supply Indicators for the State-by-State TPI

Mode/ User	#	Indicator	Possible Source	State ?	Available Year for Data
Highway – passenger and freight	1	Route Miles per 10,000 Population	National Transportation Atlas Database (NTAD), Bureau of Census	X	00, 07
Transit – Passenger	2	Miles of Transit per 10,000 Population	National Transit Database, Bureau of Census	X	00, 07
Aviation – Passenger	3	# Enplanements per population	Terminal Area Forecast, Bureau of Census	X	95, 00, 07
Aviation – Passenger	4	Average (AAR + ADR) per Hour	*Removed*		
Rail - Freight	5	Route Miles per 10,000 Population	National Transportation Atlas Database (NTAD), Bureau of Census	X	00, 07
Marine – Waterway	6	Miles of Waterways per 10,000 population	National Transportation Atlas Database (NTAD), Bureau of Census	X	00, 07
Marine - Port	7	Distance from the Center of State to the Closest International Container Port	National Transportation Atlas Database (NTAD)	X	00, 07
Intermodal	8	# Ramps per 10, 000 Population	National Transportation Atlas Database (NTAD), Bureau of Census	X	00, 07

Table 2 Quality of Service Indicators for the State-by-State TPI

Mode/ User	**#**	**Indicator**	**Possible Source**	**State ?**	**Available Year for Data**
Highway – Congestion	9	Travel Time Index	*Removed*		
Highway – Safety	10	Fatalities per 100 Million VMTs	Fatal Accident Reporting System (FARS), and Highway Performance Monitoring System (HPMS)	X	95, 00, 07
Highway – Impedance	11	% of Lane Miles with IRI Greater Than 170 in./mi.	Highway Performance Monitoring System (HPMS)	X	95, 00, 07
Highway – Impedance	12	% of Bridges Structurally Deficient or Functionally Obsolete	National Bridge Inventory (NBI)	X	95, 00, 0
Transit – Safety	17	# Incidents per 100 Million PMT	National Transit Database	X	02, 07
Aviation – Congestion	13	% of On-Time Performance of Departures	Bureau of Transportation Statistics (BTS), and Terminal Area Forecast (TAF) (# of enplanements)	X	95, 00, 07
Aviation – Safety	14	Runway Incursions per Million Operations	Runway Safety Office Runway Incursion (# incursions) and Terminal Area Forecast (TAF) (# of operations)	X	02, 07
Rail – Safety	15	# Incidents per Route Miles	Bureau of Transportation Statistics (BTS)	X	00, 07
Marine – Waterway Congestion	16	Average Lock Delay per Tow (Hrs.)	*Removed*		

Table 3 Utilization Indicators for the State-by-State TPI

Mode/ User	#	Indicator	Possible Source	State ?	Available Year for Data
Highway	18	% of Lane Miles at LOS C or Better	Highway Performance Monitoring System (HPMS)	X	95, 00, 07
Transit	20	PMT per Capacity (Standing + Seating)	National Transit Database	X	00, 07
Aviation	19	% Capacity Used between 7am and 9pm	Removed		
Rail Impedance	21	Million tons of commodity shipped per route mile	Bureau of Transportation Statistics (BTS)	X	00, 07

The process for how the state-by-state TPI was developed is summarized in Figure 4. The first step is defining the transportation sector, which was determined to include fixed facilities (e.g., roadway segments and railway tracks), flow entities (e.g., people and vehicles), and control systems that allow for the movement of goods and people.

The second step is identifying the set of indicators of supply, quality of service and utilization to represent transportation performance. The indicators for the state level were based on those selected for the national level, but were limited to the indicators which have publicly available state level data for certain years, where data for years 1995, 2000 and 2007 could easily be extrapolated or interpolated. Furthermore, the data years 1995, 2000 and 2007 were used for the state-by-state TPI because these were the years with the most retrievable data. The third step is a continuation of identifying the indicators, which is data collection. In order to ensure a consistent scaling for each of the indicators, the data needs to be collected and normalized.

The fourth step is weighing the indicators. The assigned weights for the indicators are based on vetting process, which involved surveying stakeholders using the analytic hierarchy process (AHP). AHP is a common group decision making tool that is used to analyze complex decisions, such as weighing the importance of one indicator versus another to the nation's or a state's transportation performance and contribution to the economy. The fifth and last step is to compute the index for 1995, 2000 and 2007, using the data for the indictors and their associated weights from the AHP methodology.

The process for the state-by-state TPI is similar to that used for the national TPI, except for the exclusion of two steps after the first step of defining the transportation sector, which are selecting a representative sample of MSAs and applying a hierarchy model that captures the size of the MSAs (Gallis M. , et al., 2010). As stated previously, the data for the state level is obtained without sampling; it is based directly on state data.

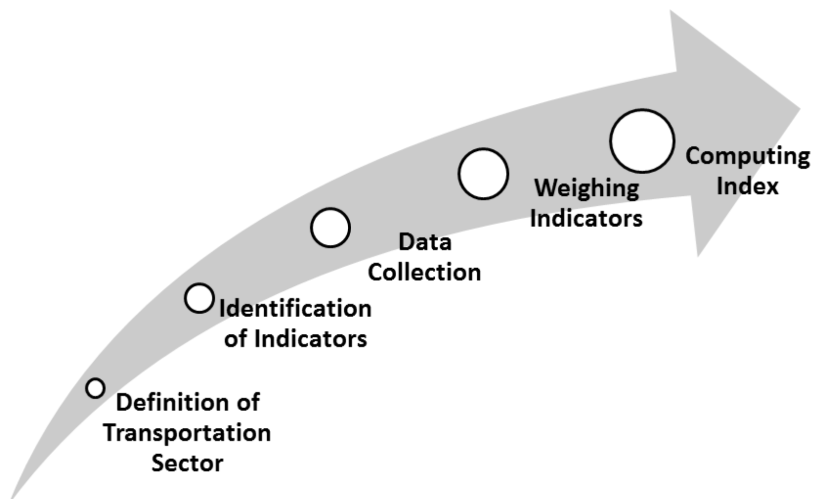

Figure 4 Summary of Steps for Developing State-by-State TPI.

Chapter 3

METHODOLOGY

Key components of the production efficiency analysis include the outputs and inputs of the DEA model as well as the environmental influences which are considered to put pressure on the TPI. In the following section, the application and origin of these components are clearly explained.

DEA Outputs and Inputs

As earlier noted in the problem statement, Equation 1, which relates GDP per capita and TPI on the national level, is used as the basis for the DEA model using state-by-state data. Consequently, there are similarities as well as some differences between Equation Equation 1 and the DEA hypotheses. For example, the output used in the DEA model is the natural log of GDP per capita, just as in Equation 1. The natural log of GDP per capita serves as a proxy for the strategic management capabilities of a state, where this is the best estimate for the effectiveness of transportation management for each individual state, since it is uniform and widely available. There are other possible measures for effectiveness of transportation management, but they vary a great deal from state to state. Then, in terms of the inputs, TPI as a representation of the quality of infrastructure, GDP as a representation of the initial level of the economy, and debt per capita (opposed to federal debt as a percentage of GDP) as a representation of the quality of the government are also used for the state level (referring back to Sala-i-Martin's time series growth model) (Gallis M. , et al., 2010).

Referring back to the DEA hypotheses, an additional input is considered: life expectancy, which is used to represent population health. TPI captures population within its calculations, but does not specifically capture quality of life. Life expectancy on the national level does not vary considerably from year to year, so it was not included in Equation 1. However, there is some noticeable variation between states for the years analyzed. As a result, life expectancy was included in the overall efficiency analysis, as seen in Equation 4.

$$\text{Production Efficiency} = \frac{\text{Outputs}(\text{lnGDPpc}_{i,t})}{\text{Inputs}(\text{TPI}_{i,t},\ \text{GDP}_{i,t},\ \text{Debtpc}_{i,t},\ \&\ \text{LE}_{i,t})}$$
$$\text{where } i = \text{state},\ t = \text{year} \tag{4}$$

Debtpc = the state debt per capita by year

LE = the state life expectancy by year

In addition, alternative variables to debt per capita and life expectancy are analyzed. These substitutions are the government performance project (GPP) infrastructure grades (Pew Center of the States, 2008) and the American Human Development Index (AHDI) (Lewis & Burd-Sharps, 2010) that are applied to the DEA model as enhanced representations of the quality of the government and the quality of life respectively. In turn, these variables may provide further insight into a state's efficiency in respect to transportation infrastructure and the economy.

The government performance project infrastructure grades are similar to TPI, but instead of grading the infrastructure itself, it grades the ability of the state to manage its infrastructure (Pew Center of the States, 2008). While debt per capita is an indicator of how well a state manages its funds, GPP directly evaluates a state's infrastructure management preparedness in terms of both maintenance and improvement. In addition, GPP was originally in the form of a letter grade but was converted into a 4.0 grade point average scale. Similarly, the American Human Development Index is a grade or score that each state is assigned and is a function of life expectancy at birth, school enrollment, educational degree attainment, as well as median annual gross personal earnings (Lewis & Burd-Sharps, 2010). Consequently, AHDI is a more multi-layered variable compared to life expectancy as a representation of quality of life.

Environmental Influences

In terms of environmental influences, there are a total of five variables that are considered to place the most pressure on TPI, and thus affect GDP per capita. These environmental influences were selected by ordering the TPI for the states for 1995, 2000 and 2007 and examining the similarities between the states with the lower TPI scores. For instance, the 10 states with the lowest TPI scores for all three years were primarily east coast states, such as Connecticut, Florida, Massachusetts, New Jersey, New York, North Carolina, Rhode Island as well as the District of Columbia. Furthermore, for 2007, Florida, New York and North Carolina are in the top 10 for annual vehicle miles traveled (VMT), with an average VMT of about 150,000. California was also ranked low for TPI for all three years and has the highest VMT for 2007, which is equal to about 330,000. High VMT places an increased demand on transportation performance; as a result it was included as a main environmental influence. In contrast, some of these same east coast states experience low annual ton miles traveled (TMT). For example in 2007, Florida, Massachusetts, Rhode Island, and D.C. are in the bottom 10 for TMT, with an average of about 900. Consequently, TMT was also included as an environmental influence.

Then in terms of population density for 2007, Connecticut, Florida, Massachusetts, New Jersey, New York, Rhode Island as well as D.C. are in the top ten, with an average population density of 2,000 people per square mile. In addition, a few of these east coast states experience very high annual increases in population growth. In

2007, Florida had a population increase of about 330,000, North Carolina had an increase of about 145,000, and New York had an increase of about 64,000.

Area was another attribute that was examined for the states with low TPI. For example, Connecticut, New Jersey, Rhode Island, and D.C. are in the bottom 10 in terms of size. Urban area was also examined and for 2007, California, Florida, Massachusetts, and New York are in the top 10. So, both area and urban area were considered.

On the other hand, states with high TPI scores for all three data years were mostly Great Plains states, such as North Dakota, South Dakota, Nebraska, Montana and Kansas. Moreover, North Dakota has the highest TPI of 2007, with a score of 85.12. Contrary to the low TPI states on the east coast, the previous Midwestern states have the lowest population density, population growth, VMT, and TMT for 2007. In addition, these states have the lowest urban area in the U.S. These converse attributes for states with low and high TPI justifies using them as the environmental influences that place the most pressure on TPI.

In summary, the environmental influences considered include population density, area, population growth, VMT and TMT. The magnitude of population density, population growth, VMT and TMT reflect the extent of the demand by users for transportation infrastructure. In turn, increases in demand are assumed to increase congestion and the rate of degradation of the physical infrastructure and thus decrease its performance (i.e., TPI) as well as its ability to provide a minimum level of service. In particular, increases in VMT and TMT reflect increases in demand by the public and businesses respectively.

Whereas the previous variables relate to the quality of transportation infrastructure, area is used as an indicator of the quantity of infrastructure that each state needs to maintain. Subsequently, it is assumed that states that have a larger area, have more transportation infrastructure and face unique challenges in regards to maintenance. Alternatively, urban area can also be used as an indicator of quantity, where urbanized areas are the hubs for transportation infrastructure. In addition, the environmental factors selected can be considered to be an amalgamation of exogenous or external variables, where their behavior is out of the control of the states. Specifically, state policies and practices have little impact on the trend of these environmental influences, as well as to what degree they influence TPI.

Data Sources and Collection Process

Similar to the development of the TPI, transparency is one of the major objectives for this research. Consequently, only free and publicly accessible data is used, allowing the results to be easily repeated. In turn, this made the data collection process a very arduous task. In total, data for the output, inputs and environmental influences needed to be obtained for all 50 states including Washington D.C. and for data years 1995, 2000 and 2007. Moreover, the success of the collection process influenced the final set of variables employed.

GDP per capita, GDP and debt per capita were obtained from the U.S. Bureau of Economic Analysis (BEA) (U.S. Department of Commerce, 2011). TPI was obtained directly from the U.S. Chamber of Commerce as a part of the "Let's Rebuild America" project (Gallis M. , et al., 2010). Life expectancy data was retrieved from multiple sources including the U.S. Census Bureau (USCB) (U.S. Census Bureau, 2011), the American Human Development Project (AHDP) (Lewis & Burd-Sharps, 2010), as well as the Center for Disease Control (CDC) (Centers for Disease Control and Prevention, 2011). The substitute inputs including GPP and AHDI were obtained from the PEW Center on the States and AHDP respectively (Pew Center of the States, 2008). In terms of environmental influences, population density, area and population growth were obtained from USCB (U.S. Census Bureau, 2011) VMT was retrieved from the Office of Highway Policy Information (HPI) (Federal Highway Adminsitration, 2011) and TMT was retrieved from the Office of Freight Management and Operation (FMO) (Federal Highway Adminstration, 2011), both of which are branches of the Federal Highway Administration (FHWA).

It is important to note that area (alternatively urban area), TMT, GPP as well as AHDI were assumed to be the same for all data years, where the base years for each are 2000, 2002, 2008 and 2010 respectively. Also, urban area was calculated for each state by summing the total area of the cities with populations greater than 50,000. For debt per capita, 1996 is used as a close approximation for 1995. In addition, debt per capita for 2000 was obtained by interpolating between 1996 and 2007. Then, for life expectancy for 1995, it was determined by extrapolating between 2000 and 2005. For Washington D.C., debt for each of the data years was difficult to come by. Nevertheless, these values were obtained by looking specifically at data for D.C. from USCB. For debt data for D.C. in 1995, debt for 1996 was used. Then, for 2000, it was determined by extrapolating from 2002 and 2007. These estimates and approximations for certain data sets should be acknowledged, since the results obtained are only as good as the data used. The sources, years available and limitations of each data set are summarized in Table 4.

Table 4 Summary of Data Sources

Data	Source	Limitations	References
GDP per capita	U.S. Bureau of Economic Analysis (BEA)	N./A.	http://www.bea.gov/itable/
TPI	U.S. Chamber of Commerce (USCC)	N./A.	http://www.uschamber.com/lra/ transportation-index
GDP	BEA	N./A.	http://www.bea.gov/itable/
Debt per capita	BEA	1996 data used for 1995, 2000 interpolated between 1996 and 2007	http://www.bea.gov/itable/
Life Expectancy	U.S. Census Bureau (USCB); Amer. Human Development Project (AHDP); Center for Disease Control (CDC)	1995 extrapolated between. 2000 and 2005	http://www.census.gov/compendia/ statab/2007/vital_statistics/life_ expectancy.html http://www.measureofamerica.org/ order/ http://www.cdc.gov/nchs/fastats/ lifexpec.htm
GPP	PEW Center of the States	2008 base year, assumed constant for all data years	http://www.pewcenteronthestates.org/uploadedFiles/Overall%20Performance.pdf
AHDI	AHDP	2010 base year, assumed constant for all data years	http://www.measureofamerica.org/ order/
Population Density	USCB	N./A.	http://www.census.gov/population/www/censusdata/density.html
Area/ Urban Area	USCB	2000 base year, assumed constant for all data years	http://www.census.gov/population/www/censusdata/density.html
Population Growth	USCB	N./A.	http://www.census.gov/population/www/censusdata/density.html
VMT	Office of Highway Policy Information (HPI)	N./A.	http://www.fhwa.dot.gov/policy/ohpi/hss/hsspubs.cfm
TMT	Office of Freight Management and Operation (FMO)	2002 base year, assumed constant for all data years	http://www.ops.fhwa.dot.gov/freight/freight_analysis/data_sources/index.htm

DEA Hypotheses

In terms of the DEA approach that is used, there are three groups of hypotheses that were developed; all of which are based on the procedure outlined in the background. Figure 5 relates each hypothesis to the production efficiency classification as shown in the short description and consistent with Figure 2.

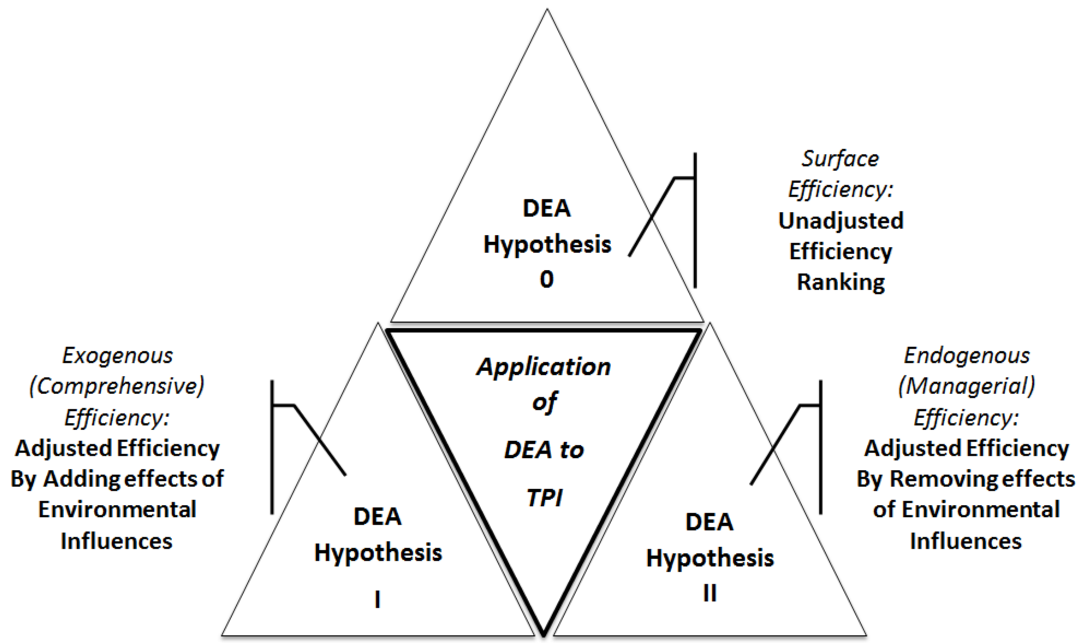

Figure 5 DEA Hypotheses Chart.

Hypothesis 0 (HP0) is a DEA model that produces an unadjusted efficiency ranking or surface efficiency ranking, where inputs and outputs are analyzed without taking into account the effects of environmental influences (see Equation 4). Consequently, HP0 serves as the base comparison for all other variations of the DEA model, specifically the other two hypotheses. Hypothesis I (HPI) and Hypothesis II

(HPII) include environmental influences in the DEA model. However, using linear regression, the former produces an adjusted efficiency ranking by adding the effects of environmental influences also known as a comprehensive efficiency analysis and the latter produces an adjusted efficiency ranking by removing the effects of environmental influences also known as a managerial efficiency analysis.

For HPI, the input, TPI, is linearly regressed on the environmental factors: population density, area, population growth, VMT and TMT, which, as previously stated, are assumed to place the most pressure on TPI. The values obtained from the linear model are then used as adjustors rather than predictors in the DEA model. Whereas TPI is used as an input in HP0, adjusted TPI (*adjTPI₁*) is used as an input in HPI. The adjusted TPI is calculated using Equation 5:

$$\begin{aligned} \mathrm{TPI}_{i,t} &= a_0 + a_1 \mathrm{Density}_{i,t} + a_2 \mathrm{Area}_{i,t} + a_3 \mathrm{PopGrowth}_{i,t} \\ &+ a_4 \mathrm{VMT}_{i,t} + a_5 \mathrm{TMT}_{i,t}; \\ &\text{where } i = \text{state},\ t = \text{year} \end{aligned} \tag{5}$$

TPI = the state TPI by year

$adjTPI_1$ = the adjusted state TPI by year (values obtained from regression)

Density = population density by state and year

Area = total land mass by state and year

PopGrowth = change in population between data years for each state

VMT = vehicle miles traveled by state and year

TMT = ton miles traveled by state and year

Moreover, there should be a clear distinction made between the inputs for the regression analysis and the inputs for the DEA model. The regression inputs are the environmental influences, and the DEA inputs are the same as the set of inputs found in Equation 4, except the adjusted TPI is used instead of the original TPI (see Figure 6).

HPII is similar to HPI in that it involves the regression of TPI for the DEA model. However, instead of adding the effects of the environmental influences, it removes them completely. This is done by applying the approach outlined by Barnum et al. (Barnum, Tandon, & McNeil, 2008) known as the Reverse Two-Stage Method, where efficiency is seen as an endogenous or internal factor to each DMU and the environmental influences are seen as exogenous or external factors that are outside of the control of the DMUs. For HPII, the efficiency ranking obtained is the managerial efficiency or the efficiency of transportation that is under the direct control of the state. In addition, this methodology was selected by examining the advantages and disadvantages of using other two stage or second stage methods investigated by both Barnum et al. (Barnum, Tandon, & McNeil, 2008) and Hoff (Hoff, 2007), which are summarized in Table 5.

Hoff concluded that OLS and Tobit regression produce acceptable results compared to the PW and Beta second-stage methods. In addition, OLS is sufficient in most cases and is less computational sensitive. For Barnum et al., the conventional Two-Stage Method and the Exclusion Method does not allow for individual efficiency scores of DMUs to be directly compared, where the former produces mean categorical efficiencies and the latter produces efficiency scores that use different environmental influences for each DMU. Consequently, the Reverse Two-Stage Method was the better option, producing individual scores and not being so easily susceptible to the statistical pitfalls of the other two-stage methods.

Table 5 List of Second Stage Methods for DEA

Second Stage Method	**Abbreviated Notation**	**Comments**
Ordinary Least Squares	OLS	• Linear model for predictive modeling, performance estimates can be poor if multicollinearity present, unless sample is large • Less specification required for distribution of efficiency interval
One-limit Tobit Regression/ Two-limit Regression	Tobit	• Parameters don't directly give effect of environmental influences on DEA scores • Tobit regressions easily mis-specified, where one-limit Tobit takes on range of: (-∞;1] and two-limit Tobit takes on range of: (0;1]
Papke and Wooldridge Method	PW	• Non-linear model; assumes that the dependent variable is equally distributed over the entire closed interval (i.e., TPI is evenly distributed over interval) • Model takes on range of: [0;1]
Unit-inflated Beta Model	Beta	• Non-linear model, where probability of being at ends of interval is different from being inside interval (i.e., flexible probability distribution)
Traditional Two-stage Method	Tradition 2^{nd} Stage	• Produces mean efficiencies for categorical groups (i.e., mean scores for states by size, population, etc.) rather than actual individual estimates for managerial efficiency • Results typically produce bias, low precision and low power, takes on range of: [0;1]
Exclusion Method	EM	• Low efficiency DMUs are biased toward greater efficiency than they actually have • Scores of DMUs incomparable because each DMU uses unique set of competitors (i.e., environmental influences), takes on range of: [0;1]
Reverse Two-Stage Method	Reverse 2^{nd} Stage	• More useful in comparing efficiencies of states because individual scores rather than means are produced • Estimates are obtained without bias, low precision and low power, takes on range of: [0;1]

In the Reverse Two-Stage Method, the first stage involves a regression of the inputs, which is only TPI in this case, on all the outputs and the external factors that are assumed to influence the inputs (see Equation 6).

$$\mathrm{TPI}_{i,t} = \mathrm{a}_0 + \mathrm{a}_1\ln\mathrm{GDPpc} + \mathrm{b}_1\mathrm{Density}_{\,i,t} + \mathrm{b}_2\mathrm{Area}_{i,t} + \mathrm{b}_3\mathrm{PopGrowth}_{i,t} + \mathrm{b}_4\mathrm{VMT}_{i,t} + \mathrm{b}_5\mathrm{TMT}_{i,t};$$
$$\text{where } \mathrm{i} = \text{state}, \ \mathrm{t} = \text{year} \tag{6}$$

Afterwards, the inputs are adjusted for environmental influences by removing the marginal influence of the external factors found in the regression analysis (see Equation 7).

$$\mathrm{adjTPI}_{2\ \,i,t} = \mathrm{TPI}_{\,i,t} + \mathrm{a}_0 - \begin{pmatrix} \mathrm{b}_1\mathrm{Density}_{\,i,t} + \mathrm{b}_2\mathrm{Area}_{i,t} + \mathrm{b}_3\mathrm{PopGrowth}_{i,t} \\ +\mathrm{b}_4\mathrm{VMT}_{i,t} + \mathrm{b}_5\mathrm{TMT}_{i,t} \end{pmatrix};$$
$$\text{where } \mathrm{i} = \text{state}, \ \mathrm{t} = \text{year} \tag{7}$$

Then, the two stage or second stage is to use the adjusted TPI (*adjTPI*$_2$) and the other inputs as a part of the DEA model (see Figure 6).

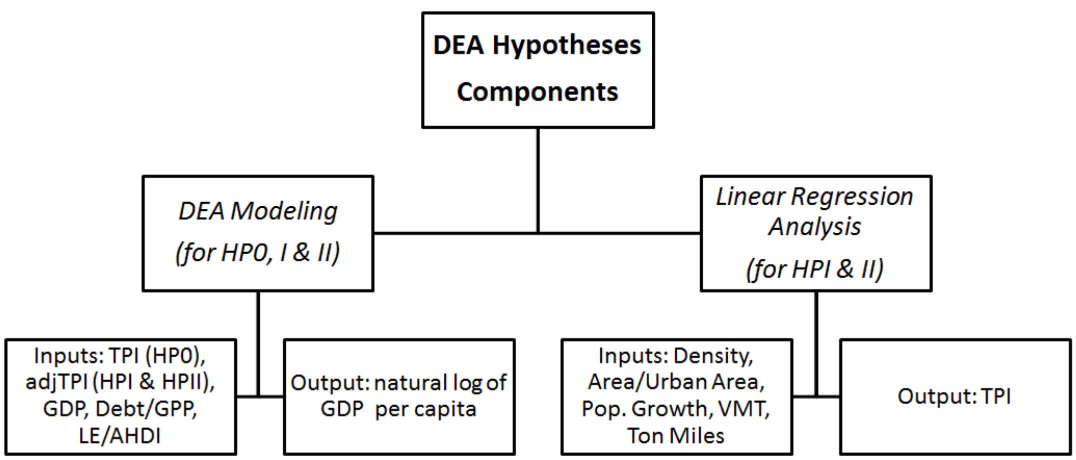

Figure 6 Modeling Components for DEA Hypotheses.

Overall, there are two *adjTPI* variables; the adjusted TPI obtained from the linear regression analysis in HPI (*adjTPI*$_1$) and the adjusted TPI obtained from the Reverse

Two-Stage Method in HPII (*$adjTPI_2$*). In addition, the Reverse Two-Stage Method can be applied to either inputs or outputs and can be done to multiple variables at the same time, where they are adjusted by their own unique set of contextual factors. For example, average yearly temperature may be an environmental influence that places pressure on the input, life expectancy, and can be adjusted for using the Reverse Two-Stage Method.

With the three DEA hypotheses (HP0, HPI, and HPII), one DEA output (*lnGDPpc*), eight DEA inputs (*TPI*, *$adjTPI_1$*, *$adjTP_2$*, *GDP*, *Debtpc, LE, GPP, AHDI)*, and six environmental influences (*Density*, *Area*, *UrbanArea*, *PopGrowth*, *VMT* and *TMT*), there are 20 different scenarios or variations of the model (see Table 6). In addition, for each scenario, data years 1995, 2000 and 2007 are analyzed. Also, for each year, DEA analysis is conducted including all states as well as excluding D.C., Alaska and Hawaii. The reasoning behind excluding these DMUs is that they are inherently different from the other states based on governmental policy and geography. Consequently, there are a total of 120 sub-scenarios that are examined. Even though running so many different versions of the model is extensive, the most logical and appropriate DEA models can be designated and used to acquire the most credible efficiency results.

The next chapter presents the DEA results including the preliminary data analysis of each of the variables, as well as the process used to construct the DEA models and the linear regression equations. Furthermore, the reasoning for selecting Equation 4 as the default DEA model, Equation 5 as the default linear regression model to calculate *$adjTPI_1$* for HPI and Equation 7 as the default linear regression model to calculate *$adjTPI_2$* for HPII is provided.

Table 6 Summary of DEA Hypotheses Scenarios

Hypothesis Type	Scenario Code	Output	Inputs								Environmental Variables		
		lnGPDpc	TPI	$adjTPI_1$	$adjTPI_2$	GDP	Debt	GPP	LE	AHDI	Area	Urban Area	Density VMT TMT PopGrowth
DEA Hypothesis 0 (unadjusted efficiency ranking)	HP0-1	✓	✓			✓	✓		✓				
	HP0-2	✓	✓			✓	✓			✓			
	HP0-3	✓	✓			✓		✓	✓				
	HP0-4	✓	✓			✓		✓		✓			
DEA Hypothesis I (adjusted efficiency ranking by adding effects of environmental influences)	HPI-1	✓		✓		✓	✓		✓		✓		✓
	HPI-2	✓		✓		✓	✓			✓	✓		✓
	HPI-3	✓		✓		✓		✓	✓		✓		✓
	HPI-4	✓		✓		✓		✓		✓	✓		✓
	HPI-5	✓		✓		✓	✓		✓			✓	✓
	HPI-6	✓		✓		✓	✓			✓		✓	✓
	HPI-7	✓		✓		✓		✓	✓			✓	✓
	HPI-8	✓		✓		✓		✓		✓		✓	✓
DEA Hypothesis II (adjusted efficiency ranking by removing effects of environmental influences)	HPII-1	✓			✓	✓	✓		✓		✓		✓
	HPII-2	✓			✓	✓	✓			✓	✓		✓
	HPII-3	✓			✓	✓		✓	✓		✓		✓
	HPII-4	✓			✓	✓		✓		✓	✓		✓
	HPII-5	✓			✓	✓	✓		✓			✓	✓
	HPII-6	✓			✓	✓	✓			✓		✓	✓
	HPII-7	✓			✓	✓		✓	✓			✓	✓
	HPII-8	✓			✓	✓		✓		✓		✓	✓

Chapter 4

RESULTS – DATA ANALYSIS AND MODEL FORMULATION

This chapter documents the first part of the DEA results into three separate sections. The first section is a preliminary data analysis of all the variables used for the DEA modeling, including the DEA output, inputs and environmental influences as well as the alternative variables. So, in total, there are 13 variables that are analyzed, not including the two adjusted TPI variables ($adjTPI_1$ and $adjTPI_2$). The preliminary data analysis includes a graphical representation of the data as histograms as well as a numerical summary of the data (also known as a five-number summary), where the minimum, the 1st quartile, the median, the 3rd quartile and the maximum of each variable is obtained. In addition, the mean is calculated as a measure of central tendency of a data set and the standard deviation is calculated as a measure of dispersion. The results of exploratory data analysis (Tukey, 1977) in the form of box-and-whisker plots are presented for each variable. As an additional visual resource, line graphs (with the states on the x-axis) are created for each variable for all three data years (see Appendix C). In summary, the preliminary data analysis has a total of five elements, which are the following: 1) histogram, 2) numerical summary, 3) mean, 4) standard deviation and 5) box-and-whisker plot. Overall, the preliminary data process is used to obtain a better understanding of the behavior of each variable and to estimate how trends within each data set may affect the overall DEA modeling.

The second section examines the construction of the DEA models, where pairwise data analysis of the output and inputs is conducted, which includes scatterplots and correlations of each data pair. Similarly, the third section examines the construction of the linear regression equations used to calculate adjusted TPI for HPI and HPII (see methodology chapter), and also begins with pairwise data analysis.

In developing the final regression equation for both of these hypotheses, a total of 12 cases are presented, as seen in Table 7. The first 6 cases (Case 1 – Case 6) relate to the dependent variable, TPI, being a function of a single independent variable or environmental influence. The next 5 cases (Case 7 – Case 11) relate to the dependent variable being a function of an increasing amount of independent variables, from two to a total of five. Then, Case 12 is similar to Case 11, but it is a normalization of the variables in order to obtain a better fit. Moreover, there are several other cases that are possible and many of these were examined, but the 12 shown have the most relevant results. For each case, the coefficients estimates for the independent variables are provided as well as the residual standard error, the adjusted R^2 values, and a plot of the residuals. All coefficients are significant at $p = 0.05$.

Table 7 Linear Regression Analysis Cases

Case Number	Case Definition	Key
1	y=f(x1)	x1 = population density $x2_a$ = area $x2_b$ = urban area x3 = population growth x4 = VMT x5 = TMT
2	y=f($x2_a$)	
3	y=f($x2_b$)	
4	y=f(x3)	
5	y=f(x4)	
6	y=f(x5)	
7	y=f(x1, $x2_a$)	
8	y=f(x1, $x2_b$)	
9	y=f(x1, $x2_a$, x3)	
10	y=f(x1, $x2_a$, x3, x4)	
11	y=f(x1, $x2_a$, x3, x4, x5)	
12	y=Norm[f(x1, x2 x3, x4, x5)]	

While this chapter focuses on the preliminary data analysis as well as the construction of the DEA models and the linear regression equations, the subsequent chapter continues focuses on the rationalizing of selecting the default DEA models and linear regression equations. In addition, the DEA ranking and benchmarking results are presented.

Preliminary Data Analysis

For the preliminary data analysis, histograms were created for each variable using the R software (Gentlema & Ihaka, 1993), which is commonly used for statistical computing and graphics. In addition, each variable is treated as a pooled data set, where there are 51 data points for each data year (1995, 2000 and 2007) representing the 50 states and the District of Columbia (D.C.) So, in total, there are 153 data points for each variable. It is important to note again that area (alternatively urban area), TMT, GPP as well as AHDI were assumed to be the same for all data years, where the base years for each are 2000, 2002, 2008 and 2010 respectively.

Histograms of DEA Outputs and Inputs

In terms of the DEA output, *lnGDPpc*, the data appears to have somewhat of a normal distribution, where it is slightly positively skewed, as seen in Figure 7.

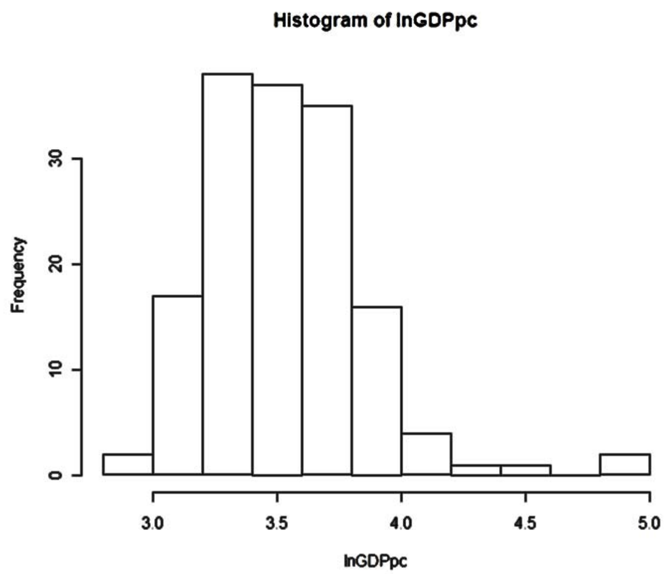

Figure 7 Histogram of the Natural log of GDP per Capita.

In terms of the DEA input, *TPI*, the histogram shows that the data has almost a perfectly normal distribution, as seen in Figure 8.

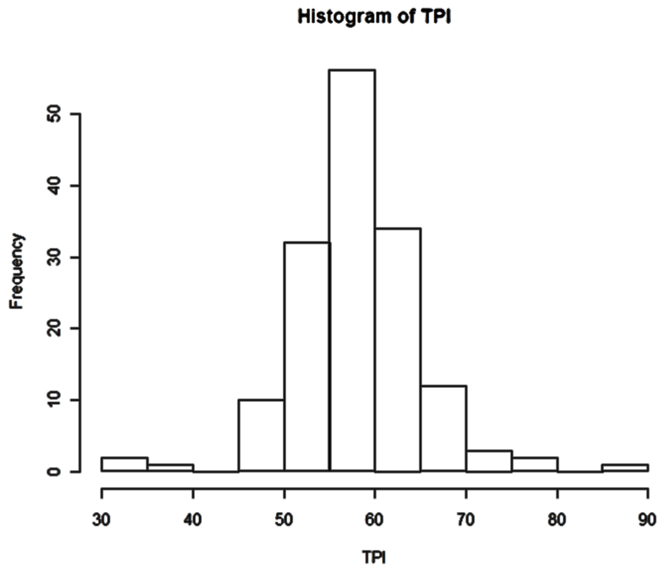

Figure 8 Histogram of TPI.

For the variable, GDP, the histogram shows that the data has an exponential distribution that is decaying, as seen in Figure 9. The majority of states have a GDP that is lower than $1,000,000 for the three data years. Also, the states which are outliers for GDP include New York, Texas and California.

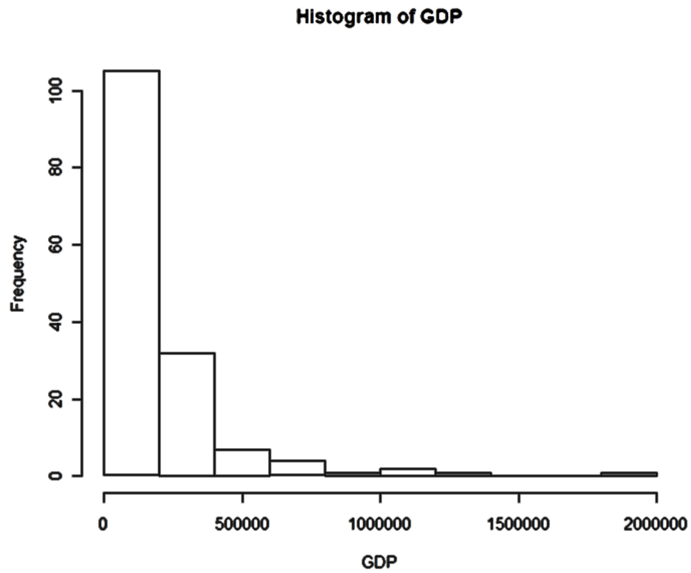

Figure 9 Histogram of GDP.

For the variable, *Debtpc*, the histogram shows that the data is positively skewed, where most states have a debt per capita that is about $2,500 per person, as seen in Figure 10. In terms of outliers, on the low end, the state with lowest debt per capita out of all three data years is Tennessee. Conversely, the state with highest debt per capita is D.C.

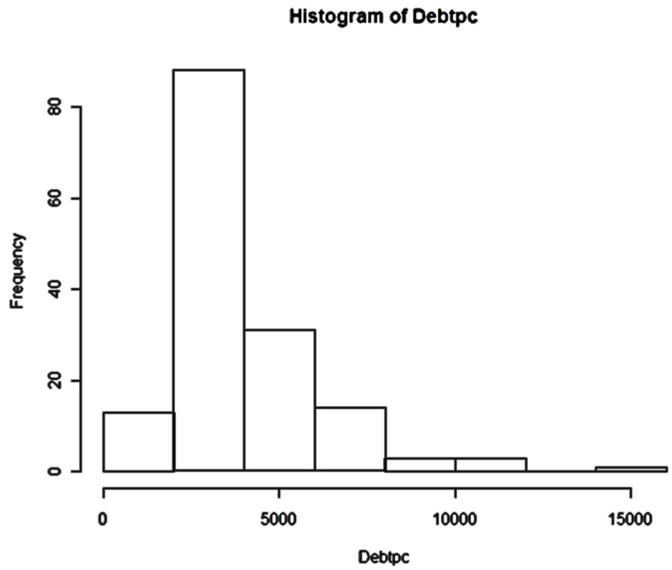

Figure 10 Histogram of Debt per Capita.

For the variable, *GPP*, which is the proposed substitute for *Debtpc* as a representation of the quality of government, the histogram shows that the data has a normal distribution, as seen in Figure 11. The behavior for *GPP* is dissimilar to *Debtpc*, which, as seen previously, is positively skewed. As a result, it can be concluded that even though both variables supposedly capture similar phenomena, they display different trends. For GPP, a GPA score of 4.0 represents the highest quality of government possible and a GPA score of 0.0 represents the lowest quality of government possible. Then for *Debtpc*, the lower the value, the better a state is assumed to be at managing its government.

Referring back to the histogram of the Government Performance Project grades, the values appear to be normally distributed around the mean GPA of 2.5. This means there is about the same amount of states with a GPA that is greater than 2.5, as there are states with a GPA that is lower than 2.5. An alternative interpretation of the histogram is that there is the same amount of states with both low and high qualities of government. On the other hand, for *Debtpc*, the majority of states have values that are on the lower end of the range. So, using *Debtpc*, it can be interpreted that the majority of states have a relatively good quality of government. With these two different trends, it is uncertain whether *GPP* or *Debtpc* would result in higher, lower or the same efficiency rankings. Nevertheless, this difference is taken into account when evaluating the DEA results.

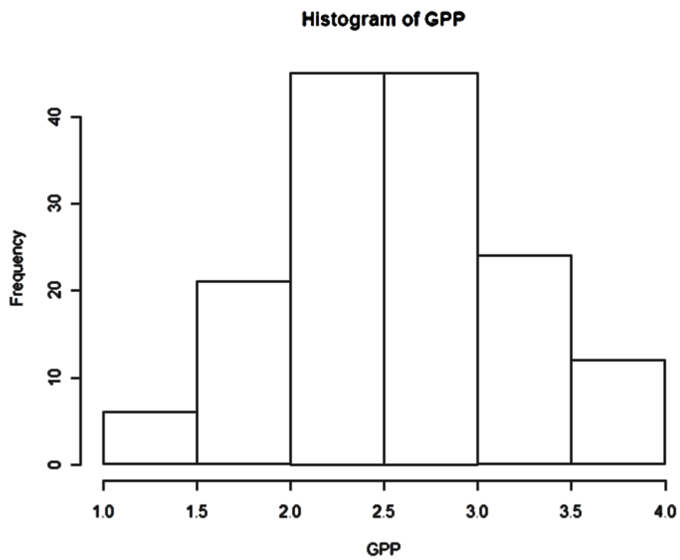

Figure 11 Histogram of Government Performance Project Grades.

For the variable, *LE*, the histogram shows that the data for life expectancy is negatively skewed, as seen in Figure 12. Most states have a life expectancy that is between 77 and 78 years. In terms of outliers, on the low end, the state with lowest life expectancy is D.C. Conversely, the state with highest life expectancy is Hawaii.

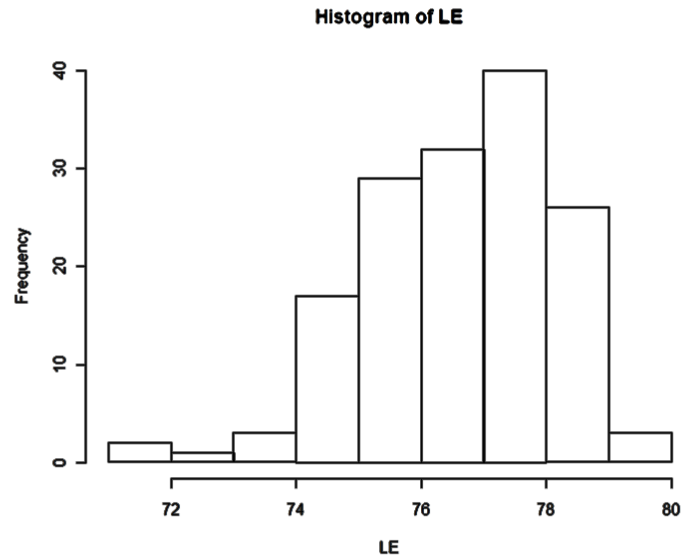

Figure 12 Histogram of Life Expectancy.

For the variable, *AHDI*, which is the proposed substitute for *LE* as a representation of the quality of life, the histogram doesn't show any distinct behavior, where values are spread throughout the given range, as seen in Figure 13.

On the other hand, *LE* showed the particular trend of being negatively skewed. As with *GPP* and *Debtpc*, both *LE* and *AHDI* supposedly capture similar phenomena, but display different trends. In addition, it is uncertain whether *LE* or *AHDI* would result in higher, lower or the same efficiency rankings. Nevertheless, this difference is once again taken into account when evaluating the DEA results.

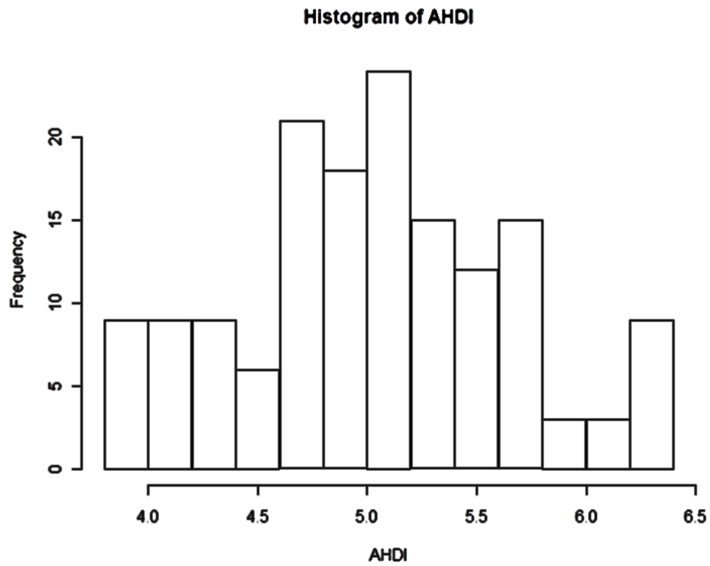

Figure 13 Histogram of American Human Development Index.

Histograms of Environmental Influences

From the histogram of population density, as seen in Figure 14, the data does not vary a great deal. The majority of the densities for states range only between 0 and 1,000 people per square mile, where there are outliers that range between 1,000 and 2,000, as well as 9,000 and 10,000 people per square mile. The former includes outliers New Jersey and Rhode Island, and the latter includes D.C. as an outlier.

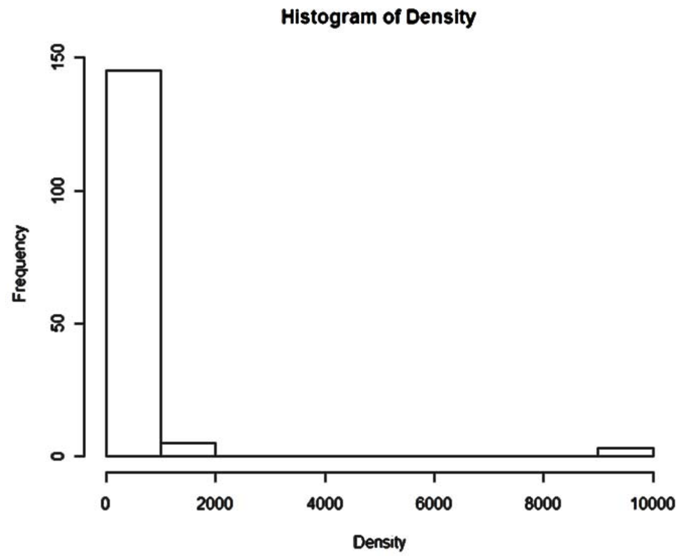

Figure 14 Histogram of Population Density.

From the histogram of area, as seen in Figure 15, the data can be described as having an exponential distribution that is decaying. The majority of states have total area that is less than 200,000 square miles. The outliers include Texas and Alaska with an area of about 262,000 and 570,000 square miles respectively.

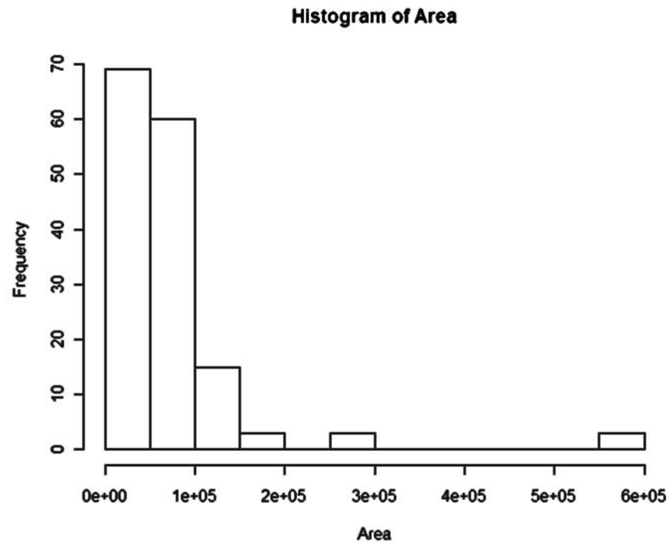

Figure 15 Histogram of Area.

In terms of urban area, which is used as a substitute for area, the histogram shows that the data also has an exponential distribution that is decaying and has a local maximum between 5,000 and 6,000 square miles, as seen in Figure 16. So, in this case, both area and urban area capture the same phenomenon and display similar trends. In turn, it can be projected that they result in similar efficiency rankings. However, this can't be known for certain just by comparing the histograms.

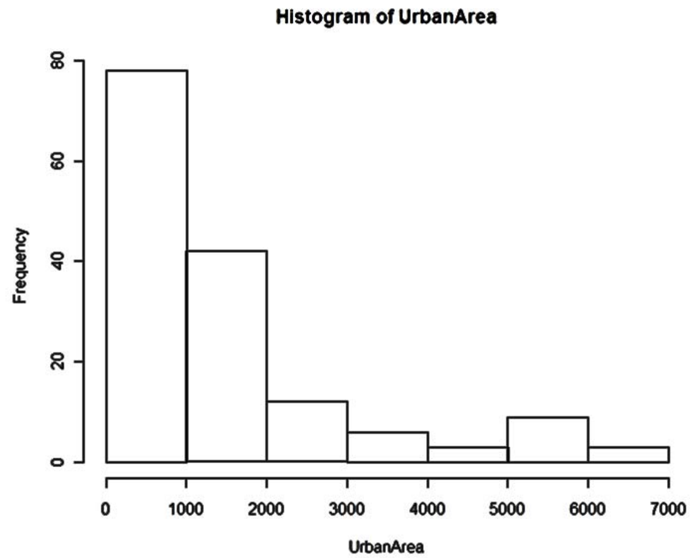

Figure 16 Histogram of Urban Area.

From the histogram of population growth, as seen in Figure 17, the data can be described as being positively skewed. In addition, population growth is the only variable that has both negative and positive values within the data set, where a negative value indicates a decrease in population and a positive value indicates an increase in population between the given years.

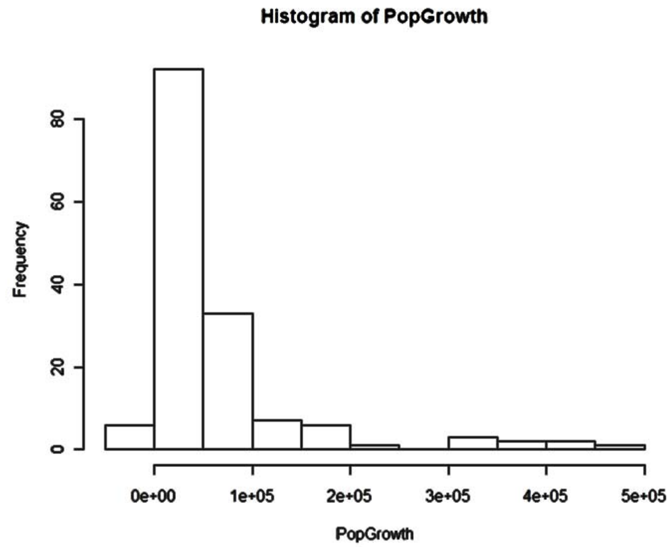

Figure 17 Histogram of Population Growth.

From the histogram of VMT, which can be seen in Figure **18**, the data can be described as having an exponential distribution.

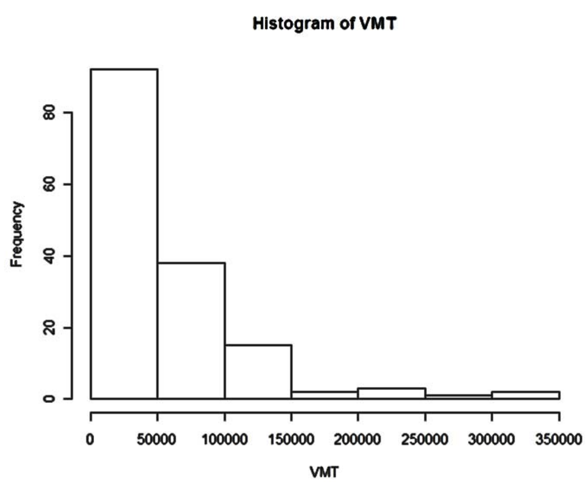

Figure 18 Histogram of VMT.

From the histogram of TMT, which can be seen in Figure 19, the data follows an exponential distribution with a local maximum between 350,000 and 400,000 ton miles. In addition, due to incomplete data, TMT is the only variable that has a minimum of 0.

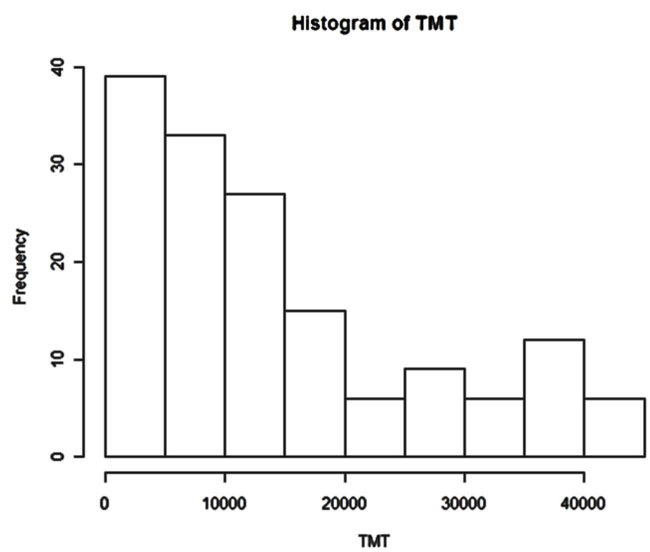

Figure 19 Histogram of TMT.

Using the histograms for each of the variables, different trends and patterns were able to be identified. Even though a substantial amount of information is not able to be obtained from the visualizations of the data, they do provide better insight in regards to how the data sets behave as a whole. In turn, these observations can be used to project their individual effects on the overall efficiency rankings for the states, and can be used as a gauge for which variables should be examined more closely.

Numerical Summaries of Variables

The next step in the preliminary analysis is to obtain the numerical summaries for the variables, including the standard deviation. As with the histograms, the numerical summaries provide a limited amount of additional information, but do help in understanding how the data behaves.

Table 8 Numerical Summaries of DEA Output and Inputs

Statistical Measure	lnGDPpc	TPI	GDP ($ mil)	Debtpc	LE (years)	GPP	AHDI
Minimum	2.98	31.25	13,867	667	71.47	1.40	3.85
1st Quartile	3.32	54.07	49,512	2,571	75.48	2.40	4.65
Median	3.49	58.74	116,986	3,390	76.80	2.70	5.05
3rd Quartile	3.71	61.33	247,725	4,652	77.71	3.00	5.53
Maximum	4.99	85.12	1,801,762	15,204	80.00	4.00	6.30
Mean	3.53	58.00	200,651	3,977	76.62	2.66	5.04
Standard Deviation	0.32	6.94	254,246	2,149	1.51	0.62	0.63

Table 8 shows that the DEA output and inputs have very different scales. On the one hand, the natural log of GDP per capita just ranges approximately between 3 and 5, while GDP ranges from about 14,000 to 1.8 million. Then, in terms of standard deviation, the variables that have narrower ranges, such as LE, have lower variability and the variables with wider ranges, such as GDP, have higher variability. In addition, both GPP and AHDI have about the same level of variability, having a standard deviation of about 0.62. Comparing the different statistical measures by value is not as effective as comparing them visually, which is addressed in the following section using exploratory data analysis for each variable.

Table 9 Numerical Summaries of Environmental Influences

Statistical Measure	Density	Area	Urban Area	PopGrowth	VMT	TMT
Minimum	1.06	68.30	43.42	-13,265	3,465	0
1st Quartile	40.21	30,865.00	343.25	11,614	15,035	3,545
Median	91.30	53,997.00	957.08	34,497	40,849	10,824
3rd Quartile	203.43	81,823.00	1,635.51	65,633	67,446	23,849
Maximum	9,581.30	570,374.00	6,563.85	456,530	328,312	42,170
Mean	361.05	69,344.60	1,412.63	61,582	53,610	14,112
Standard Deviation	1,297.84	84,952.40	1,572.10	88,472.30	55,895.30	12,431

In terms of the environmental influences, from examining Table 9, it can be seen that majority of variables have a very wide range, excluding density and urban area. In addition, population growth has a range that goes negative and TMT has a range that begins at 0. These observations, for the environmental influences, support normalizing the data for linear regression analysis, as seen in Case 10. Using normalization, the underlying characteristics within the data sets can be compared, where the data are brought to a common scale.

Exploratory Data Analysis of Variables

The exploratory data analysis takes the results from a numerical summary, specifically the minimum, the 1st quartile, the median, the 3rd quartile and the maximum, and shows the data graphically as a box-and-whisker plot. Figure 20 and Figure 21 show the plots for the DEA variables and the environmental influences respectively. Refer to Appendix D, for individual box-and-whisker plots for each variable.

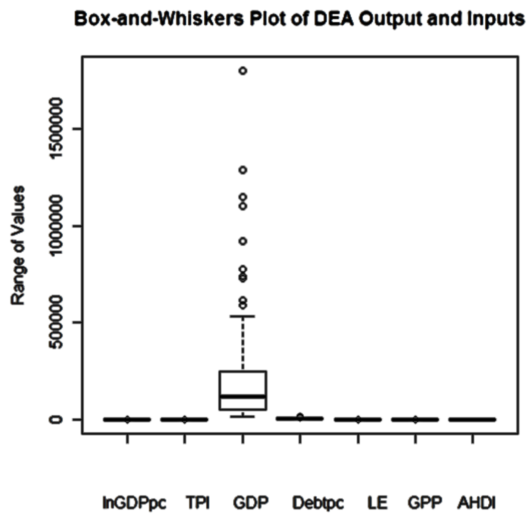

Figure 20 Box-and-whisker Plots of DEA Output and Inputs.

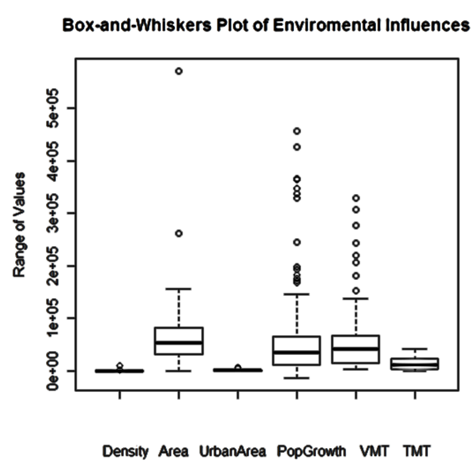

Figure 21 Box-and-whisker Plots of Environmental Influences.

From the box-and-whiskers plots, the differences in the range of values for the variables are much more apparent. From Figure 20, it can be seen that GDP has the widest and most dissimilar range compared to other DEA variables. Then, from Figure 21, density and urban area are shown to have much narrower ranges compared to the other environmental influences. In addition, these results further support normalizing the environmental influences as an appropriate LRA case, where variables will be placed on same scale, while preserving the variability relative to the range. In sum, each step of the preliminary data analysis, from the histograms to the box-and-whisker plots, provided some information about the each of the variables that could prove useful in conducting the DEA hypotheses and interpreting the subsequent results.

Construction of the DEA Models

To construct the DEA models for HP0, HPI and HPII, pairwise data analysis provides some insights into the relative importance of different variable. While the variables selected are based on Equation 1 (see introduction chapter), an evaluation of whether the variables are appropriate prior to constructing the models is wise. The pairwise data analysis includes constructing scatterplots and calculating correlations for each data pair. For the DEA output and inputs, there are a total of 49 data pairs, as seen in Figure 22, which also shows the best fit line between the data points. Best fit lines produced by the R software are not linear, but have a polynomial order. In addition, the fits are not forced to pass through the origin.

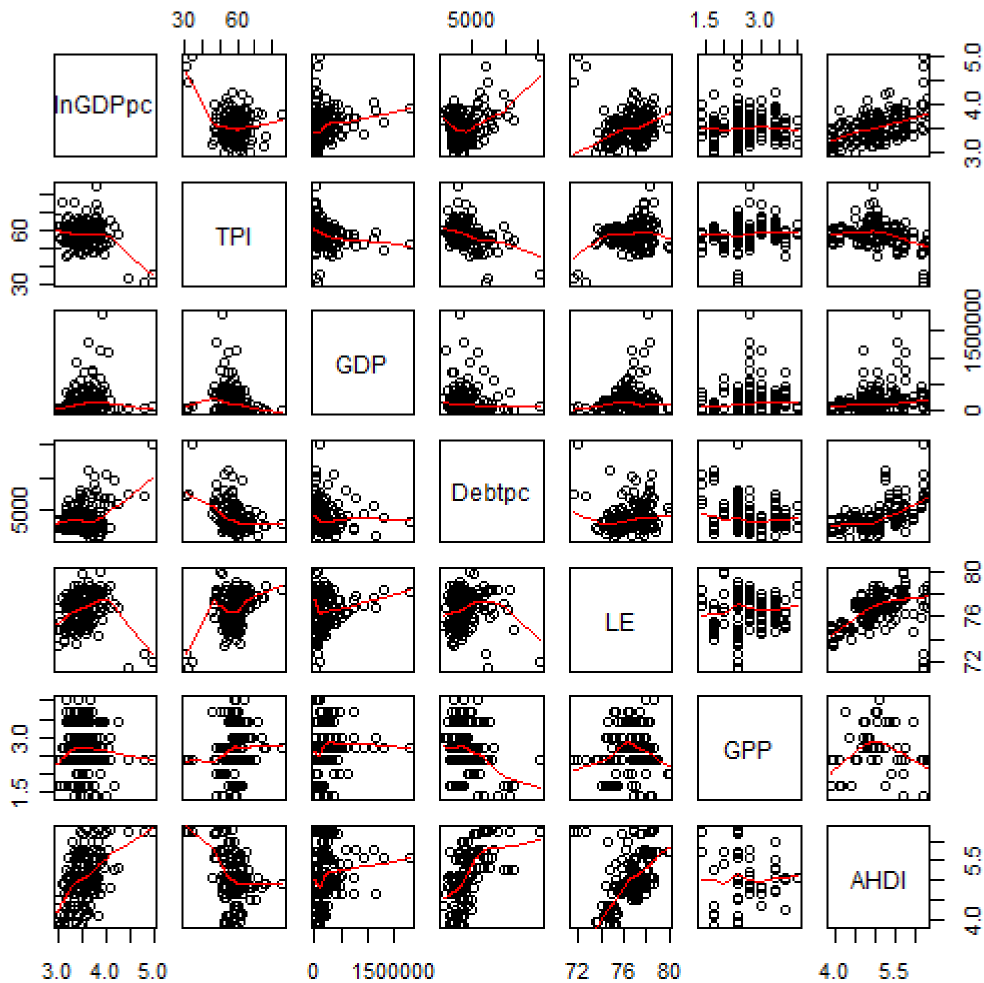

Figure 22 Scatterplots of DEA Output and Inputs Data Pairs.

As a complement to Figure 22, the coefficient of correlation for each of the data pairs can be seen in Table 10.

Table 10 Coefficients of Correlation for Data Pairs

Variables	lnGDPpc	TPI	GDP	Debtpc	LE	GPP	AHDI
lnGDPpc	1.00	-0.29	0.23	0.40	0.05	-0.01	0.52
TPI	-0.29	1.00	-0.24	-0.46	0.33	0.13	-0.35
GDP	0.23	-0.24	1.00	-0.07	0.10	0.13	0.21
Debtpc	0.40	-0.46	-0.07	1.00	0.02	-0.26	0.60
LE	0.05	0.33	0.10	0.02	1.00	0.07	0.45
GPP	-0.01	0.13	0.13	-0.26	0.07	1.00	-0.003
AHDI	0.52	-0.35	0.21	0.60	0.45	-0.003	1.00

From Table 10, the coefficient of correlation with the highest absolute magnitude (not equal to 1) is between *AHDI* and *Debtpc*, which has a value of about 0.60. In terms of *LE* and *AHDI*, where *AHDI* is a substitution for *LE* as a representation of quality of life, the coefficient of correlation is about 0.45. This value is relatively high, and is as expected despite *AHDI* and *LE* having different distributions, since both variables are intended to represent the same phenomena. Then for *Debtpc* and *GPP*, the magnitude of correlation, -0.26, is moderate. Like *AHDI* and *LE, Debtpc* and *GPP* have different distributions. However, the correlation results make sense, since the variables are intended to represent the same phenomena.

In terms of the other data pairs, the correlations are not that significant. Moreover, as stated previously, DEA is not affected by collinearity, where even if two or more variables are highly correlated, the results will not change drastically with small changes to the model or data (see background chapter). Also, whereas the preliminary data analysis provided information about how the variables behaved, the pair data analysis provides information about how the variables are related to one another.

Construction of the Linear Regression Equations

In terms of the construction of the linear regression analysis (LRA) cases for adjusted TPI in relation to HPI and HPII, pair data analysis was conducted. The pair data analysis includes obtaining scatterplots and correlations for the environmental influences as well as TPI, which is the dependent variable for the linear regression equations. In total, there are a 49 data pairs, as seen in Figure 23, which also shows the best fit line between the data points.

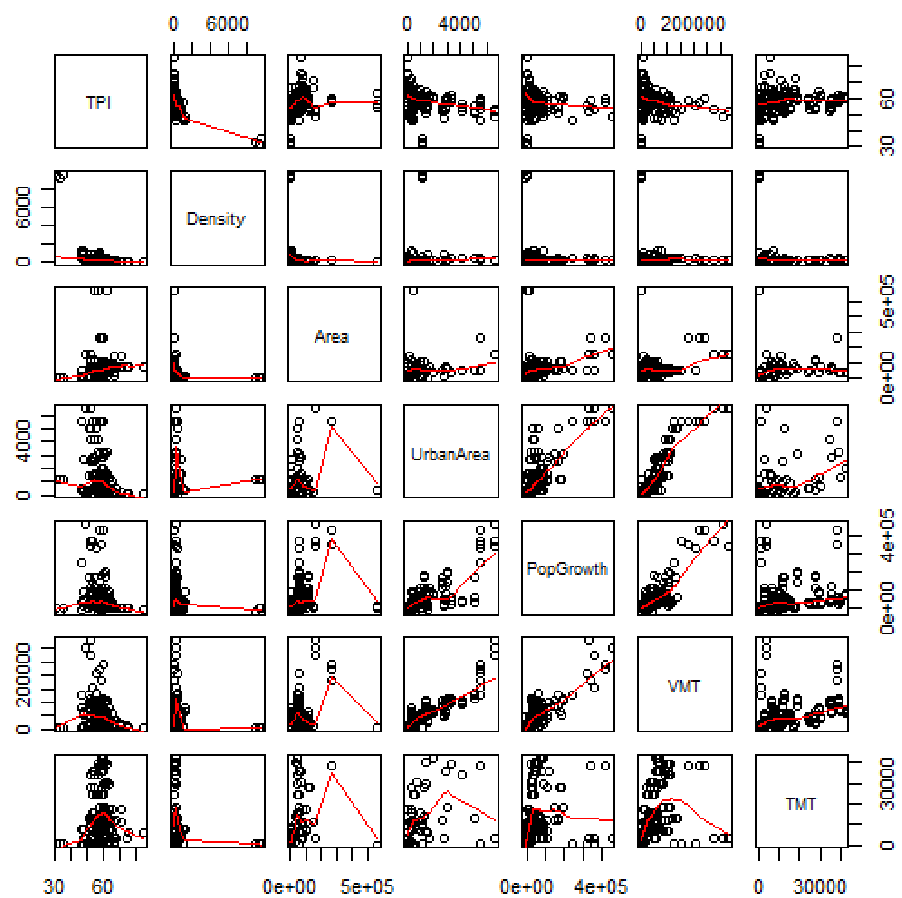

Figure 23 Scatterplots of Environmental Influences and TPI Data Pairs.

As a complement to Figure 23, the coefficient of correlation for each of the data pairs can be seen in Table 11.

Table 11 Coefficients of Correlation for Environmental Influences and TPI Data Pairs

Variables	TPI	Density	Area	Urban Area	Pop Growth	VMT	TMT
TPI	1.00	-0.59	0.14	-0.30	-0.18	-0.21	0.12
Density	-0.59	1.00	-0.18	0.01	-0.10	-0.10	-0.19
Area	0.14	-0.18	1.00	0.10	0.24	0.13	0.02
UrbanArea	-0.30	0.01	0.10	1.00	0.78	0.91	0.28
PopGrowth	-0.18	-0.10	0.24	0.78	1.00	0.86	0.17
VMT	-0.21	-0.10	0.13	0.91	0.86	1.00	0.29
TMT	0.12	-0.19	0.02	0.28	0.17	0.29	1.00

From Table 11, it is evident that there are a few highly correlated pairs. First, the coefficient of correlation between *UrbanArea* and *PopGrowth* as well as *UrbanArea* and *VMT* are very high, being about 0.78 and 0.91 respectively. Even though it is known that correlation doesn't necessarily imply causality, population growth may indeed increase urban area and induce more travel as measured by VMT. Between 1870 and 1970, the percent of the population in rural and urban communities shifted. In 1870, 75% of the U.S. population lived in rural areas, whereas 25% of the population lived in urban areas. By 1970, it was completely reversed, with 25% of the population in rural areas and 75% of the population in urban areas (U.S. Census Bureau, 2011). Second, the coefficient of correlation between *PopGrowth* and *VMT* is approximately 0.86, and the same logic applies.

For all three data pairs, collinearity becomes an issue of concern; it can result in erratic changes in the coefficient estimates when there are slight alterations to the linear regression model or the data itself. Therefore, this issue is examined more closely when comparing the different LRA cases. From the results of the different cases, the effects of using *UrbanArea*, *PopGrowth,* and *VMT* can be observed and taken into account when evaluating the DEA results. In addition, it is interesting that the correlation between *Area* and *UrbanArea* is almost 0, indicating there is almost no statistical relationship between the two variables despite having similar distributions but representing somewhat different phenomenon. Consequently, this observation is also taken account when analyzing the DEA results.

Linear Regression Analysis Cases

In terms of the results for the first 6 LRA cases, the intercept and the coefficient estimate for the independent variables were obtained. In addition, the residual standard error and the adjusted R^2 values were calculated, as seen in Table 12.

Table 12 Summary of LRA Results for Case 1 – 6

Case	Intercept	x1 Density	$x2_a$ Area	$x2_b$ Urban Area	x3 Pop Growth	x4 VMT	x5 TMT	Resid. Std. Error	Adj. R^2
y=f(x1)	59.13	-3.14e-3	-	-	-	-	-	5.64	0.34
y=f($x2_a$)	57.19	-	1.17e-5	-	-	-	-	6.89	0.01
y=f($x2_b$)	59.87	-	-	-1.32e-3	-	-	-	6.65	0.08
y=f(x3)	58.86	-	-	-	-1.40e-5	-	-	6.85	0.03
y=f(x4)	59.38	-	-	-	-	-2.58e-5	-	6.81	0.04
y=f(x5)	57.09	-	-	-	-	-	6.45e-5	6.91	0.01

From the above table, it is apparent that increases to *Density*, *UrbanArea*, *PopGrowth*, and *VMT* cause decreases to *TPI*, whereas increases to *Area* and *TMT* cause increases to *TPI.* So, despite area and urban area supposedly representing the same phenomenon, they lead to opposite changes in TPI. Thus far, area and urban area have similar distributions, no correlation and coefficient estimates that are different in direction, where the former is positive and the latter is negative. In addition, urban area is high correlated with two other environmental influences. Overall, these are important facts about the data for area and urban area, and are used as a part of the analysis of the DEA results.

The residual standard errors for cases 1 thru 6 do not vary a great deal, where the standard deviation of the error is about 0.5. Density produces the lowest error as well as the highest adjusted R^2 value, which is equal to 0.3401. So, compared to the other environmental influences, density is the best predictor or adjustor for TPI. Furthermore, the R^2 values for the other environmental influences are all less than 1. In Figure 24, plots of the residuals vs. fitted values for Case 1 to Case 6 can be seen.

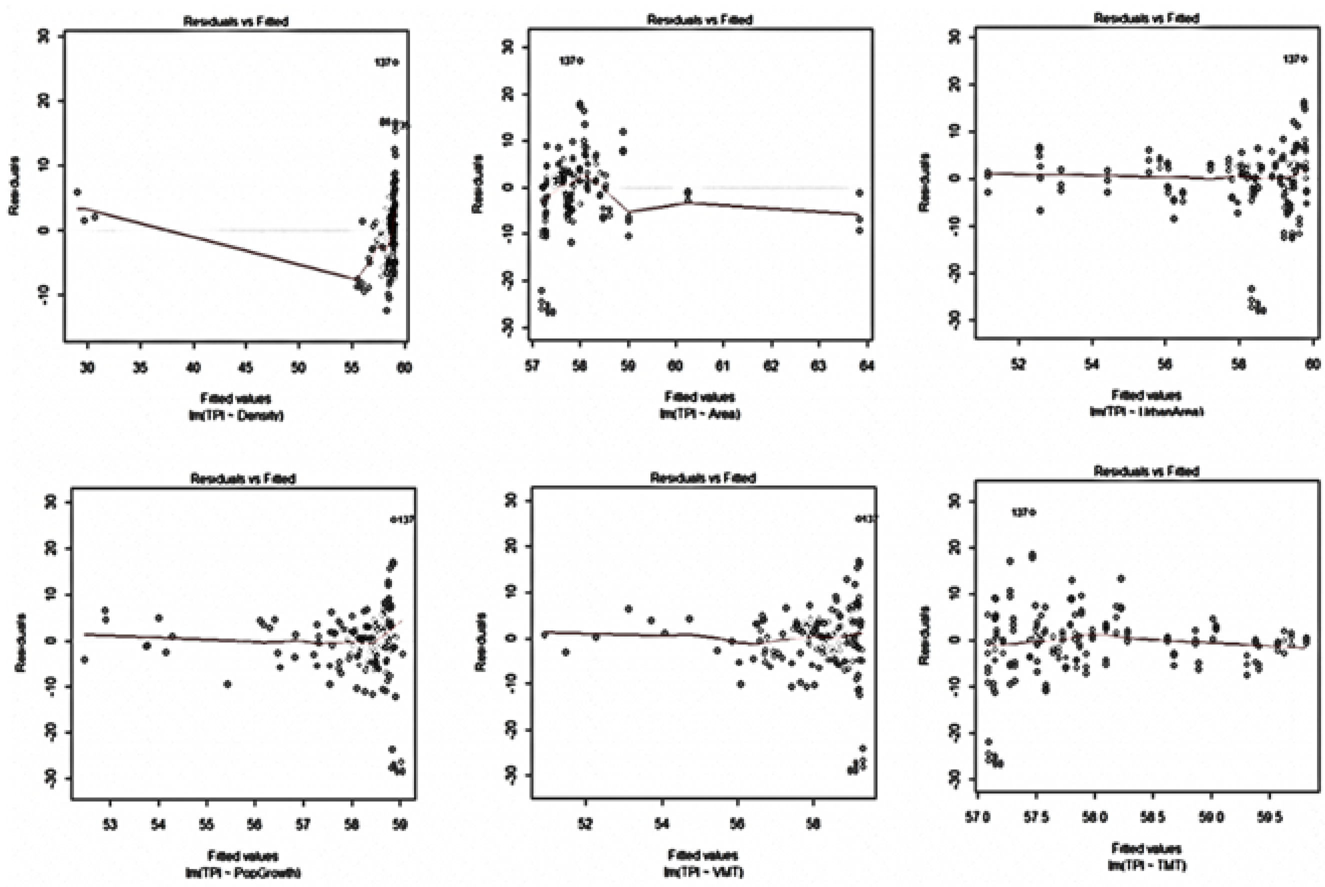

Figure 24 **Plots of Residuals vs. Fitted Values for Cases 1 – 6.**

From the residual plots above, it is evident that the points are somewhat randomly dispersed around the horizontal axis. However, for the most part, the points are either located to the far left or the far right of the plots. TMT is the only plot that appears to have points that are truly randomly dispersed. So, based on the adjusted R^2 values and the residual plots, it is clear that a LRA model based on any single explanatory variable is not a good fit.

For LRA cases 7 to 11, the coefficient estimate for the independent variables, the residual standard error and the adjusted R^2 values were all obtained, as seen in Table 13.

Table 13 Summary of LRA Results for Case 7 – 11

Case	Intercept	x1 Density	$x2_a$ Area	$x2_b$ Urban Area	x3 Pop Growth	x4 VMT	x5 TMT	Resid. Std. Error	Adj. R^2
$y=f(x1...x2_a)$	58.90	-3.10e-3	3.13e-6	-	-	-	-	5.65	0.3372
$y=f(x1...x2_b)$	60.96	-3.12e-3	-	-1.30e-3	-	-	-	5.27	0.4234
y=f(x1...x3)	59.84	-3.18e-3	8.25e-6	-	-2.06e-5	-	-	5.38	0.3986
y=f(x1...x4)	60.50	-3.21e-3	6.64e-6	-	-5.44e-6	-2.72e-5	-	5.34	0.4069
y=f(x1...x5)	59.98	-3.14e-3	6.66e-6	-	-3.40e-6	-3.29e-5	4.72e-5	5.33	0.4093

By comparing Table 12 and Table 13, it can be seen that the direction of the coefficient estimates for each variable remained the same. In addition, the adjusted R^2 values improved, with the average value being about 0.40. In terms of magnitude, the coefficient for density remained about the same, whereas the coefficients for the other variables changed slightly. For example, the magnitude of the coefficient estimate for area increased with three variables, decreased with four, and then increased again with five.

Then, in terms of residual standard error, the values were slightly lower in Table 13 than Table 12, and still don't vary a great deal. So, the addition of other variables produce better fits for TPI compared to LRA models with a single independent variable. In Figure **25**, plots of the residuals vs. fitted values for Case 7 to Case 11 can be seen.

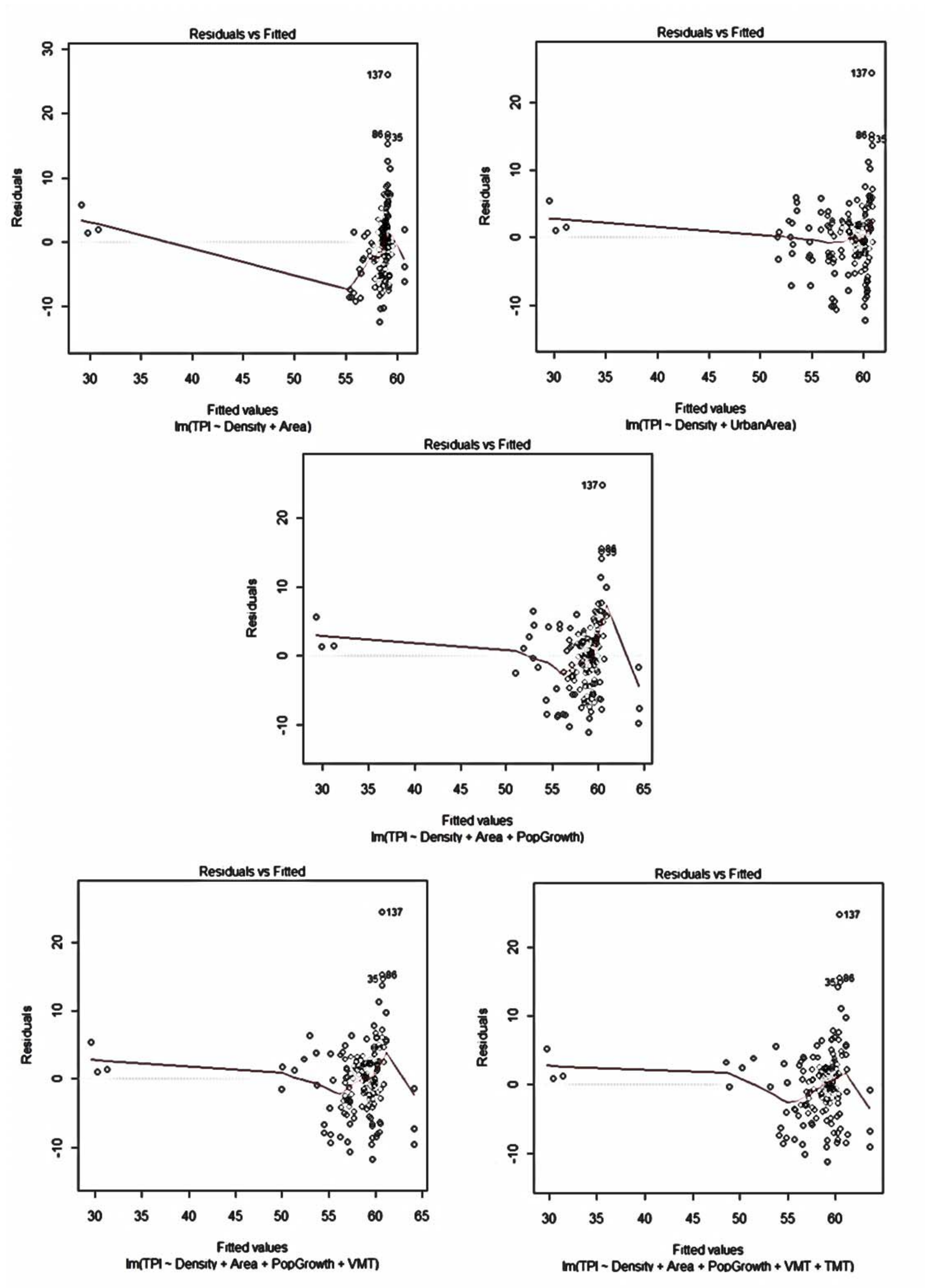

Figure 25   Plot of Residuals vs. Fitted Values for Cases 7 – 11.

From the residual plots above, it is evident that for LRA cases with an increased number of independent variables, the points are somewhat randomly dispersed around the horizontal axis.

The last LRA case examined is Case 12 (see Figure 26), which is similar to Case 11 but the variables are normalized using the maximum and minimum values within each data set (see Equation 8).

$$X_{norm} = \frac{(x_i - x^{MIN})}{(x^{MAX} - x^{MIN})} \tag{8}$$

By normalizing the data, all the variables share a common scale of 0 to 1, which allows for underlining characteristics within the data to be compared. In Table 14, the residual standard error and the adjusted R^2 values can be seen.

Table 14 Summary of LRA Results for Case 12

Case	Inter-cept	x1 Density	$x2_a$ Area	x3 Pop Growth	x4 VMT	x5 TMT	Resid. Std. Error	Adj. R^2
y= N[f(x1...x5)]	0.53	-0.56	0.07	-0.03	-0.20	0.04	0.10	0.4287

From comparing Table 14 results with the other cases, it can be seen that the direction of the coefficient estimates for each variable remained the same. In addition, the adjusted R^2 value improved, having the highest value of all 12 cases. The residual standard error for Case 12 was also the lowest of all the cases.

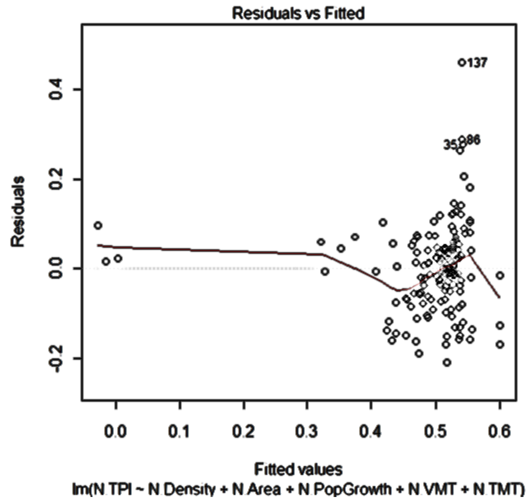

Figure 26 Plot of Residuals vs. Fitted Values for Cases 12.

From the residual plot above, it is evident that the points are somewhat randomly dispersed around the horizontal axis. In addition, the residual plot is very similar to that of Case 11 (Figure 25). So, normalizing the data produces about the same fit as non-normalized data.

Overall, it can be concluded that there are certain patterns and trends that are inherent to each data set, such as a specific distribution, a narrow or wide range, as well as a high or low correlation with other variables. These observed patterns and trends are in turn used to develop logical and applicable DEA models. In the following section, the actual DEA results are presented, beginning with a summary of the approach used to develop the three DEA hypotheses as well as their respective scenarios. Next, the default DEA model is rationalized using the insights from the preliminary data analysis as well as HP0 results for the variable substitutions. In addition, the default LRA model for HPI and HPII is rationalized using the results from the preliminary data analysis, comparing each of the LRA cases as well as HPI and HPII results for the variable substitutions.

Subsequently, the efficiency rankings and benchmarks for each of the three DEA hypotheses (using the default models) are displayed for the most recent data year, 2007, making comparisons to 1995 and 2000.

Chapter 5

RESULTS – DEA EVALUATION

This chapter includes the second part of the results. First, the effects of using the substitute variables are evaluated, and in turn used to certify the final selection of the default DEA model and LRA case. Next, the efficiency rankings and benchmarks for each of the three DEA hypotheses are displayed for the most recent data year, 2007, making comparisons to 1995 and 2000. The complete DEA results can be found in Appendices E, F and G.

As stated in the "DEA Hypotheses" section of Chapter 4, there are three hypotheses that were developed, including HP0, HPI and HPII. HP0 is based on surface efficiency, which calculates the efficiency of the states in respect to transportation and the economy without taking into account the effects of the environment. HPI is based on comprehensive efficiency, which calculates the efficiency of the states by adding the effects of the environmental influences that place pressure on TPI. Then, HPII is based on managerial efficiency, which calculates efficiency of the states by removing the effects of the environmental influences that place pressure on TPI. In addition, for each hypothesis, there are several different scenarios defined by the substitution of DEA inputs, the substitution of environmental influences, the data year as well as the grouping of the states.

In total, there are 120 different scenarios (20 hypotheses, 2 scenarios – with and without District of Columbia, Hawaii and Alaska, 3 years – 1995, 2000 and 2007) that were analyzed (see Table 6). The reason for such an extensive list of DEA models was to determine the affect slight changes, such as variable substitution or grouping of DMUs, have on the models themselves.

For each scenario, the efficiency is computed and plotted for each state. For states that are not efficient (score is 1), benchmarks are identified. However, for the results, only the benchmarks for 2007 are presented, since it is the most recent year. The complete graphs for the efficiency scores for HP0, HP1 and HPII can be seen in Appendix E, Appendix F, and Appendix G respectively. The next section of the thesis begins by rationalizing the choice of variables and then examines the rankings and efficiency scores.

Rationalizing Selection of Default Models

In order to select a set of default models for further analysis and interpretation, the scenarios with alternative variables are compared. In selecting the default DEA and linear regression models, there are specific attributes of the data that were examined. For the DEA model, the first attribute examined was the availability of the data sets. As previously noted, the DEA input, *Debtpc*, is used as a representation of the quality of government, where it is assumed that state governments with minimal debt are operating efficiently. In addition, the government performance project grades (*GPP*) is considered as a possible substitute for *Debtpc*, where *GPP* pertains to how well states are managing their infrastructure. While the data for *Debtpc* is available or estimated for each of the years analyzed, *GPP* is only available for 2008 and is assumed to be the same for all data years (see Table 4). By assuming that *GPP* is the same over a 12 year period, the accuracy of the model decreases, where realistically the quality of government changes over time. This issue of assuming the same data over multiple years also occurs with the American Human Development Index (*AHDI*), which is considered as a possible substitute for life expectancy as a representation of the quality of life. The base year for *AHDI* is 2010.

The second attribute examined in order to select the default DEA model was the behavior of the data sets. When comparing *Debtpc* and *GPP*, it was found that they have dissimilar distributions and a correlation of -0.26. So, despite being proposed to represent the same phenomenon, they are statistically different. Also, conceptually, *GPP* is a more appropriate input than *Debtpc* because it directly relates to transportation infrastructure. In terms of *LE* and *AHDI*, they have dissimilar distributions and a correlation of 0.45. So, they are somewhat positively correlated and statistically capture the same phenomenon. However, *AHDI* is a more robust representation of quality of life, since it is a function of *LE* and other relevant variables.

The third and last attribute examined was the trend of the efficiency graphs for HP0; specifically comparing the model scenarios with only a single variable substitution (see Table 6). Accordingly, the effects of *Debtpc* vs. *GPP* on the DEA results are compared by inspecting the graphs of HP0-1 and HP0-3 for all three data years, as seen in Figure **27**, Figure 28 and Figure 29.

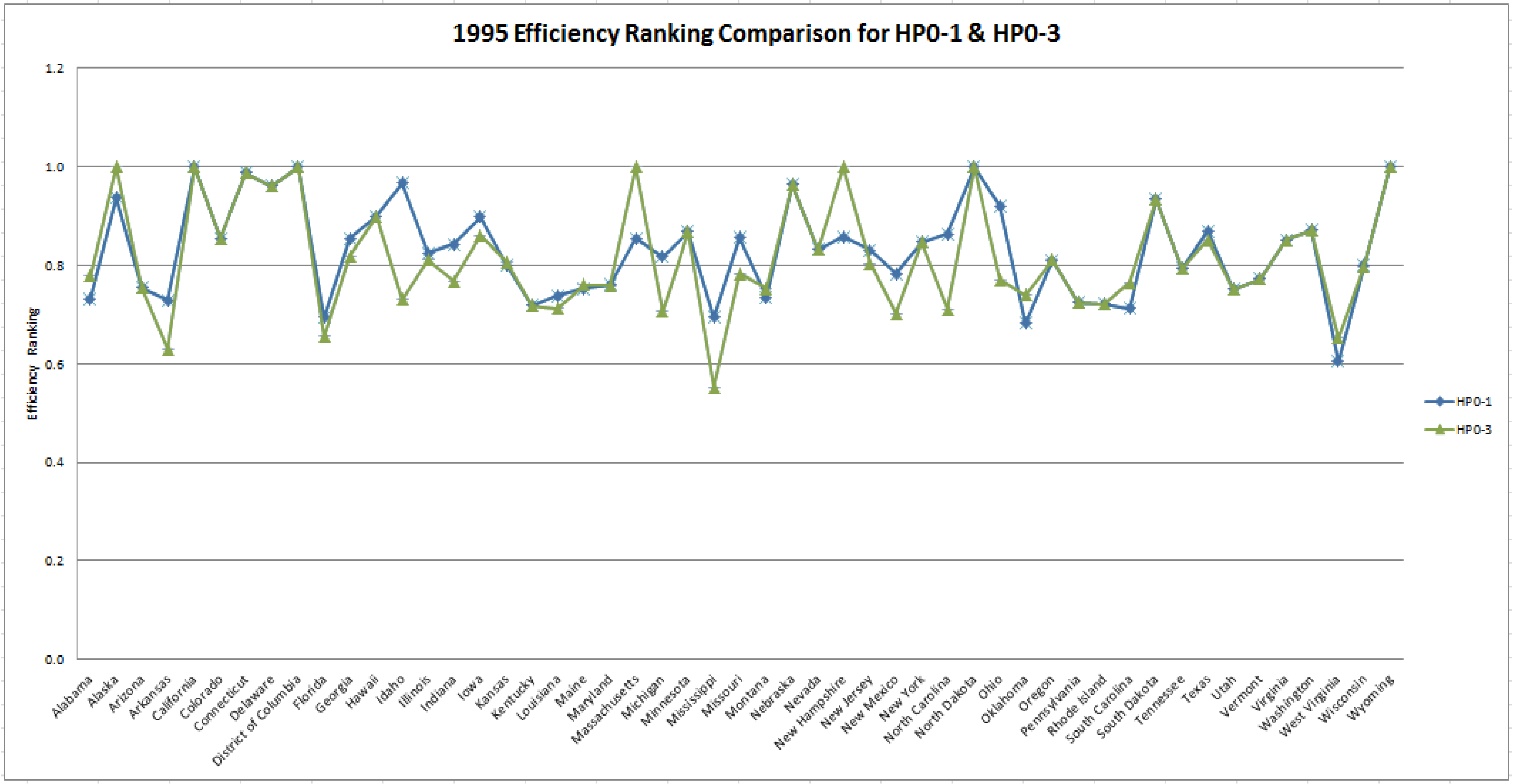

Figure 27 1995 Efficiency Ranking Comparison for HP0-1 & HP0-3.

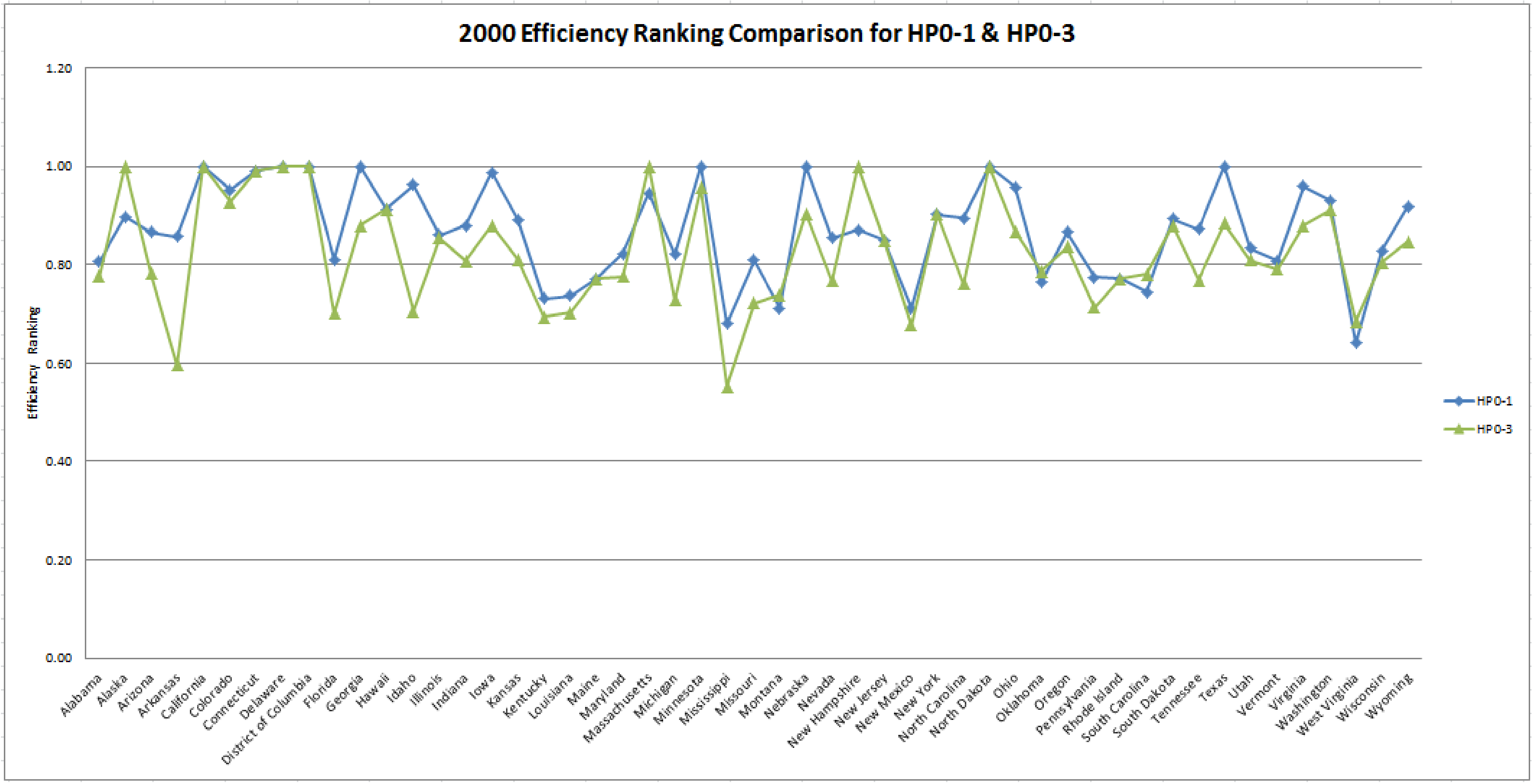

Figure 28 2000 Efficiency Ranking Comparison for HP0-1 & HP0-3.

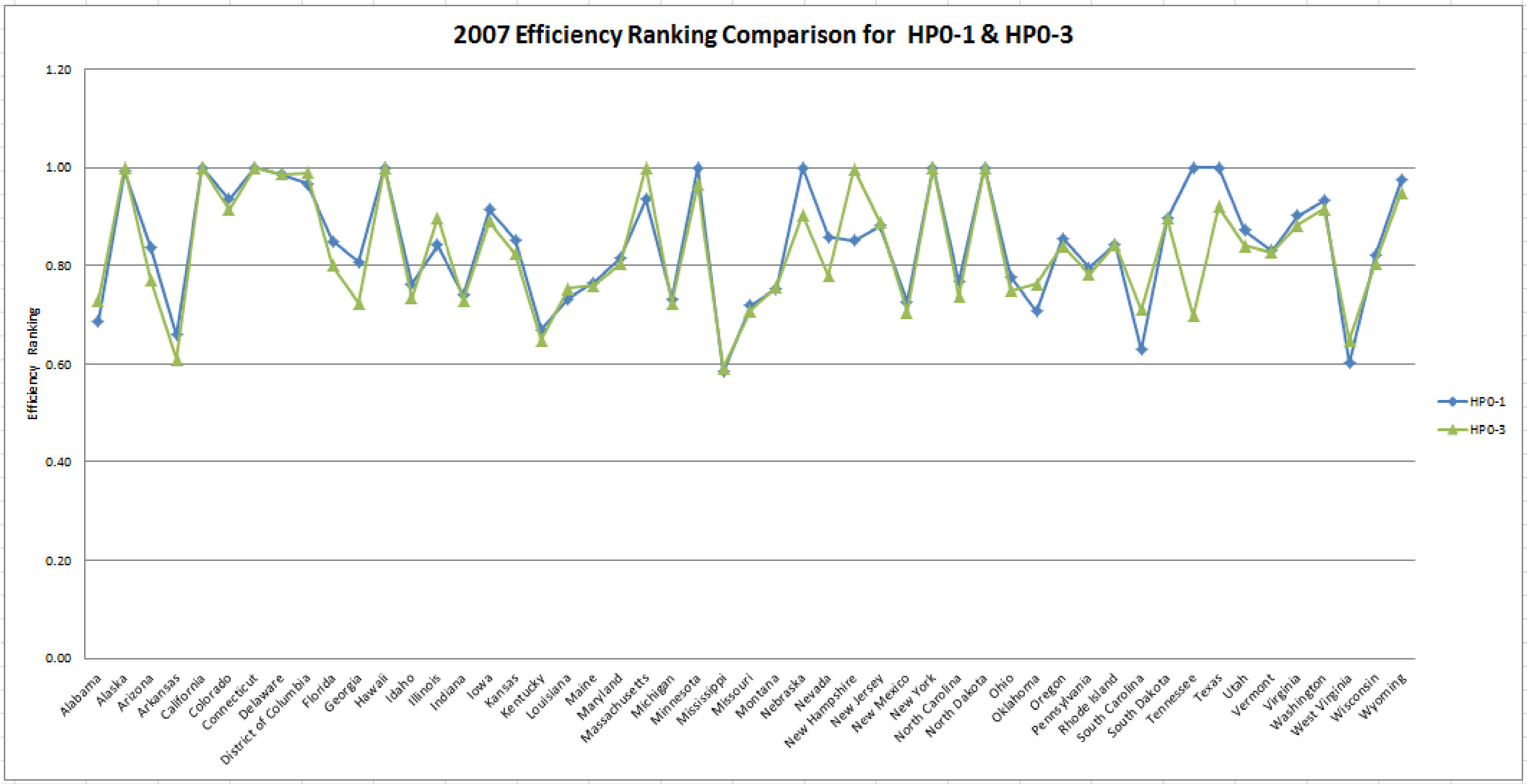

Figure 29 2007 Efficiency Ranking Comparison for HP0-1 & HP0-3.

From the three figures above, it is evident that the graphs for HP0-1 and HP0-3 do not vary that much, especially for 2007. Even though both models produce about the same efficiency values for each state, HP0-1 has a slightly narrower range with fewer extremes. Consequently, when comparing *Debtpc* and *GPP*, while taking into account the availability and behavior of the two data sets, *Deptpc* is the more applicable input for the DEA model as a representation of the quality of government.

In terms of comparing the effects of *LE* and *AHDI*, the graphs of HP0-1 and HP0-2 are inspected for all three data years, as seen in Figure 30, Figure **31** and Figure 32.

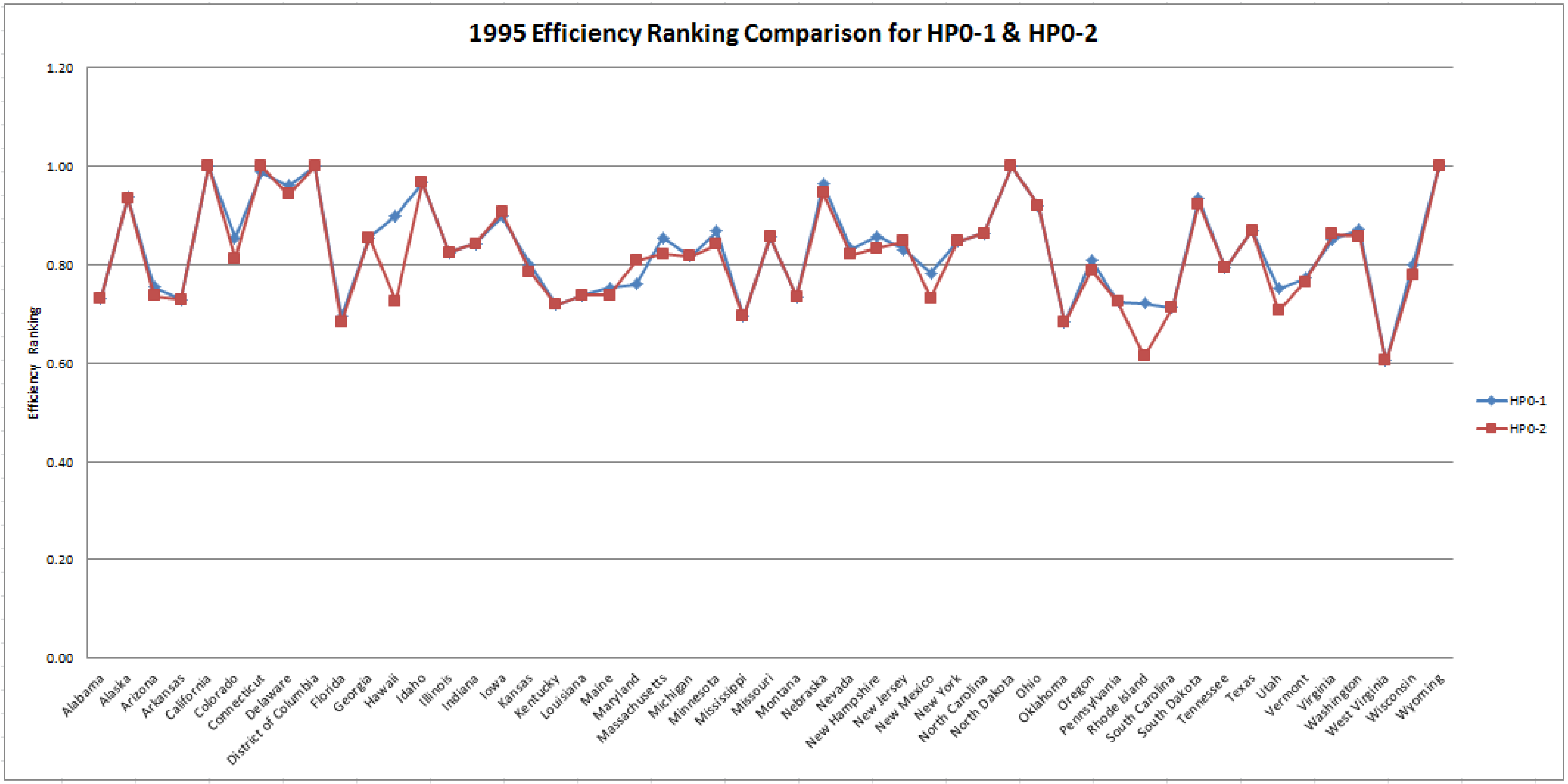

Figure 30 1995 Efficiency Ranking Comparison for HP0-1 & HP0-2.

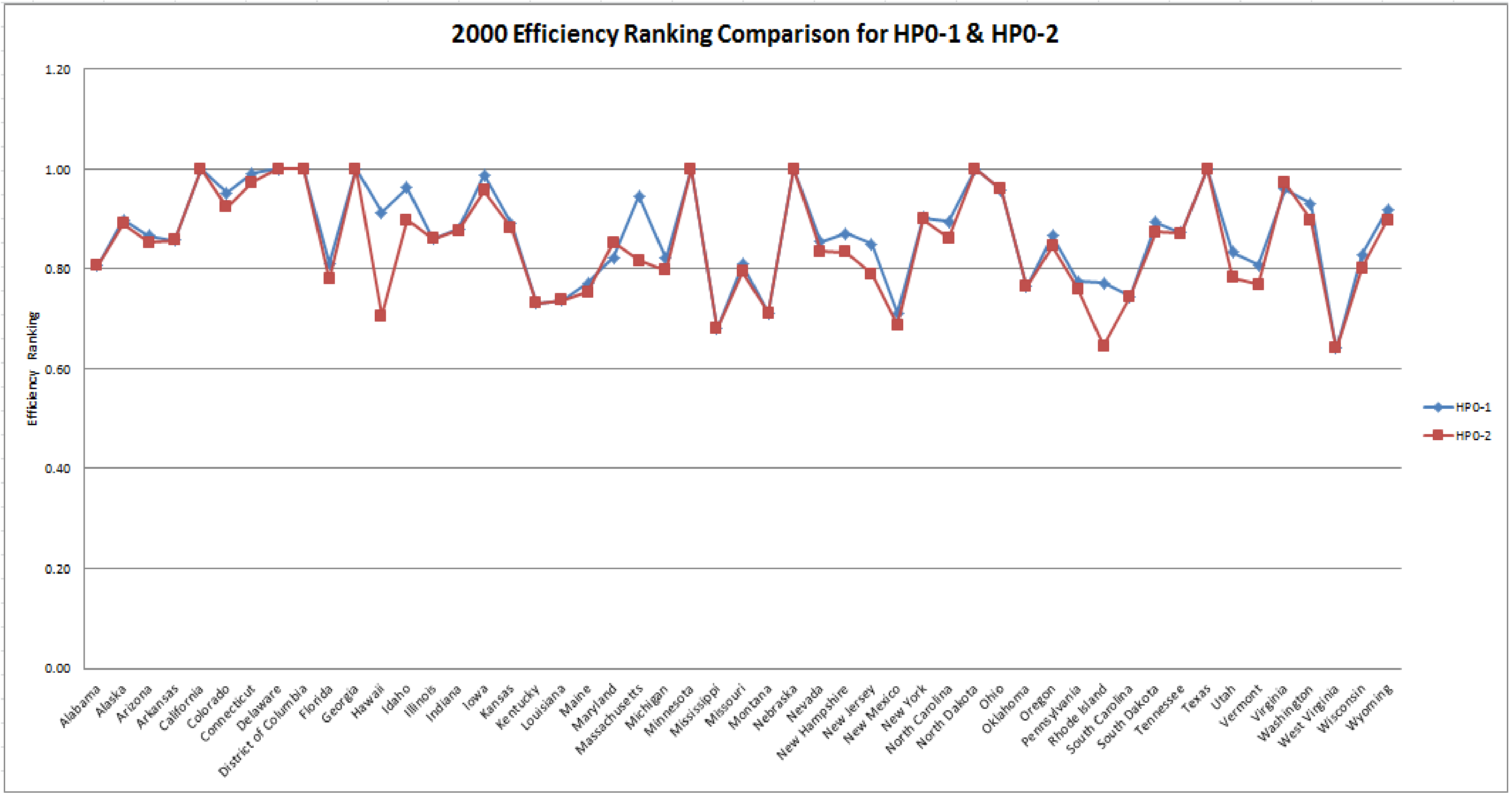

Figure 31 2000 Efficiency Ranking Comparison for HP0-1 & HP0-2.

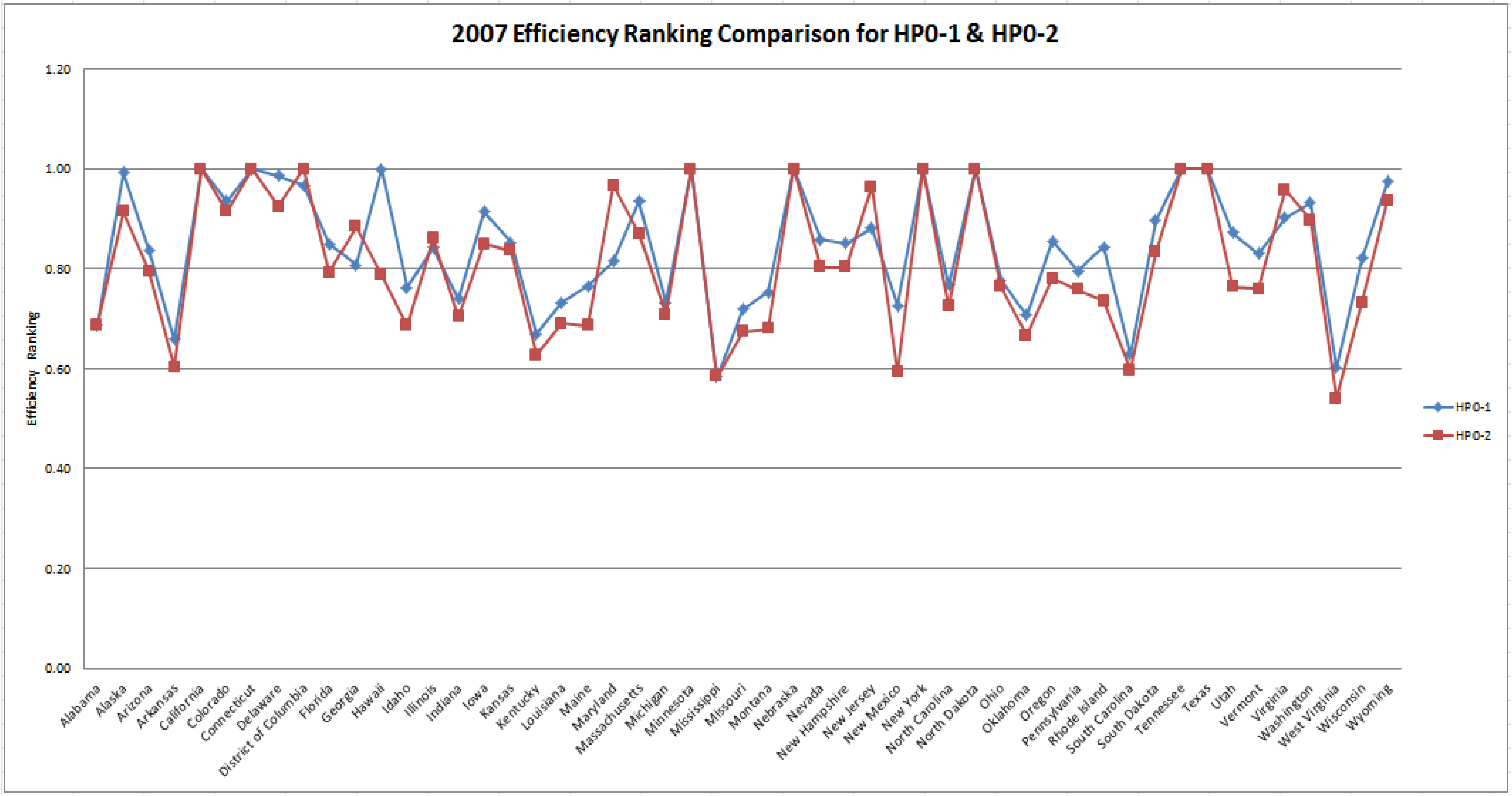

Figure 32 2007 Efficiency Ranking Comparison for HP0-1 & HP0-2.

From the three figures above, it is evident that the graphs for HP0-1 and HP0-2 do not vary that much for 1995 and 2000, but slightly more for 2007. In addition, HP0-1 tends to produce higher efficiency scores compared to HP0-2. Consequently, when comparing *LE* and *AHDI*, while taking into account the availability and behavior of the two data sets, *LE* is the more applicable input for the DEA model as a representation of the quality of life.

Overall, the default inputs for the DEA model include *Debtpc* and *LE* as well as *TPI* and *GDP*. The graphs for all HP0 scenarios can be seen in Appendix D. In addition, the effect of the substitute inputs on the DEA models is assumed to be same for HPI and HPII.

In selecting the default linear regression models for HPI and HPII, there are specific attributes of the data that were examined, just as with selecting the default DEA model. The first attribute examined was the availability of the data sets. In terms of *Area* and *UrbanArea*, data was only available for 2000, and was assumed to be the same for all data years (see Table 4). For *Area*, this assumption is valid due to the fact that the total size of states can be considered as constant, only varying based on the primary source examined and the addition of certain bodies of water in the total area calculation (Coutsoukis, 2011). However, for *UrbanArea*, this is not the case, where it is defined by cities with populations greater than 50,000. Consequently, over a 12 year period, population fluctuates and in turn, so does the set of locations that are considered to be urban within a given year. Therefore, compared to *Area*, *UrbanArea* would have a higher degree of variability.

The second attribute examined in order to select the default linear regression equations was the behavior of the data sets. When comparing *Area* and *UrbanArea*, it was found that they have similar exponential distributions and a correlation of 0.1. So, despite being proposed to represent the same phenomenon, they are statistically different. Also, conceptually, *Area* is a more appropriate input than *UrbanArea* because the later refers to the total state and the former refers to only a very small portion of the total. Moreover, TPI is calculated by a state-by-state basis, not just the urban areas of the state.

The third attribute examined was the statistical properties of each of the different LRA cases. In total, there were 12 cases examined. For the first 6 cases, it was concluded that a LRA model based on any single explanatory variable is not a good fit, having fairly low adjusted R^2 values. For cases 7 thru 11, the adjusted R^2 values improved. When comparing Case 7 and Case 8, where the former includes *Density* and *Area* and the latter includes *Density* and *UrbanArea*, Case 8 had an adjusted R^2 value that was only 0.09 more than Case 7. For Case 12, the normalization of the data greatly decreased the residual standard area, but the adjusted R^2 value was about the same as cases 7 thru 11. In addition, for DEA, the CRS model is used, which maximizes the outputs and minimizes the inputs. So, if TPI was first normalized and then minimized, the characteristics inherent to the data would be removed. Overall, the LRA cases show that the data is very messy and linear regression is applicable only to a limited extent.

The fourth and last attribute examined was the trend of the efficiency graphs for HPI and HPII; specifically comparing the model scenarios with *Area* and the model scenarios with *UrbanArea* (see Table 6). Accordingly, the effects of *Area* vs. *UrbanArea* on the DEA results are compared by inspecting the graphs of HPI-1 and HPI-5 as well as HPII-1 and HPII-5 for all three data years, as seen in the following six graphs (see Figure 33– Figure 38).

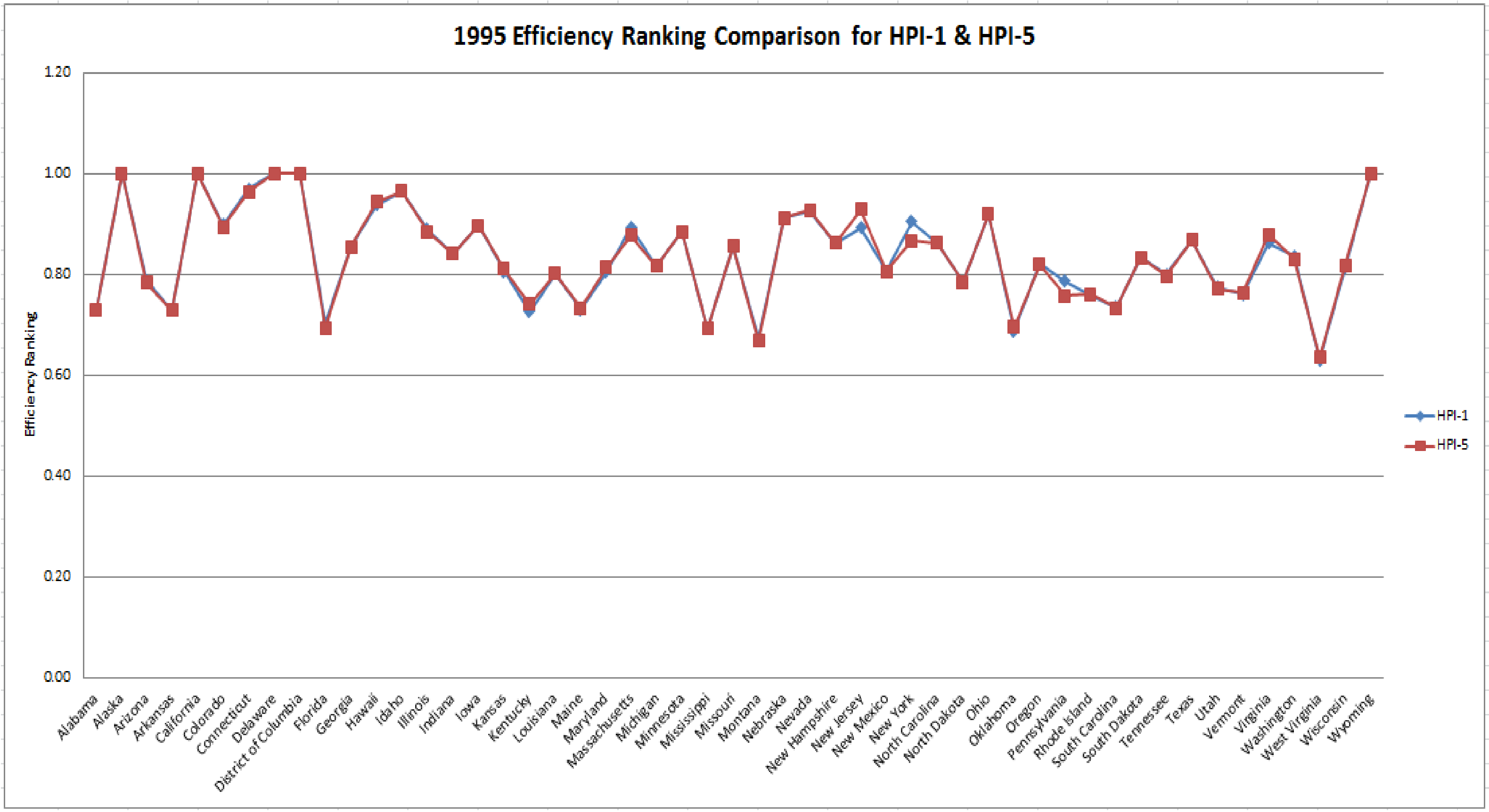

Figure 33 1995 Efficiency Ranking Comparison for HPI-1 & HPI-5.

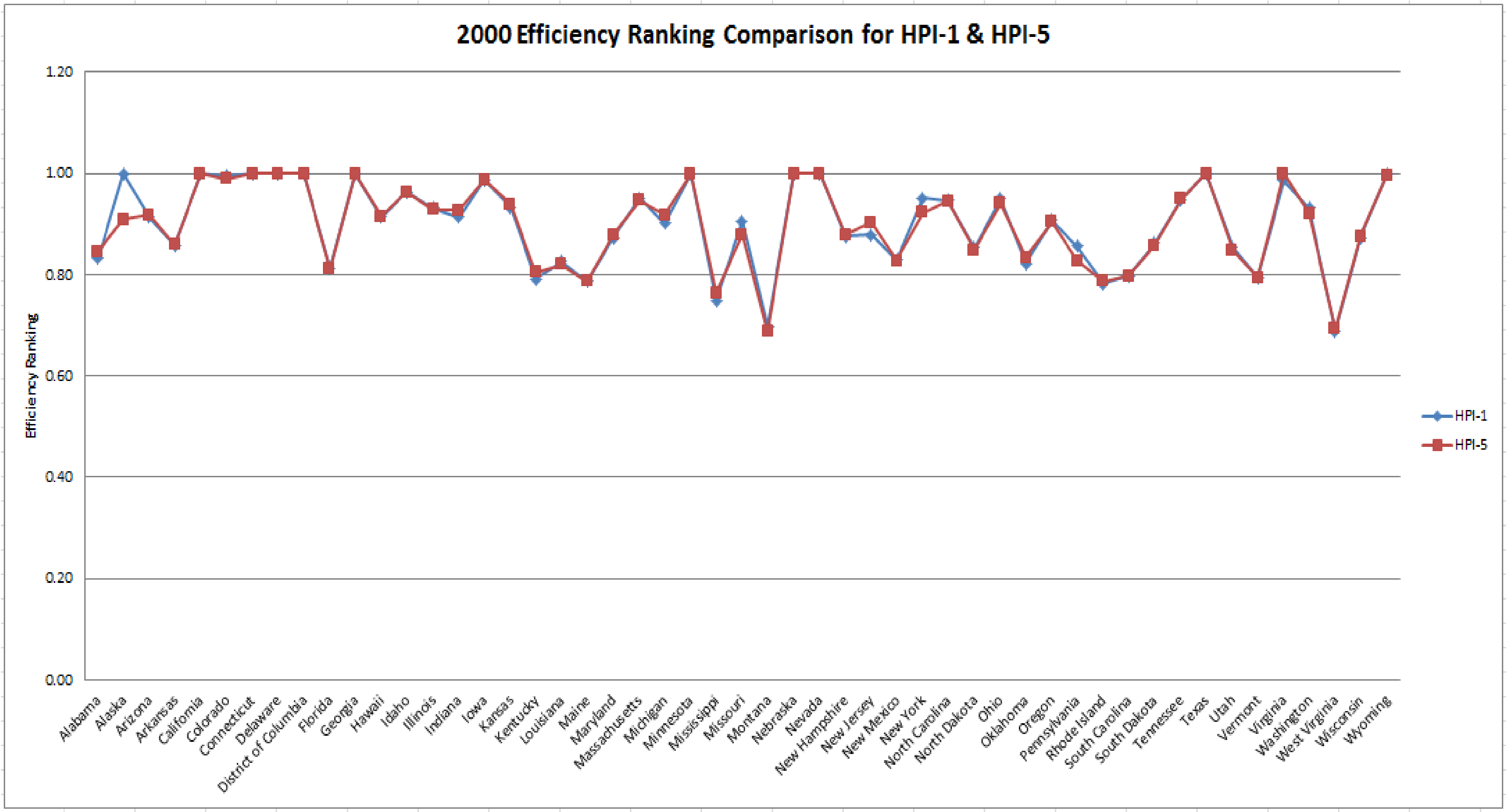

Figure 34 2000 Efficiency Ranking Comparison for HPI-1 & HPI-5.

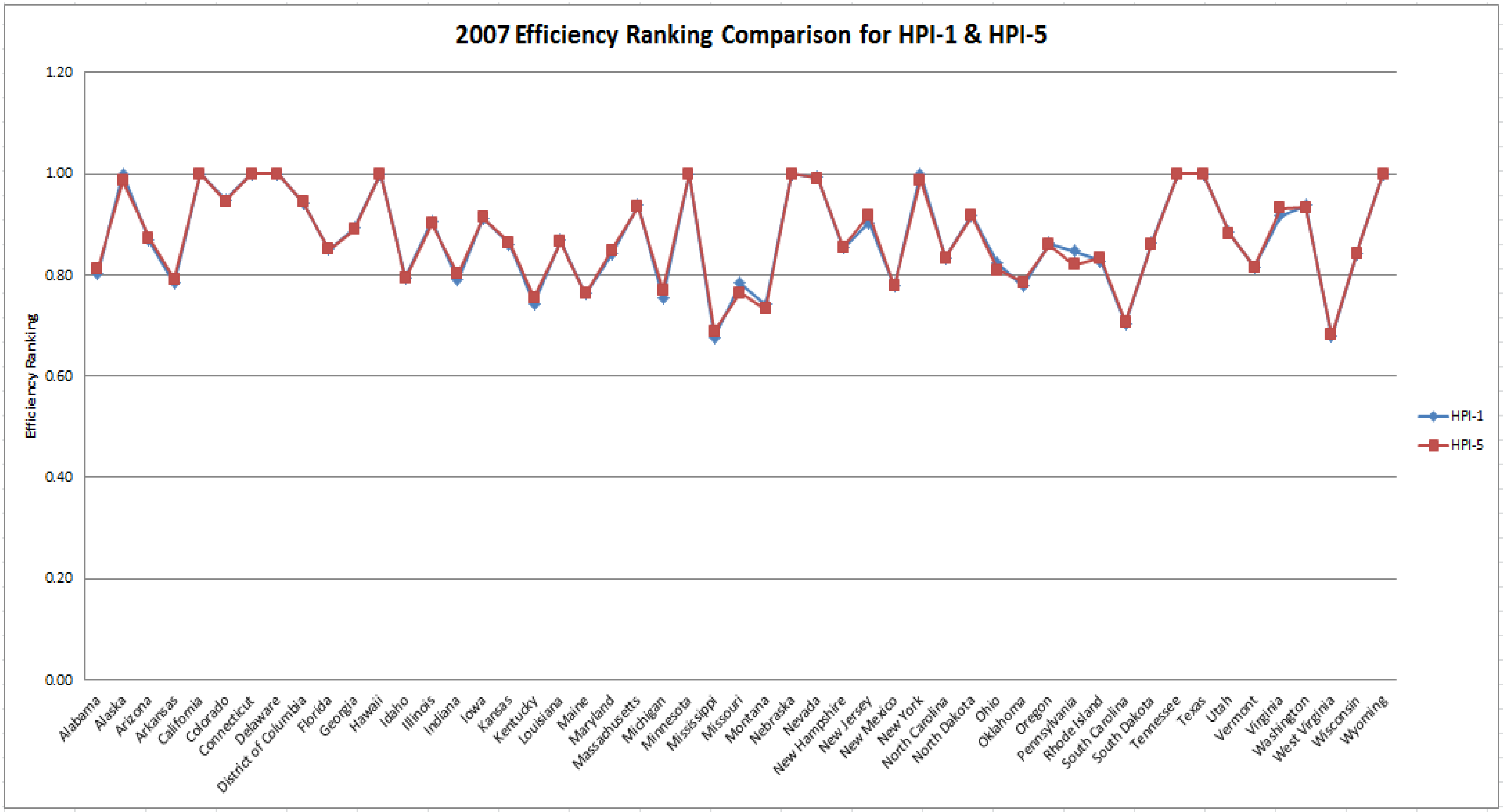

Figure 35 2007 Efficiency Ranking Comparison for HPI-1 & HPI-5.

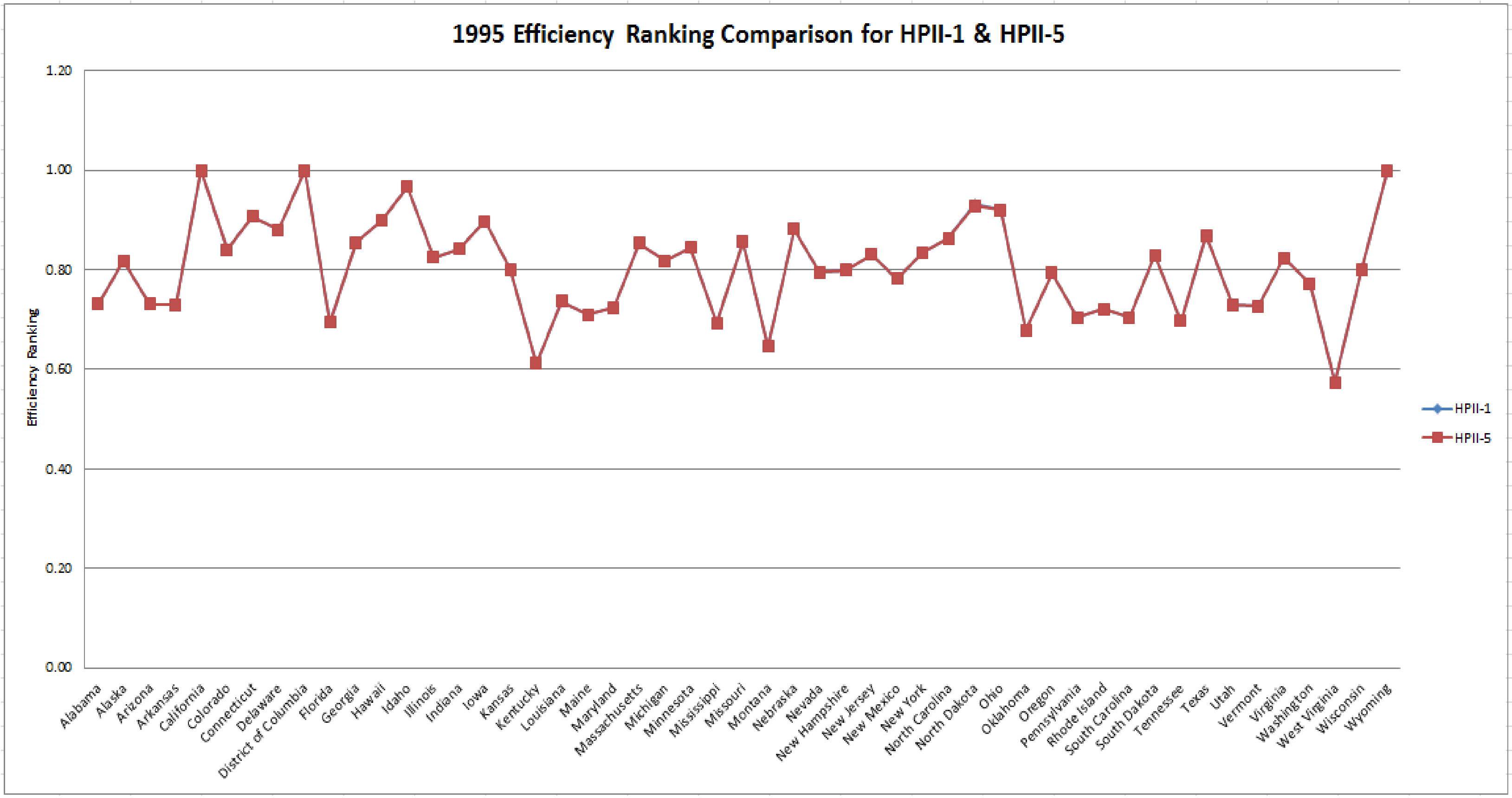

Figure 36 1995 Efficiency Ranking Comparison for HPII-1 & HPII-5.

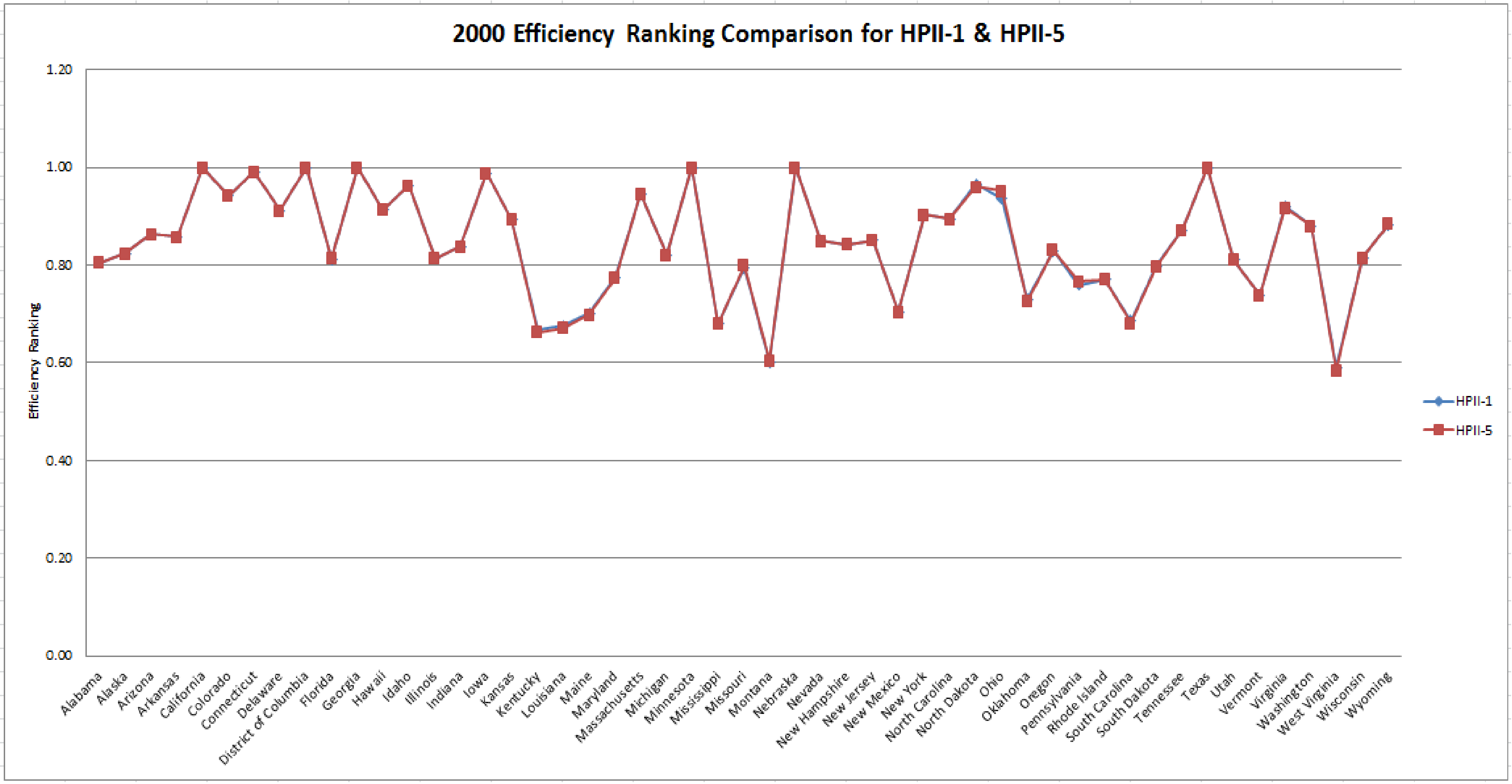

Figure 37 2000 Efficiency Ranking Comparison for HPII-1 & HPII-5.

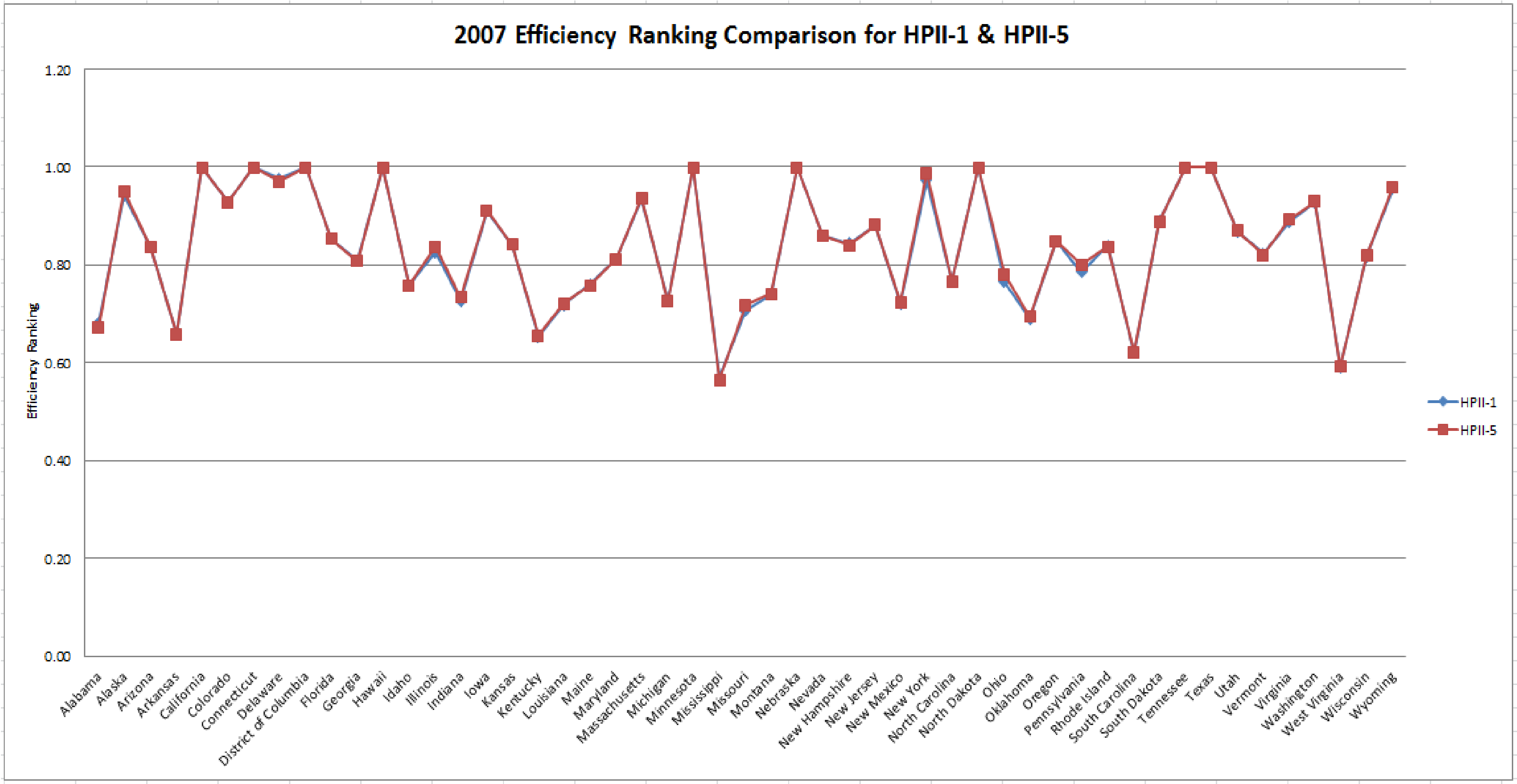

Figure 38 2007 Efficiency Ranking Comparison for HPII-1 & HPII-5.

From the six figures above, it is evident that the graphs for HPI-1 and HPI-5 as well as HPII-1 and HPII-5 vary very little for the three data years. The only discernible differences are generally in highly urbanized states such as New Jersey, New York and Pennsylvania. Consequently, when comparing *Area* and *UrbanArea*, while taking into account the availability and behavior of the two data sets, either one would be applicable. However, *Area* is the more appropriate input for the linear regression equations in terms of data collection as well as conceptually. The graphs for all HPI and HPII scenarios can be seen in Appendices F and G respectively. Overall, the default linear regression equations for the HPI and HPII are based on LRA Case 11, include *Density*, *Area*, *PopGrowth*, *VMT*, and *TMT*.

DEA Ranking and Benchmark Results

Before presenting and interpreting the DEA results, how to interpret the results warrants further explanation. First, in terms of the benchmarks, these are the states that receive an efficiency score equal to 1 and are considered to be the most efficient of the DMUs. However, there are some DMUs whose efficiency scores round to 1 but are not benchmarks. Therefore, all benchmarks have an efficiency score of 1, but not all DMUs with an efficiency score of 1 are benchmarks.

Second, a major part of the DEA methodology is improving efficiency scores by determining which inputs need to be adjusted and to what degree. For example, Barnum et al. uses DEA to compare the efficiency of bus routes, where the main inputs are seat hours and seat miles (Barnum, Tandon, & McNeil, 2008). By adjusting these inputs, the outputs, such as ridership, can be improved and overall efficiency increased. However, for this research, DEA is done on a macro-scale, where for Barnum et al., the work is on a micro-scale level. For a micro-scale analysis, the adjusting of inputs is practical and has real world application. Seat hours and seat miles are controllable inputs that are directly related to a specific policy or practice. On the other hand, inputs such as *TPI*, *GDP*, *Debtpc* and *LE* are not directly controllable and are very complex being affected by a slew of factors. So, increasing a specific variable, such as *TPI*, may improve the efficiency of a state but it has no real meaning. The key issue is not just increasing *TPI* but determining which specific tactics or policies improve *TPI*. In turn, the DEA results presented should serve primarily as an informational resource, rather than a decision making tool.

Third, for the DEA hypotheses, the set of DMUs were separated into two groups for analysis. The first group includes all the states and D.C. as DMUs and the second group includes only the continental states (excluding District of Columbia, Hawaii and Alaska) as DMUs. In order to determine the effects of the different state groupings on the DEA results, the average percent difference of the efficiency scores for each scenario was calculated, as well as for each data year, as seen in Table 15.

Table 15 Average Percent Difference of Efficiency Scores Based on State Grouping

Scenario Code	Avg. % Diff. for 1995	Avg. % Diff. for 2000	Avg. % Diff. for 2007
HP0-1	4%	1%	0%
HP0-2	4%	3%	0%
HP0-3	5%	3%	2%
HP0-4	5%	4%	4%
HPI-1	3%	0%	0%
HPI-2	3%	1%	0%
HPI-3	7%	3%	5%
HPI-4	10%	4%	7%
HPI-5	3%	0%	0%
HPI-6	2%	1%	0%
HPI-7	6%	2%	4%
HPI-8	6%	3%	0%
HPII-1	7%	3%	0%
HPII-2	10%	8%	2%
HPII-3	14%	12%	4%
HPII-4	27%	29%	19%
HPII-5	7%	3%	0%
HPII-6	10%	9%	1%
HPII-7	14%	13%	4%
HPII-8	27%	29%	18%

From the above table, the most apparent trend is that all the percent changes are positive. So, by decreasing the number of DMUs, the individual efficiency scores of the remaining DMUs actually increase. In addition, the average percent change of the efficiency scores generally decreases moving forward in time. In other words, the more recent the data set is, the less of an impact removing DMUs has on the individual efficiencies. Also, the highest average percentage change is 29%, and the highest percent change for an individual DMU is 42%.

If the scenarios in Table 15 are grouped by four, the percent change general increases, where using the substitute variables cause a greater percent difference in efficiency. For example, HP0-1, HP0-2, HP0-3 and HP0-4 are the first group of four and HP1-1, HP1-2, HP1-3 and HP1-4 are the second group of four. In total, there are five consecutive groups of four. So, by using the default DEA and linear regression models, specifically referring to HP0-1, HPI-1 and HPII-1, the effect of grouping the states are minimized and the results are more stable. Overall, when comparing the scenarios by the two state groupings, either one would be relevant, where useful information can be obtained from both. However, the scenarios including all the states are more appropriate since each state contributes to the overall level of performance of transportation infrastructure in the U.S. So, for the following DEA results, only scenario 1 for each of the hypotheses is presented.

In terms of comparing the results for HP0-1, HPI-1 and HPII-1, Figure 39, Figure **40** and Figure 41 respectively, group each of the DEA hypotheses by year for all states and the District of Columbia.

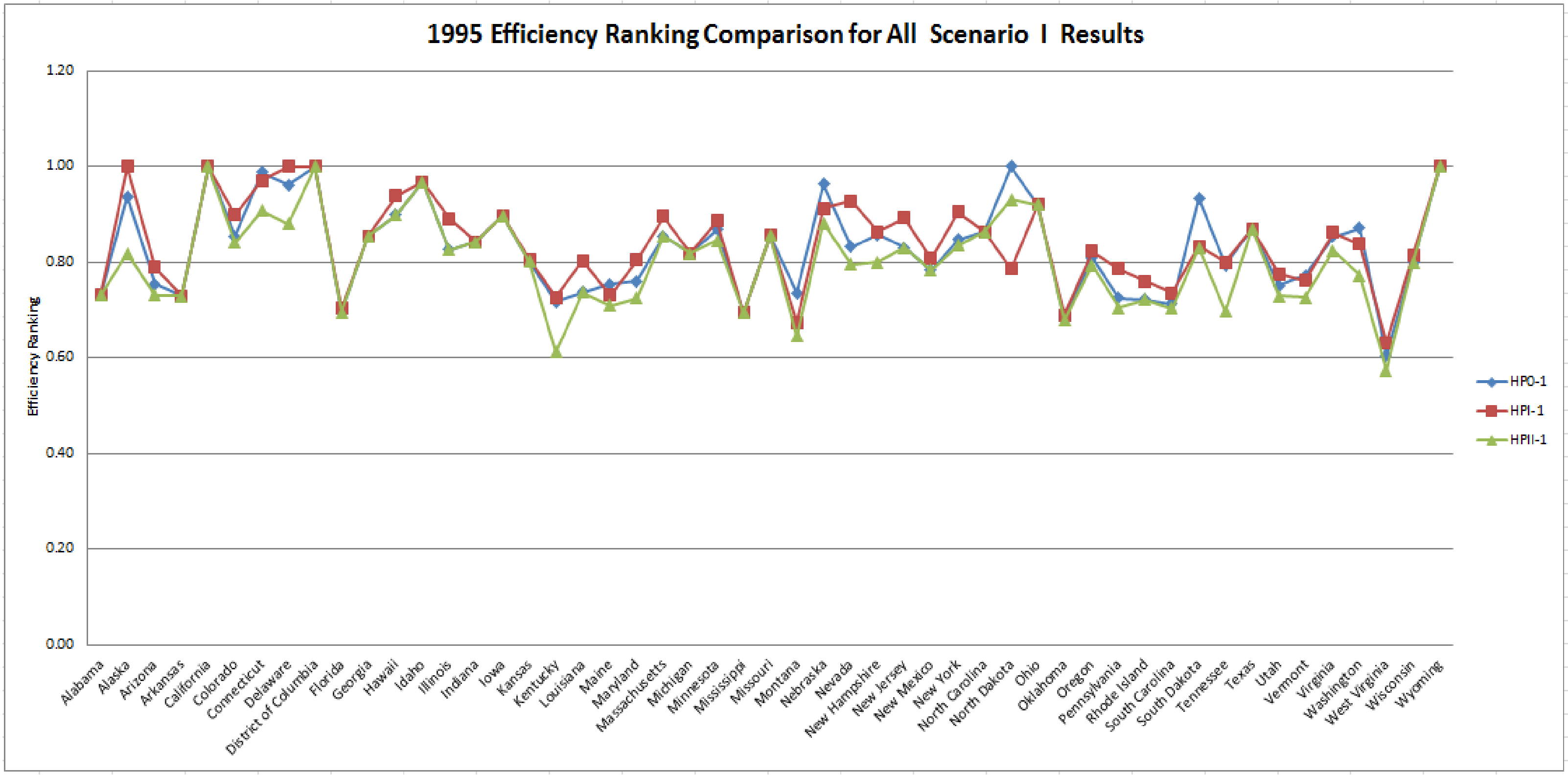

Figure 39 DEA Hypotheses Comparison for 1995.

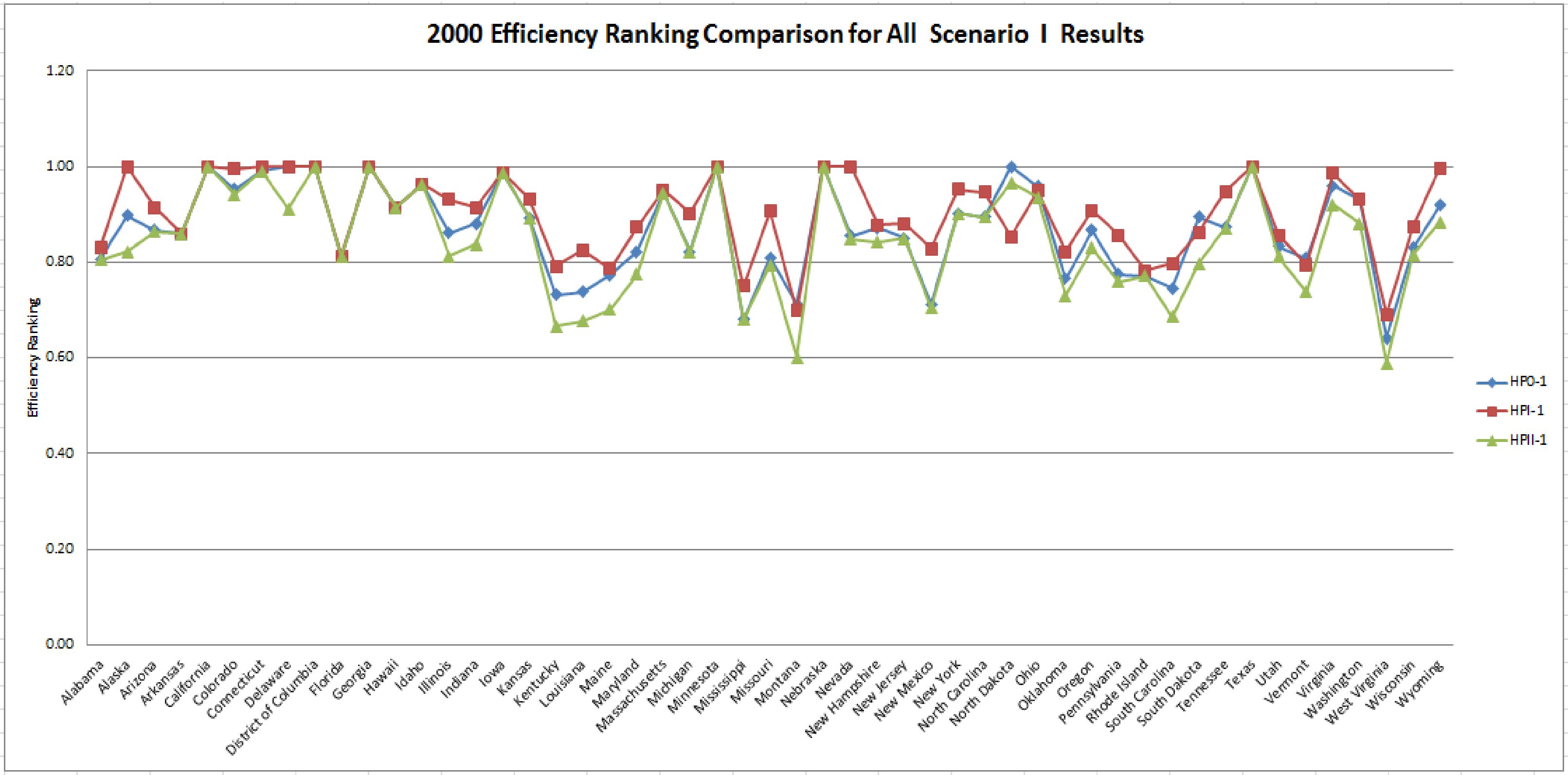

Figure 40 DEA Hypotheses Comparison for 2000.

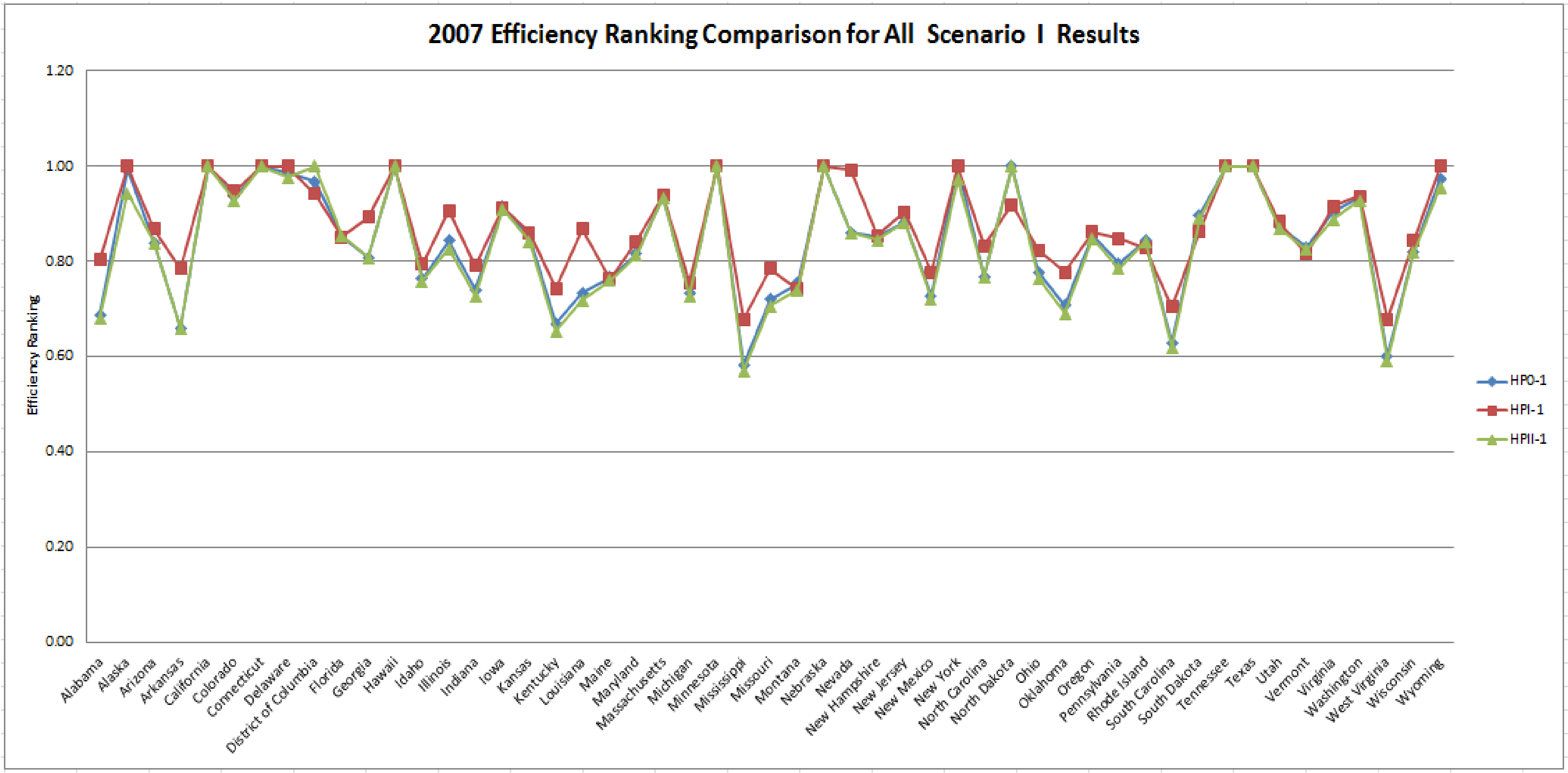

Figure 41 DEA Hypotheses Comparison for 2007.

From the three figures above, it can be seen that variability between the results for the DEA hypotheses decreases as you move forward in time, as observed with Table 15. In addition, managerial efficiency is the lowest efficiency score out of all three DEA hypotheses for most DMUs. As a whole, the differences between the scores for surface, comprehensive and managerial efficiency are minor. However, when examining the benchmarks for scenario 1 hypotheses, the differences become more apparent. Table 16 notes the total number of benchmarks, as well as lists the benchmarks for each state.

Table 16 Benchmarks for Scenario 1 Results

Scenario Code	Benchmarks for 1995	Benchmarks for 2000	Benchmarks for 2007
HP0-1 (Surface Efficiency)	4 (California, District of Columbia, North Dakota, & Wyoming)	8 (California, Delaware, District of Columbia, Georgia Minnesota, Nebraska North Dakota, & Texas)	8 (California, Connecticut, Hawaii, Minnesota, Nebraska, North Dakota, Tennessee & Texas)
HPI-1 (Comprehensive Efficiency)	5 (Alaska, California, Delaware, District of Columbia & Wyoming)	10 (Alaska, California, Connecticut, Delaware, District of Columbia, Georgia, Minnesota, Nebraska, Nevada & Texas)	11 (Alaska, California, Connecticut, Delaware, Hawaii, Minnesota, Nebraska, New York, Tennessee, Texas & Wyoming)
HPII-1 (Managerial Efficiency)	3 (California, District of Columbia & Wyoming)	6 (California, District of Columbia, Georgia, Minnesota, Nebraska & Texas)	9 (California, Connecticut, District of Columbia, Hawaii, Minnesota, Nebraska, North Dakota, Tennessee & Texas)

In terms of the above table, it can be seen that the total number of benchmarks increases as you move forward in time. The highest number of benchmarks observed is 11 and the lowest is 3. In addition, the only benchmark to appear for each year for HP0-1, HPI-1 and HPII-1 is California. The overall trend of the efficiency scores is that they increase from 1995 to 2000 and then decrease from 2000 to 2007. However, the efficiency scores are generally still greater in 2007 than 1995. These observations are supported by calculating average efficiencies scores, as shown Table 17.

Table 17 Average Efficiency Scores for Scenario 1 Results

Scenario Code	Average Efficiency for 1995	Average Efficiency for 2000	Average Efficiency for 2007
HP0-1 (Surface Efficiency)	0.83	0.87	0.84
HPI-1 (Comprehensive Efficiency)	0.84	0.90	0.87
HPII-1 (Managerial Efficiency)	0.80	0.84	0.84

Managerial Efficiency Gap Results

With the results of scenario 1 hypotheses for all data years summarized, the focus can now be shifted to addressing the main objective of the research, which is how much influence environmental factors have on the relationship between transportation infrastructure and economic growth. In order to meet this objective, the managerial efficiency results for all three data years are presented and analyzed. As previously noted, managerial efficiency represents the efficiency that is under the control of the states. It only examines the practices and policies of each state and completely removes the effects of the environment. Moreover, managerial efficiency does not refer to a specific agency or organization, but the state as a whole.

Figure 42 gives the impression that managerial efficiency generally increases over time. Closer inspection of managerial efficiency indicates that while most states experience an upward trend, changes over time are more complex and can be summarized as follows:

- Managerial Efficiency Remains Unchanged: 2 States
    - California and District of Columbia

- Managerial Efficiency Consistently Improves: 20 States
    - Alaska, Connecticut, Delaware, Florida, Hawaii, Maryland, Nevada, New Hampshire, New Jersey, New York, North Dakota, Oregon, Pennsylvania, Rhode Island, Tennessee, Utah, Vermont, Washington, West Virginia and Wisconsin
- Managerial Efficiency Consistently Degrades: 5 States
    - Idaho, Indiana, Mississippi, Missouri, and South Carolina
- Managerial Efficiency Degrades (95-00) and then Improves (00-07): 7 States
    - Illinois, Louisiana, Maine, Montana, New Mexico, South Dakota, and Wyoming
- Managerial Efficiency Improves (95-00) and then Degrades (00-07): 17 States
    - Alabama, Arizona, Arkansas, Colorado, Georgia, Iowa, Kansas, Kentucky, Massachusetts, Michigan, Minnesota, Nebraska, North Carolina, Ohio, Oklahoma, Texas and Virginia

So, in terms of managerial efficiency, the majority or 39% of DMUs increase over time. The second largest trend was improving and then degrading managerial efficiency, which equals to 33% of DMUs. Then, the third largest trend was degrading and then improving managerial efficiency, which equals to 14% of DMUs. The fourth largest trend was consistently degrading managerial efficiency, which equals to 10% of DMUs. Then, the fifth and last trend was for DMUs with managerial efficiency that remained unchanged, which equals to 4% of DMUs. In addition, these DMUs, which include California and D.C., had a score of 1 or were benchmarks for all three years.

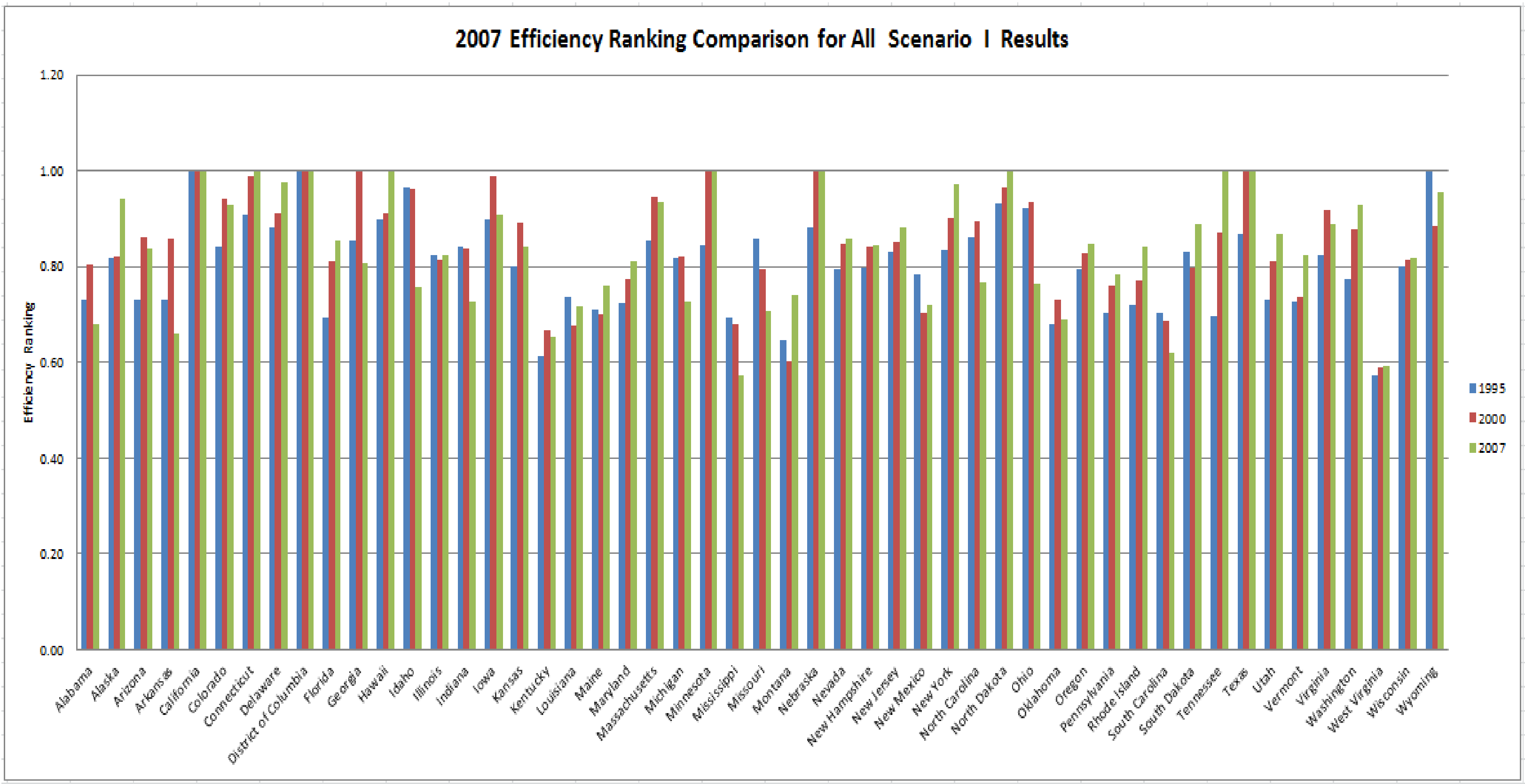

Figure 42 2007 Efficiency Comparison for All Scenario 1 Results.

Then, in terms of comparing the effects of adding environmental factors versus removing environmental factors, the managerial efficiency gap or change in efficiency for 2007 is presented, where 2007 is the most recent data year (see Table 18). The managerial efficiency gap is developed by comparing the comprehensive efficiency and the managerial efficiency of the states. In turn, the managerial efficiency gap reflects how well states deal with environmental factors and their effect on the performance of transportation infrastructure.

For Table 18, the results can be interpreted as follows: higher scores are worse and lower scores are better when comparing efficiency results that add the effects of environmental factors versus removing the effects of environmental factors. If the efficiency score is higher for managerial efficiency than comprehensive efficiency and thus the change in efficiency is positive, the environment for the DMU has a negative impact on efficiency. Conversely, if the efficiency score is the same or lower for managerial efficiency than comprehensive efficiency and thus the change in efficiency is zero or negative, the environment's effect is negligible. Overall, the focus is on DMUs whose change in efficiency is positive and whose change in efficiency is relatively large. In addition, DMUs with a fairly high or low managerial gap are in red.

Of the 51 DMUs, 38 became more efficient, 7 remained the same and 6 became less efficient. In terms of the 7 DMUs that remained the same, they were all benchmarks, including California, Connecticut, Hawaii, Minnesota, Nebraska, Tennessee and Texas. Then for the 6 DMUs that became worse, they include North Dakota, District of Columbia, South Dakota, Rhode Island, Vermont and Florida. These DMUs have an environment that has a negative impact on efficiency, where North Dakota has the highest negative impact from the environment and Florida has the least. It is also important to note that there are DMUs that are right on the boundary of being worse or better, and thus the change in efficiency is not that significant. In total, there are 27 combinations of benchmarks for HPII-1 for 2007.

Table 18 Managerial Efficiency Gap for 2007

Number	State	HPi-1	HPii-1	Change	Change	Benchmarks for HPii-1	TPi
1	Alabama	0.8030	0.6803	better	-0.12	24, 28, 35, 44	60.48
2	Alaska	1.0000	0.9434	better	-0.06	7, 9	62.70
3	Arizona	0.8680	0.8376	better	-0.03	24, 44	61.05
4	Arkansas	0.7841	0.6588	better	-0.13	24, 44	55.52
5	California	1.0000	1.0000	same	0.00	5	51.76
6	Colorado	0.9481	0.9282	better	-0.02	5, 7, 24, 35	61.52
7	Connecticut	1.0000	1.0000	same	0.00	7	53.81
8	Delaware	1.0000	0.9765	better	-0.02	5, 7, 24, 35	57.43
9	District of Columbia	0.9422	1.0000	worse	0.06	9	35.08
10	Florida	0.8506	0.8530	worse	0.00	5, 24, 35, 44	55.26
11	Georgia	0.8928	0.8082	better	-0.08	24, 28, 44	59.72
12	Hawaii	1.0000	1.0000	same	0.00	12	49.98
13	Idaho	0.7943	0.7585	better	-0.04	12, 24	63.03
14	Illinois	0.9057	0.8260	better	-0.08	5, 7, 24, 35	58.33
15	Indiana	0.7905	0.7274	better	-0.06	5, 7, 24, 35	61.32
16	Iowa	0.9126	0.9095	better	0.00	7, 24, 35	67.65
17	Kansas	0.8603	0.8421	better	-0.02	5, 24, 35, 44	66.78
18	Kentucky	0.7427	0.6537	better	-0.09	5, 24, 35, 44	59.51
19	Louisiana	0.8682	0.7178	better	-0.15	5, 7, 24, 35	56.37
20	Maine	0.7627	0.7603	better	0.00	5, 7, 24, 35	66.15
21	Maryland	0.8408	0.8117	better	-0.03	5, 7, 24, 35	58.57
22	Massachusetts	0.9383	0.9349	better	0.00	5, 7	52.19
23	Michigan	0.7558	0.7276	better	-0.03	5, 7, 24, 35	60.67
24	Minnesota	1.0000	1.0000	same	0.00	24	65.02
25	Mississippi	0.6775	0.5709	better	-0.11	24, 28, 35, 43	61.68
26	Missouri	0.7842	0.7061	better	-0.08	5, 7, 24, 35	59.60
27	Montana	0.7412	0.7395	better	0.00	5, 7, 9, 35	70.89
28	Nebraska	1.0000	1.0000	same	0.00	28	71.66
29	Nevada	0.9922	0.8596	better	-0.13	24, 44	51.64
30	New Hampshire	0.8536	0.8445	better	-0.01	7, 24, 35	59.48
31	New Jersey	0.9030	0.8819	better	-0.02	5, 7, 12, 24	46.71
32	New Mexico	0.7774	0.7216	better	-0.06	5, 7, 12, 24	52.59
33	New York	1.0000	0.9728	better	-0.03	5, 7, 9	55.19
34	North Carolina	0.8330	0.7671	better	-0.07	5, 24, 44	53.39
35	North Dakota	0.9184	1.0000	worse	0.08	35	85.12
36	Ohio	0.8224	0.7654	better	-0.06	5, 24, 35, 44	59.64
37	Oklahoma	0.7774	0.6903	better	-0.09	5, 24, 35, 44	62.34
38	Oregon	0.8620	0.8486	better	-0.01	5, 7, 24, 35	64.72
39	Pennsylvania	0.8475	0.7849	better	-0.06	5, 7, 12, 24	56.16
40	Rhode Island	0.8278	0.8409	worse	0.01	7, 9	57.29
41	South Carolina	0.7047	0.6198	better	-0.08	5, 7, 24, 35	60.38
42	South Dakota	0.8631	0.8898	worse	0.03	5, 7, 24, 35	74.47
43	Tennessee	1.0000	1.0000	same	0.00	43	60.44
44	Texas	1.0000	1.0000	same	0.00	44	59.46
45	Utah	0.8837	0.8684	better	-0.02	7, 12, 35	63.37
46	Vermont	0.8154	0.8241	worse	0.01	7, 24, 35	66.26
47	Virginia	0.9161	0.8872	better	-0.03	7, 24, 35, 44	63.77
48	Washington	0.9372	0.9281	better	-0.01	5, 7, 24 , 35	62.06
49	West Virginia	0.6782	0.5910	better	-0.09	5, 7, 24 , 35	57.76
50	Wisconsin	0.8433	0.8185	better	-0.02	5, 7, 12 , 24	57.26
51	Wyoming	1.0000	0.9550	better	-0.05	5, 7, 24 , 35	65.56

Next, the TPI state-by-state results for 2007 are directly compared to the DMUs that became less efficient, as seen in Figure 43.

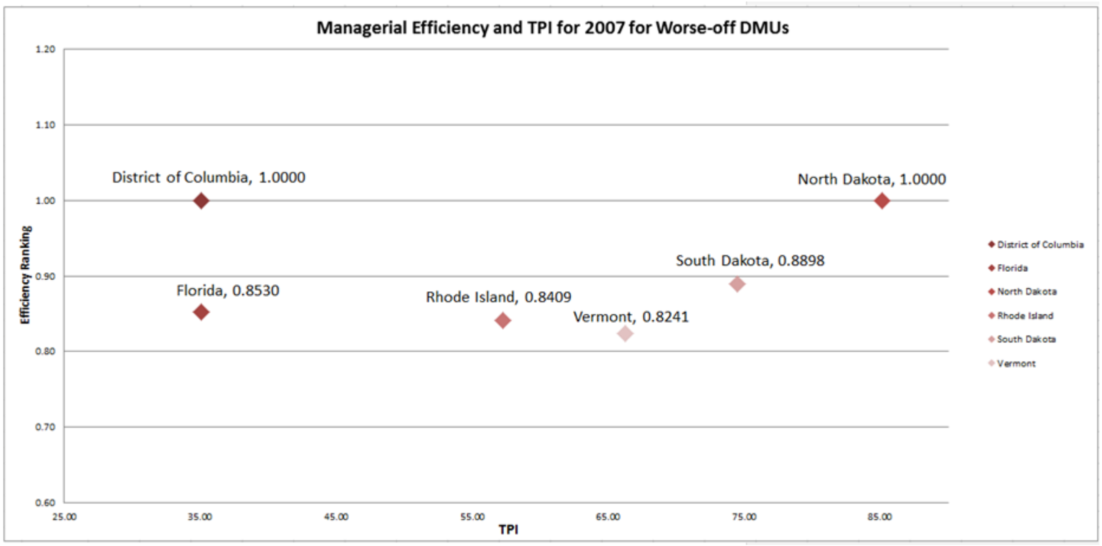

Figure 43 Managerial Efficiency and TPI for 2007 for Worse-off DMUs

From Figure 43, it can be seen that both North Dakota and D.C. are benchmarks. However, in terms of TPI, North Dakota is substantially higher than D.C. Furthermore, North Dakota has the highest TPI for 2007, and D.C. has the lowest. So, despite having very different TPI, both are considered to be the most efficient in terms of managerial efficiency. Also, both have environments that have negative impact on efficiency, when comparing comprehensive and managerial efficiency.

In terms of the relationship between transportation infrastructure and economic growth, environmental influences do have an effect. However, the majority of states are able to overcome their constricting environments. For 2007, there were only 6 states for which removing the effects of the environment caused them to be less efficient. In addition, using the managerial efficiency gap results along with TPI provides a different perspective that the TPI alone does not. For example, by only examining the TPI results, it is evident that North Dakota is performing very well. However, the managerial efficiency gap shows that the state can do more to improve its efficiency in relation to its environment. In summary, DEA is a useful tool that provides additional insights when interpreting the TPI results.

Chapter 6

DEA CASE STUDY: DELAWARE

The following chapter pertains to the main contribution of the research, which is a case study of Delaware's current economic conditions and transportation infrastructure. The case study provides a more in depth analysis of the economy and transportation infrastructure of Delaware, using the DEA results, TPI and historical information as the basis for the analysis.

Table 19 shows the efficiency scores for Delaware. These scores are relatively high for all three DEA hypotheses. In addition, for HPI-1, Delaware was an efficient DMU or a benchmark for all three data years. The benchmarks are summarized in Table 20. In total, Delaware had 7 different benchmarks, including itself. The two benchmarks with the highest associated weight are Connecticut and D.C. DEA produces a single comprehensive score for each DMU, which is the ratio of the weighted outputs to the weighted inputs. The specific weights for each DMU are determined to maximize the score. As a result, comparisons should be made between these states and Delaware, specifically the DEA output and inputs, as seen in Table 21.

Table 19 Summary of DEA and TPI Results for Delaware

Summary of DEA and TPI Results	1995	2000	20007
HP0-1 (Surface Efficiency)	0.96	1.00	0.99
HPI-1 (Comprehensive Efficiency)	1.00	1.00	1.00
HPII-1 (Managerial Efficiency)	0.88	0.91	0.98
TPI	54.70	57.11	57.43

Table 20 Benchmarks for Delaware with Associated Weight

Scenario Code	Benchmarks for 1995	Benchmarks for 2000	Benchmarks for 2007
HP0-1 (Surface Efficiency)	2 (District of Columbia, λ = 0.379 & Wyoming, λ = 0.491)	1 (Delaware, λ = 1.00)	3 (California, λ = 0.113; Connecticut, λ = 0.681; & North Dakota, λ = 0.341)
HPI-1 (Comprehensive Efficiency)	1 (Delaware, λ = 1.00)	1 (Delaware, λ = 1.00)	1 (Delaware, λ = 1.00)
HPII-1 (Managerial Efficiency)	1 (District of Columbia, λ = 0.676)	1 (District of Columbia, λ = 0.702)	9 (California, λ = 0.106; Connecticut, λ = 0.719; Minnesota, λ = 0.040; & North Dakota, λ = 0.262)

Table 21 Comparison of 2007 DEA Output and Inputs for Delaware and Benchmarks

DEA Variable	Delaware	D.C.	Connecticut
lnGDPpc	4.26	4.99	4.11
TPI	57.43	35.08	53.81
adjTPI (HPI-1)	58.34	29.78	56.91
adjTPI (HPII-1)	59.26	69.29	57.28
GDP	61,545	92,516	212,252
Debtpc	6,105	15,204	6,812
LE	76.8	72.0	78.7

From Table 21, it can be seen that the attributes for all three states are somewhat similar. For example, for *Debtpc*, both Delaware and Connecticut are about the same level. Also, the values for *lnGDPpc*, *TPI*, and *adjTPI* for HPI-1 and HPII-1 are about the same. In comparing Delaware and D.C., the connection is not as clear. Furthermore, Delaware should be compared to its benchmarks in terms of environmental influences to identify any similarities or differences. However, the more useful comparison would be particular practices and actions that each of these states are currently undertaking.

For example, according to the report, "Enterprising States – Recovery and Renewal for the 21st Century", by the U.S. Chamber of Commerce and the National Chamber Foundation, Delaware is ranked 1st in economic output per job (Kotkin, et al., 2011). Also, in terms of transportation infrastructure, Delaware has implemented a variety of different programs. For instance, there is the "Building Delaware's Future Now" program being proposed, where new sources of state revenue will be allocated towards upgrading critical public infrastructure. Another program being considered is the "New Jobs Infrastructure Fund" which would direct funds specifically to rebuilding assets that will attract new businesses to move to Delaware. In terms of Delaware's benchmarks, similar programs are being implemented to improve their economy and the way business is conduct in their state. For example, in Connecticut, new programs are primarily focused on creating jobs in the science and technology fields through high levels of investment in research.

In regards to TPI, Delaware has about the same value for all three years, with a slightly increasing trend. In addition, for TPI, Delaware was ranked the 34th highest in 1995, the 28th highest in 2000 and then 35th highest in 2007. So, even though Delaware has a moderate TPI for all the data years, it still maintains high efficiency scores for surface, comprehensive and managerial efficiency. Overall, the results for DEA and TPI are limited, only representing three data points. Nevertheless, the analysis of just three years provides some insight into what makes Delaware efficient. In addition, the case study approach can be done for any state as a way to get a better understanding of how it measures up against the other DMUs.

Chapter 7

CONCLUSIONS, CONTRIBUTIONS AND FUTURE WORK

Conclusions

In summary, the application of DEA to exploring the relationship between transportation and the economy revealed that environmental influences do have an effect, but not to a great extent. The effect of environmental influences on the relationship between transportation and the economy is shown to decrease the more recent the year of analysis. This conclusion is based on the set of environmental influences that were selected and deemed to place the most pressure on TPI. With a different set of environmental influences, it is very likely a completely different trend would be observed. In regards to the debate of transportation infrastructure investment and economic growth that is currently underway, the DEA results show there is a lot more that can be explored about this relationship dynamic. Also, more importantly, more needs to be known about under which circumstances assumptions and understandings about this relationship should be applied to making policy decisions.

Furthermore, from the DEA results, it is evident that the majority of states are able to overcome their constricting environments. For 2007, there were only 6 states for which removing the effects of the environment caused them to be less efficient. In addition, using the managerial efficiency gap results along with TPI provides a different perspective that the TPI alone does not provide. For instance, from just examining the state-by-state TPI results, it is evident that North Dakota is performing very well from 1995 to 2000 and from 2000 to 2007. However, the managerial efficiency gap shows that the state can do more to improve its efficiency in relation to its environment for 2007. Therefore, DEA can serve as a useful tool that provides additional insights when interpreting TPI.

Contributions

The major contribution of my research is the application of data envelopment analysis to explore the relationship between transportation and the economy as well as the effect environmental influences has on this relationship. In addition, this unique application of DEA provides additional insights in terms of interpreting TPI. DEA efficiency rankings can be used in association with TPI for a better understanding of the reasons for differences in transportation infrastructure performance by state. Consequently, my work has not only provides an alternative perspective to TPI, but also draws closer attention to the complexity of the relationship between transportation investment and economic growth. My work has also expanded the current literature on applications of DEA in the transportation domain. In particular, while DEA is a powerful decision making tool, my work promotes DEA as a powerful informational or exploratory tool. DEA can be used to make decisions in regards to efficiency, but it is also great at expounding variable relationships between outputs and inputs as well as between inputs themselves. In turn, my work has established the foundation for future research opportunities that relate to more detailed and specific levels of analysis.

Future Work

In terms of future work, there are many opportunities for analysis of this rich data set. In this research, 3 main hypotheses or model formulations were explored. However, other models using different alternative variables as well as variable combinations can be analyzed. For example, other groupings of the set of DMUs could be examined, where DEA models could be run with just Midwestern states or New England states. Another example of a different model formulation would be the use of both *Area* and *UrbanArea* simultaneously rather than substitute environmental influences. In addition, the application of the DEA methodology on the national level for years 1990 to 2008 could be done, where the efficiency for the country as a whole can be calculated and compared from year to year. Alternatively, another opportunity for future work would be to apply the equation for the national data to the state level, taking into account the differences in time-steps.

Also, whereas linear regression was used to calculate an adjusted TPI for HPI and HPII, it would be interesting to see the effects of using non-linear regression within DEA and other types of regression models for the second stage method. In addition, it would worthwhile to try and to use the DEA results for 1995, 2000 and 2007 to predict future efficiency scores. In conclusion, there are many directions the research can go, and chances to improve and modify the current DEA methodology presented.

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Appendix A

ABBREVIATIONS

AAR:	Airport Arrival Rate
ADR:	Airport Delay Rate
$adjTPI_1$:	adjusted transportation performance index for Hypothesis-I
$adjTPI_2$:	adjusted transportation performance index for Hypothesis-II
AHDI:	American Human Development Index
AHDP:	American Human Development Project
AHP:	Analytical Hierarchical Process
ARRA:	The American Recovery and Reinvestment Act
ASCE:	American Society of Civil Engineers
BEA:	Bureau of Economic Analysis
BTS:	Bureau of Transportation Statisitics
CCR:	Charnes, Cooper and Rhodes
CDC:	Center for Disease Control
CRS:	Constant Return to Scale
DEA:	Data Envelopment Analysis
Debtpc:	Debt per Capita
DMU:	Decision Making Unit
EM:	Exclusion Method
FARS:	Fatal Accident Reporting System
FHWA:	Federal Highway Administration
FP_0:	Fractional Program

FMO:	Office of Freight Management and Operation
GDP:	Gross Domestic Product
GPP:	Government Performance Project
HP0:	Hypothesis-0
HPI:	Hypothesis-I
HPI:	Office of Highway Policy Information
HPII:	Hypothesis-II
HPMS:	Highway Performance Monitoring System
IMD:	International Institute for Management Development
IRI:	International Roughness Index
lnGDPpc:	natural log of Gross Domestic Product per Capita
LOS:	Level of Service
LRA:	Linear Regression Analysis
LRA-Index:	Let's Rebuild America Index
MSA:	Metropolitan Statistical Area
NBI:	National Bridge Inventory
NTAD:	National Transportation Atlas Database
OLS:	Ordinary Least Squares
PMT:	Passenger Miles Traveled
PW:	Papke and Wooldridge Method
RA:	Regression analysis
TAF:	Terminal Area Forecast
TMT:	Ton Miles Traveled
TPI:	Transportation Infrastructure Performance Index
USCB:	United States Census Bureau
USCC:	United States Chamber of Commerce
VMT:	Vehicle Miles Traveled

Appendix B

PROCEDURE FOR RUNNING DEAFRONTIER SOFTWARE

STEP 1	Organize variables for DEA model into excel spreadsheet with name of DMU in first column (i.e., state), followed by input columns, then a blank column and last output columns.
STEP 2	Transform variables using normalization so that the correct variables are maximized or minimized, and place transformed variables in new tab named "Data".
STEP 3	Using transformed variables, select DEA from the Excel add-ins. Click "Envelopment Model" from top of menu. Then on the pop-up screen, select model orientation to be "input-oriented" and frontier type-returns to scale to be "CRS" (which are the default settings) and click "OK".
STEP 4	After running DEA model, three additional tabs are produced, including: target, slack and efficiency tabs. Efficiency tab includes efficiency scores of each of the DMUs included in analysis.

Appendix C

ADDITIONAL GRAPHS OF VARIABLES

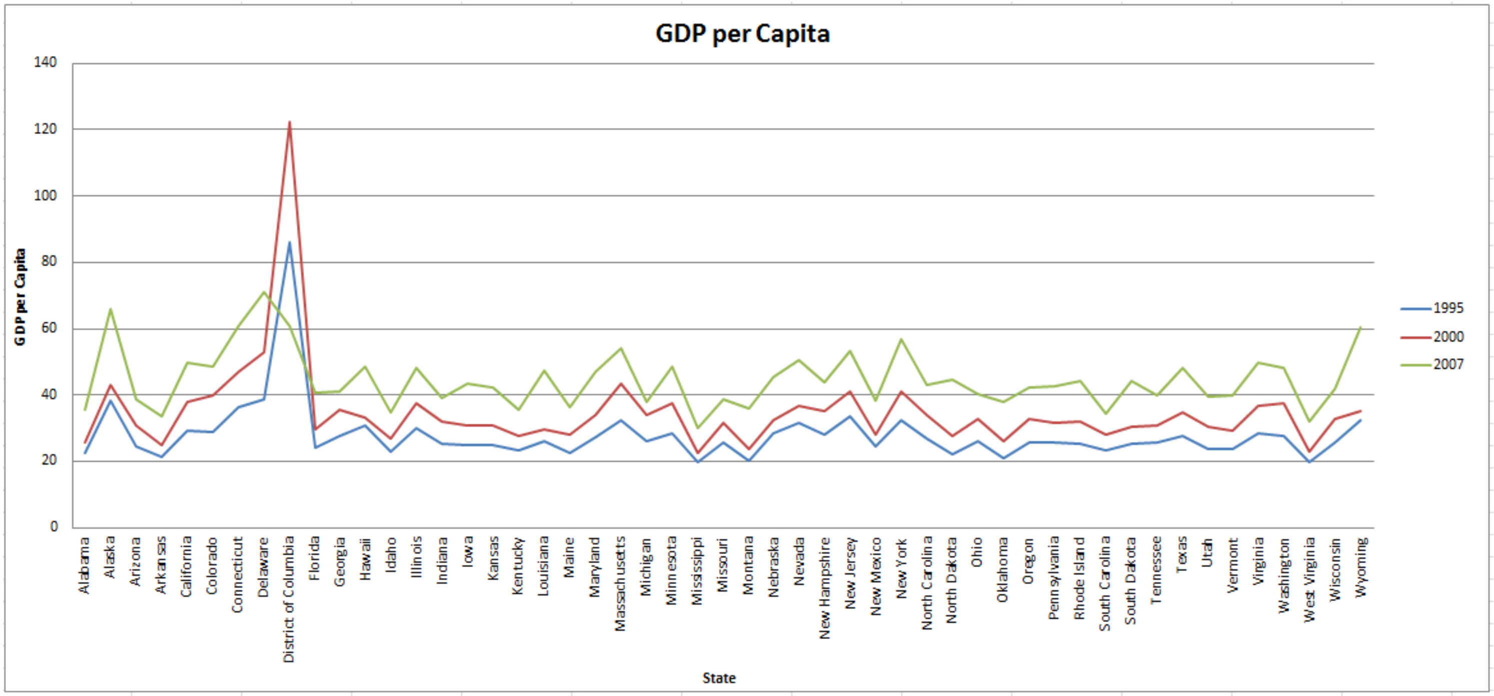

Figure C1 State-by-State GDP per Capita by Year.

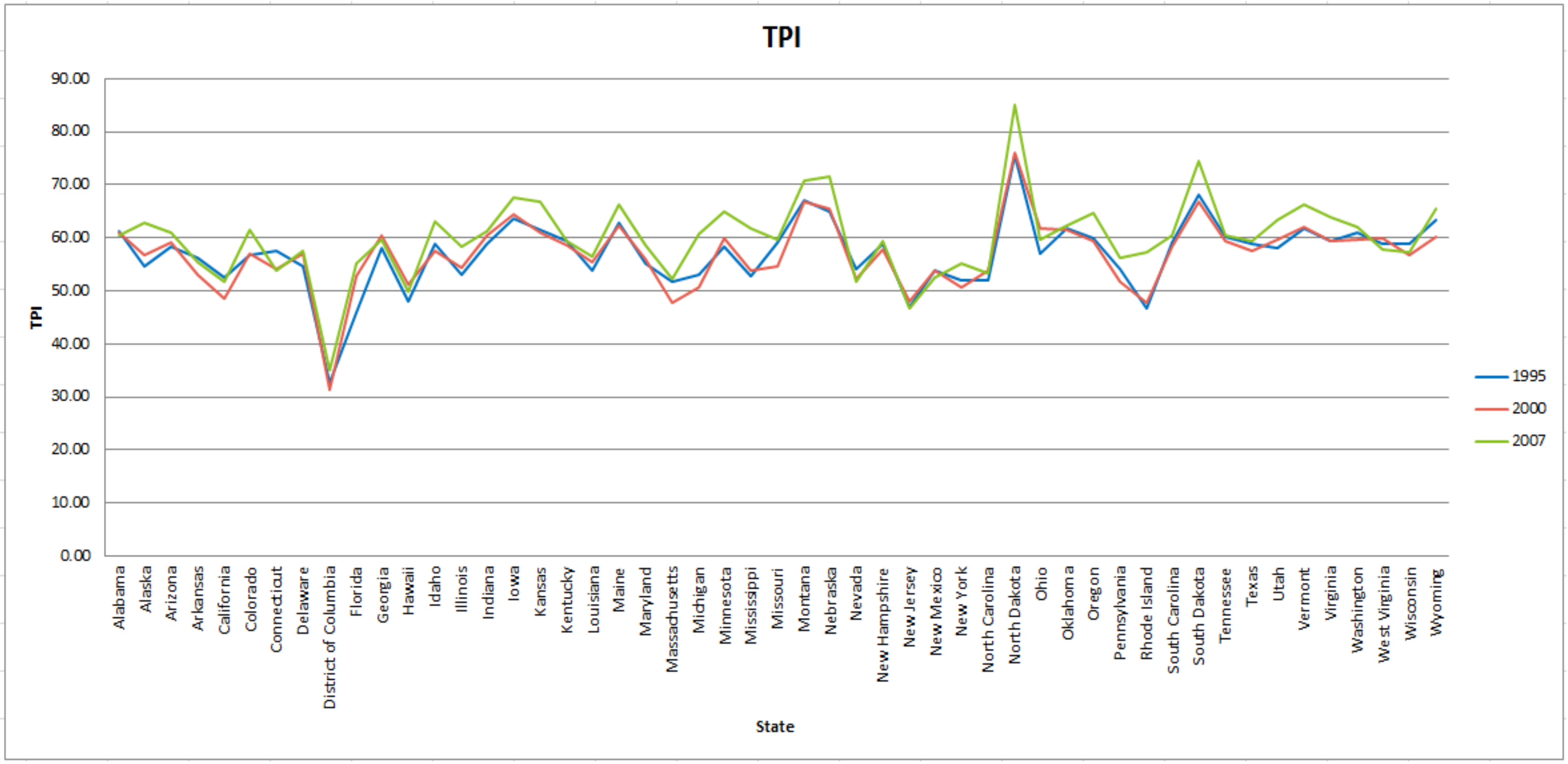

Figure C2 State-by-State Transportation Performance Index by Year.

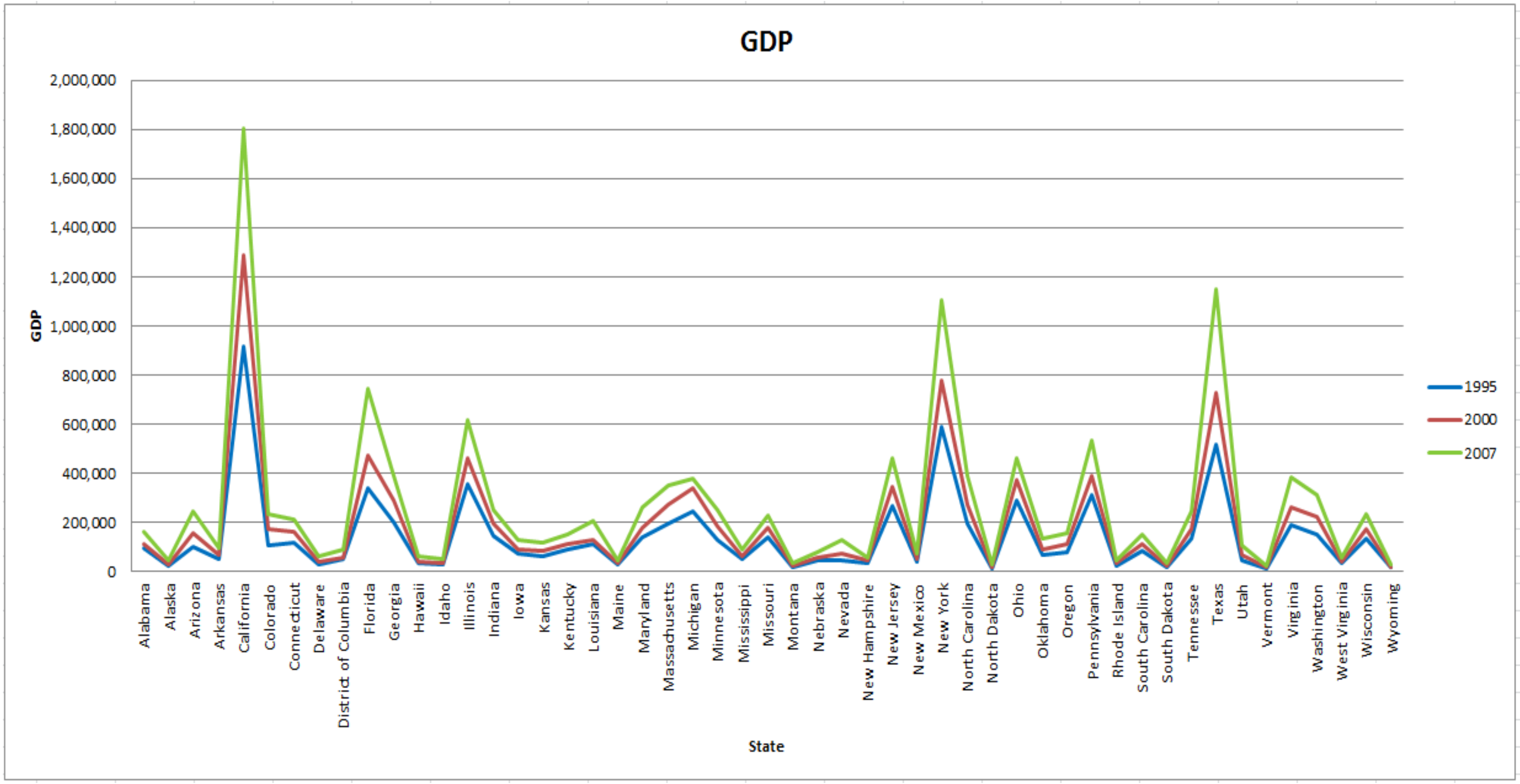

Figure C3 State-by-State GDP by Year.

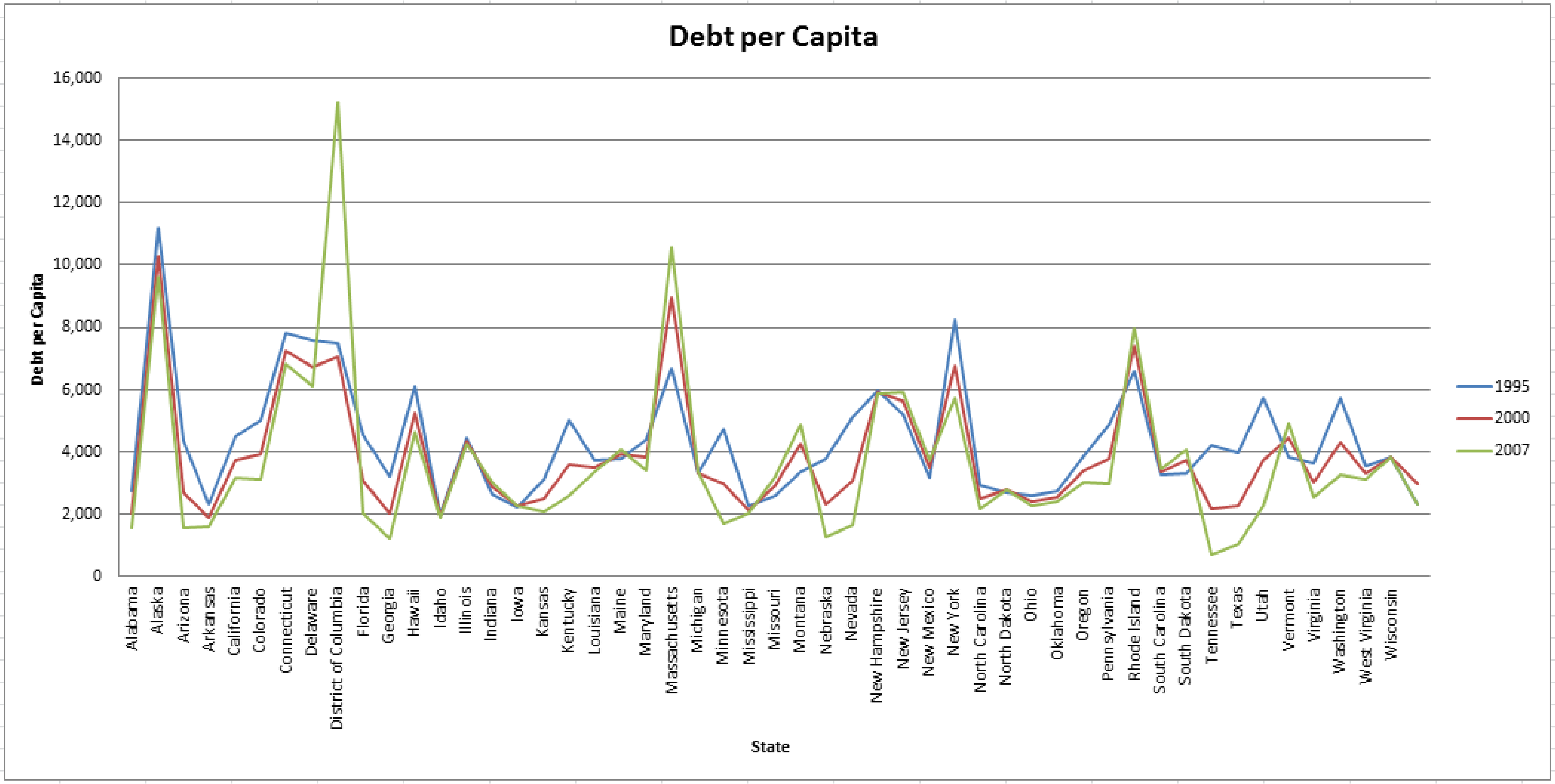

Figure C4 State-by-State Debt per Capita by Year.

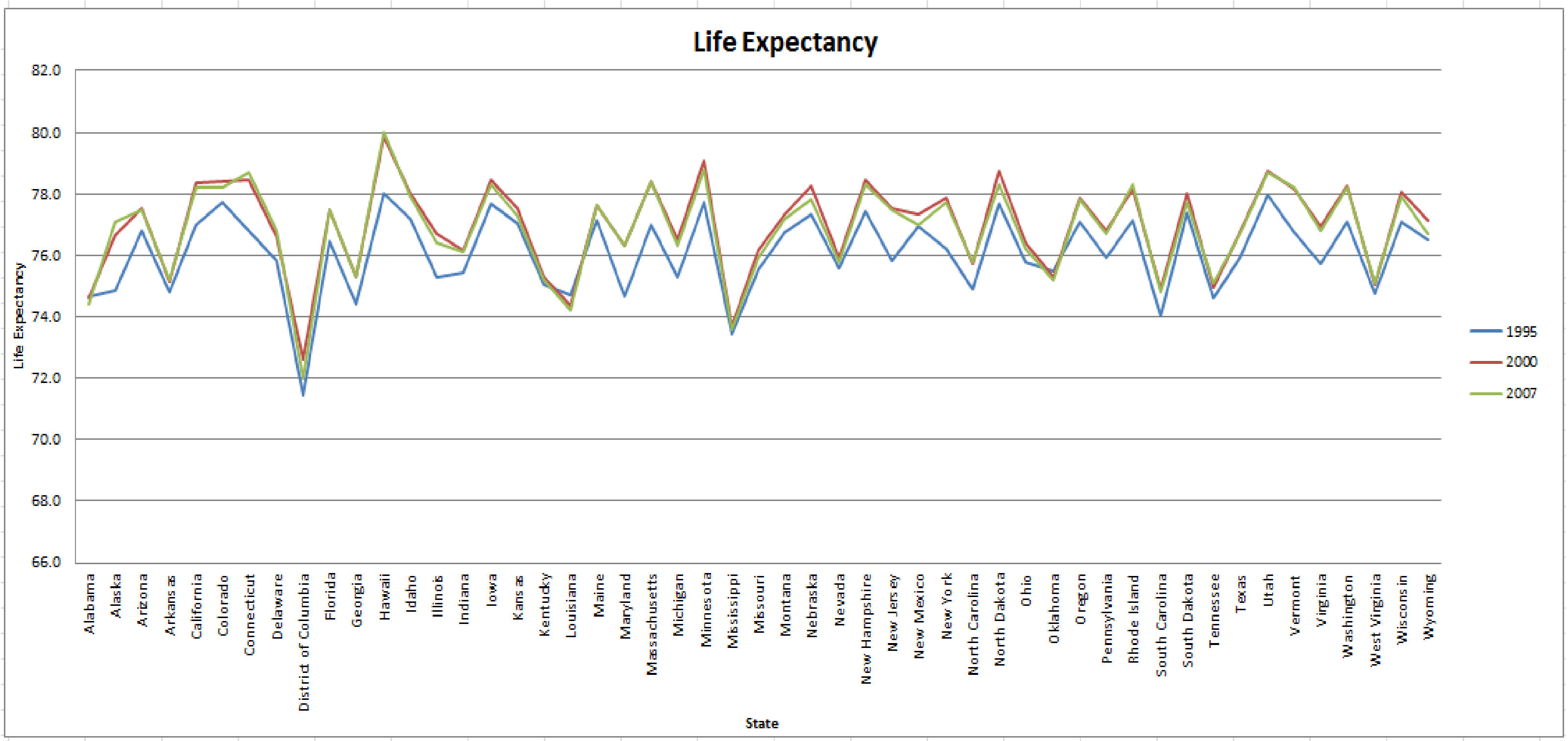

Figure C5 State-by-State Life Expectancy by Year.

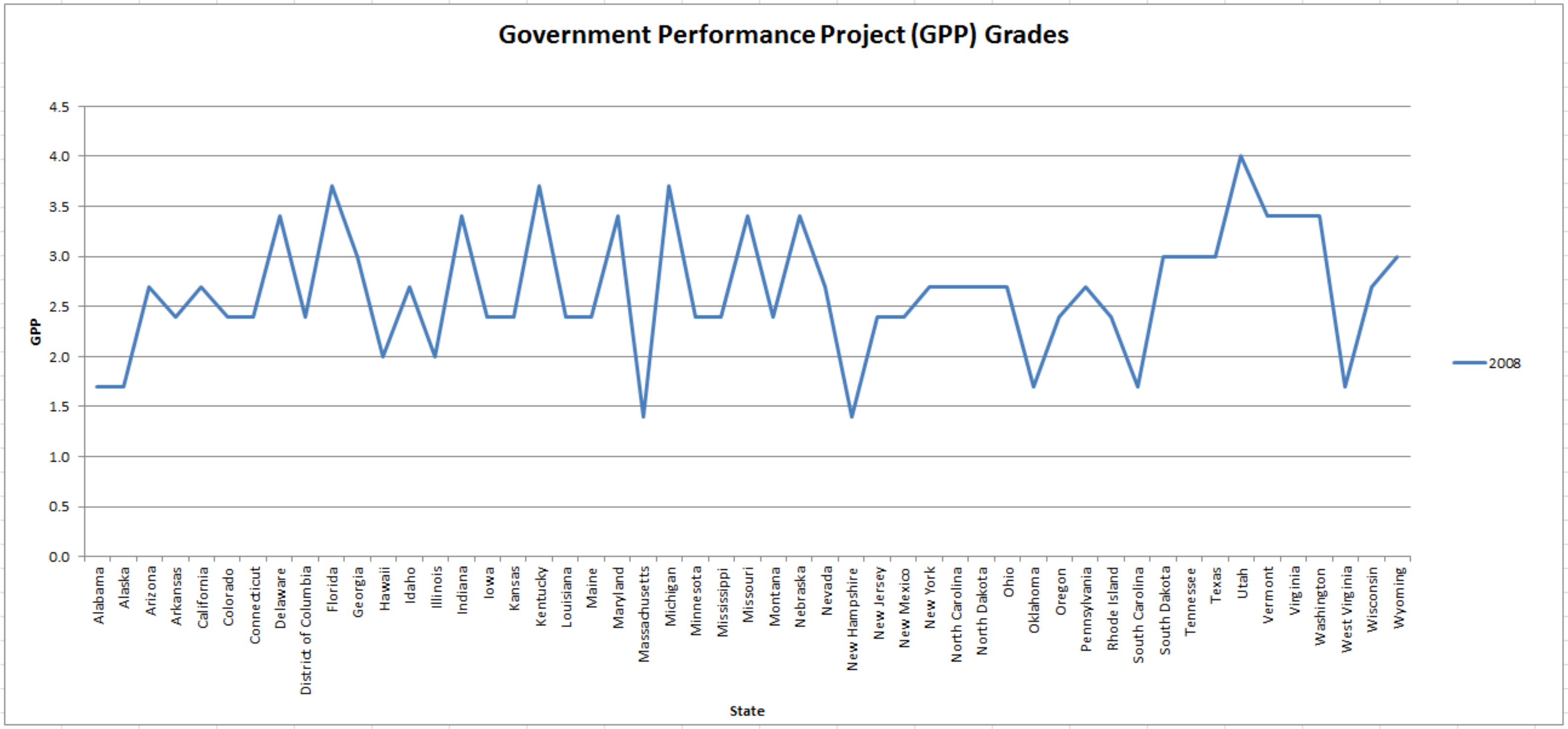

Figure C6 State-by-State Government Performance Project Grades (GPP) by Year.

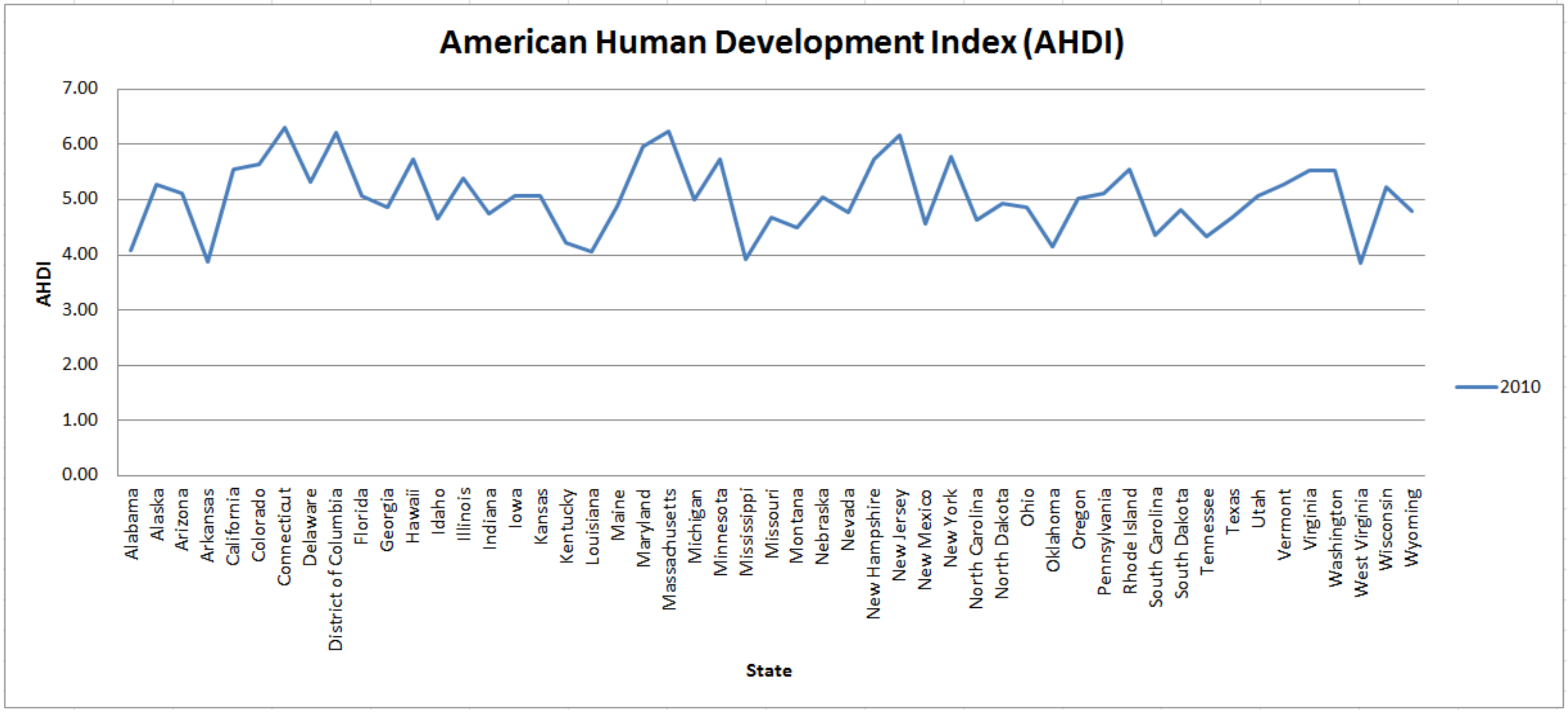

Figure C7 **State-by-State American Human Development Index (AHDI) by Year.**

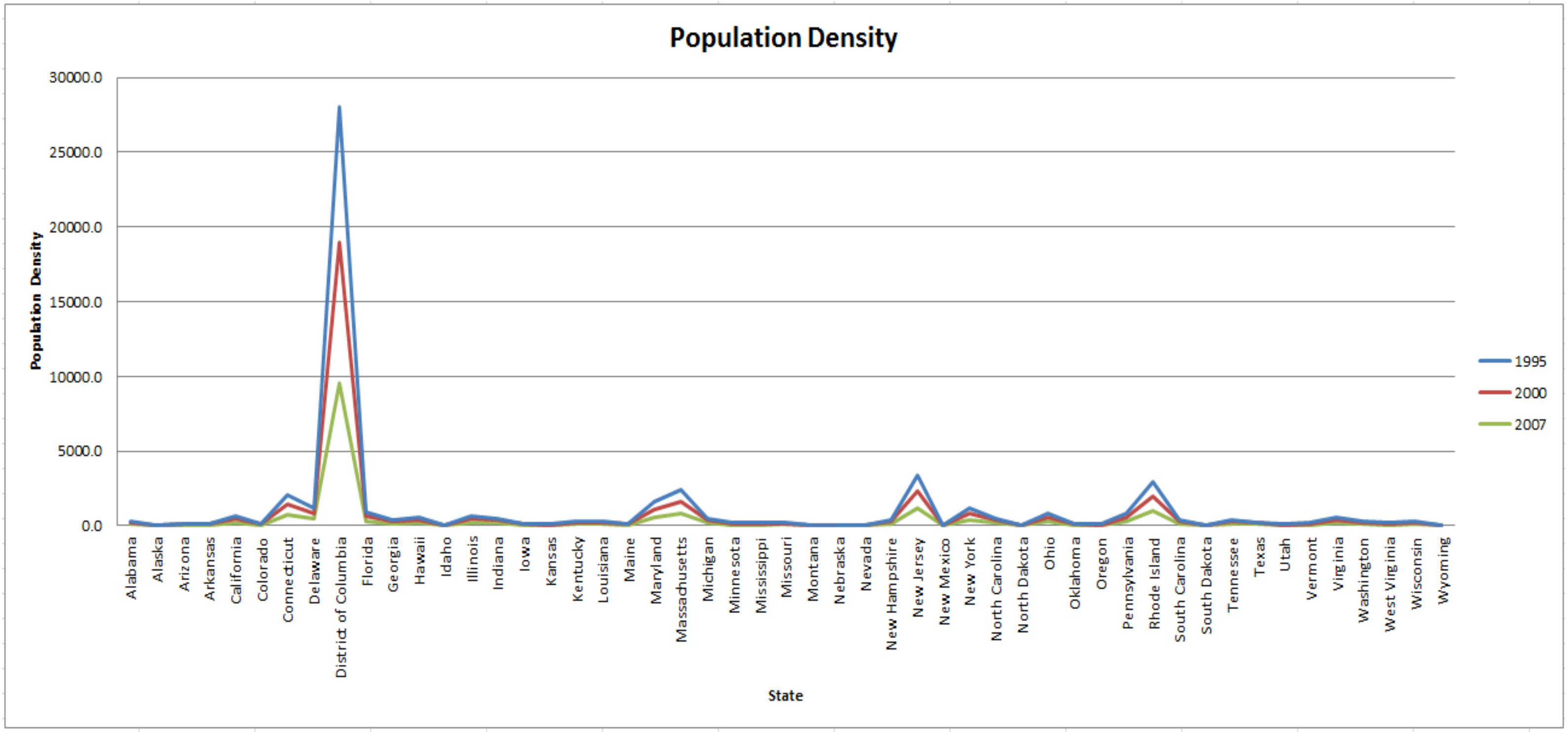

Figure C8 State-by-State Population Density by Year.

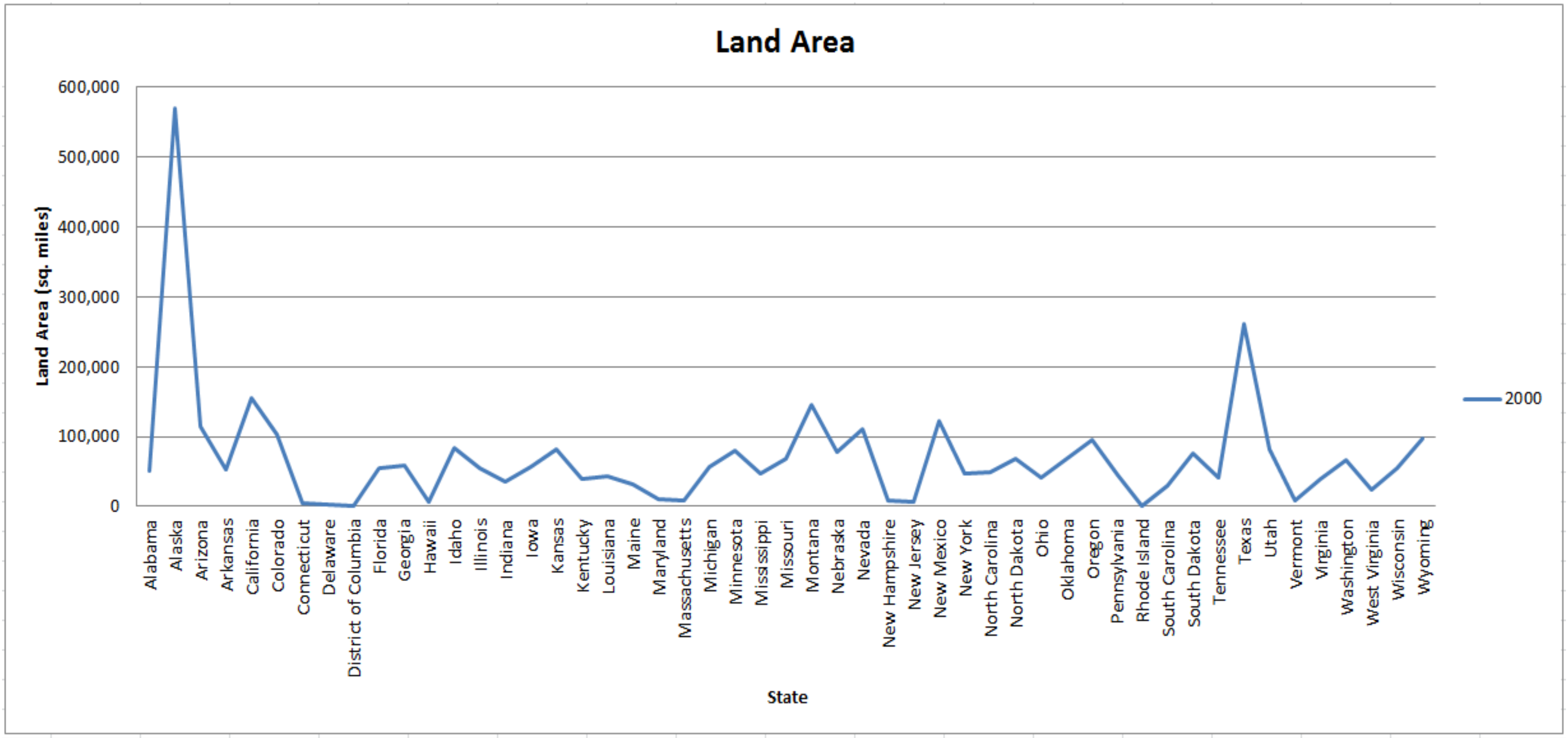

Figure C9 State-by-State Land Area by Year.

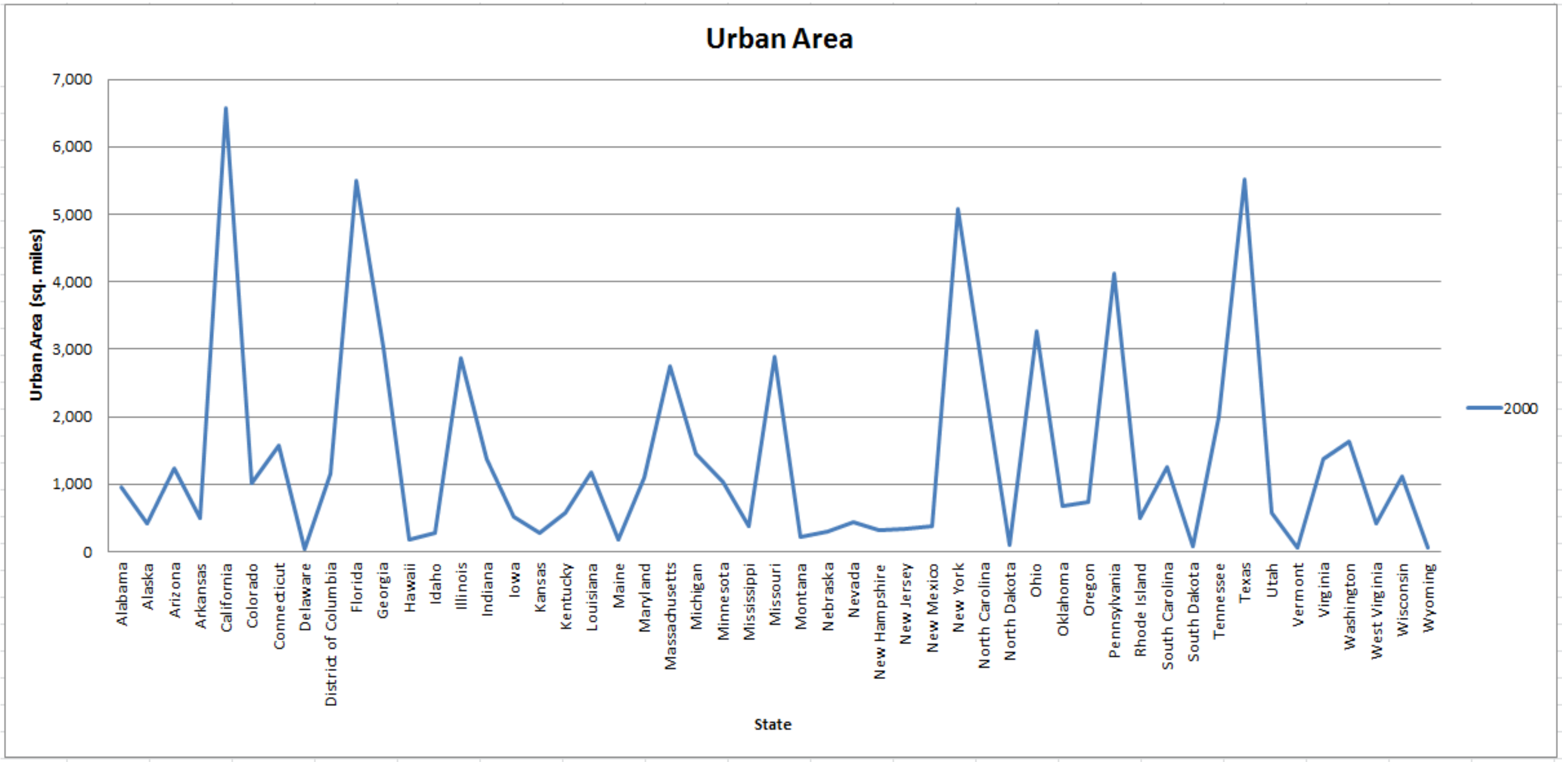

Figure C10 State-by-State Urban Area by Year.

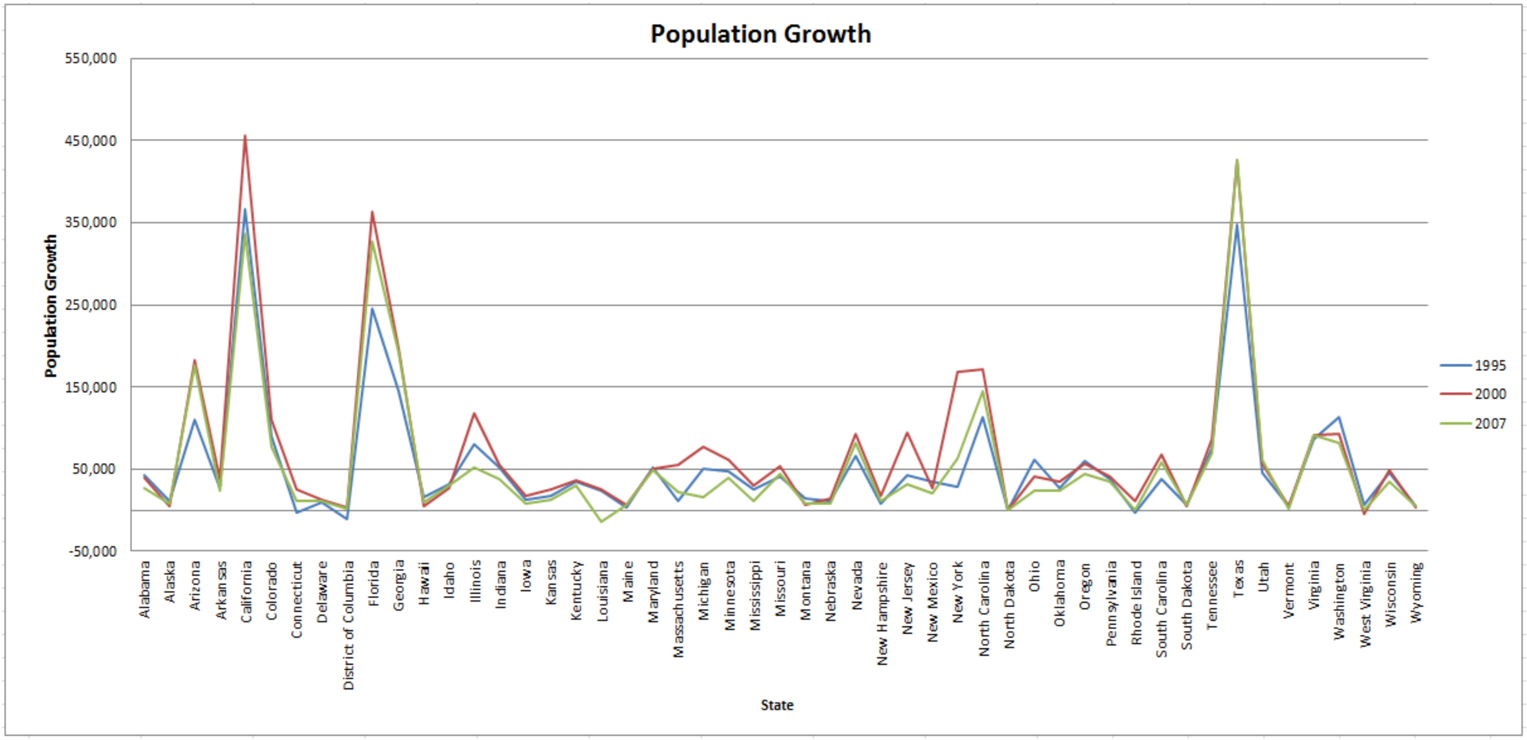

Figure C11 State-by-State Population Growth by Year.

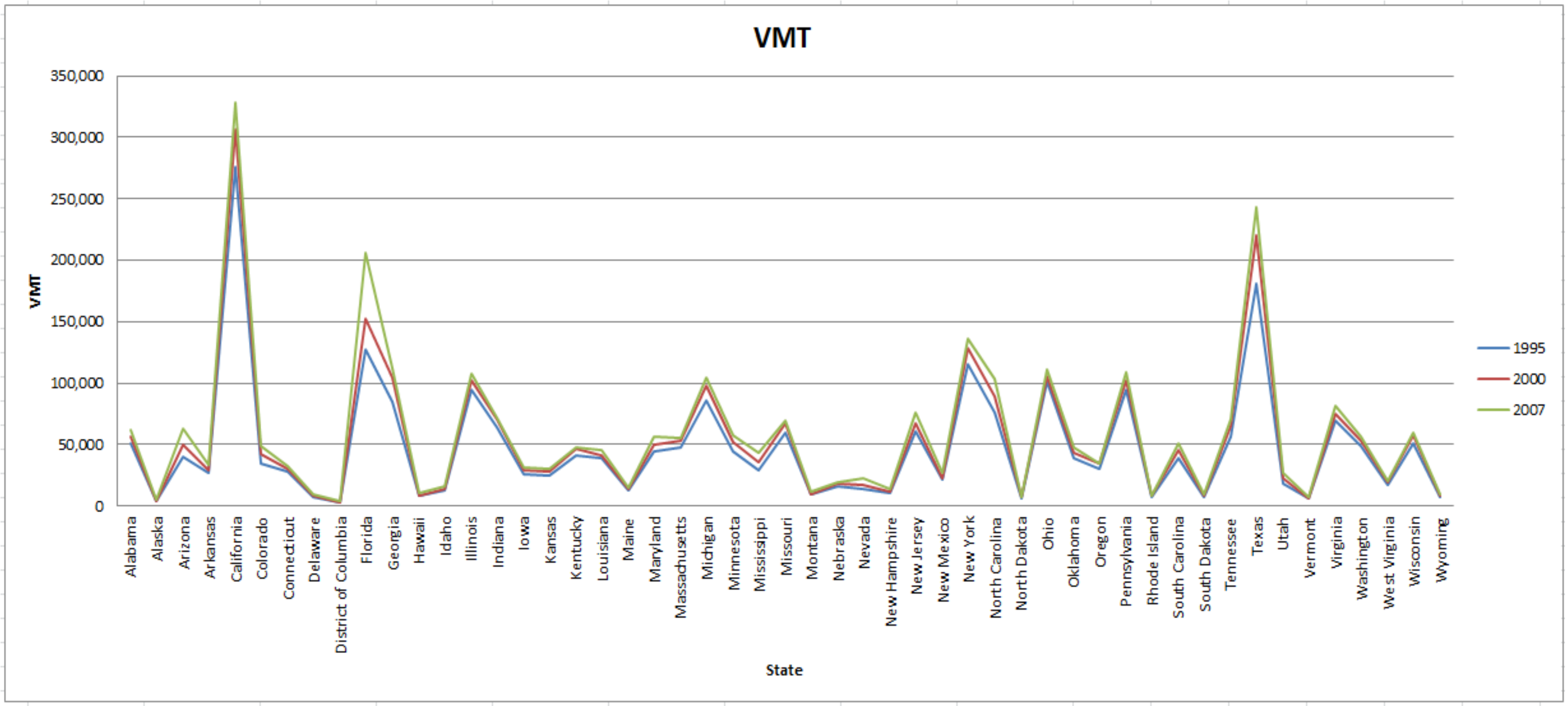

Figure C12 State-by-State Vehicle Miles Traveled (VMT) by Year.

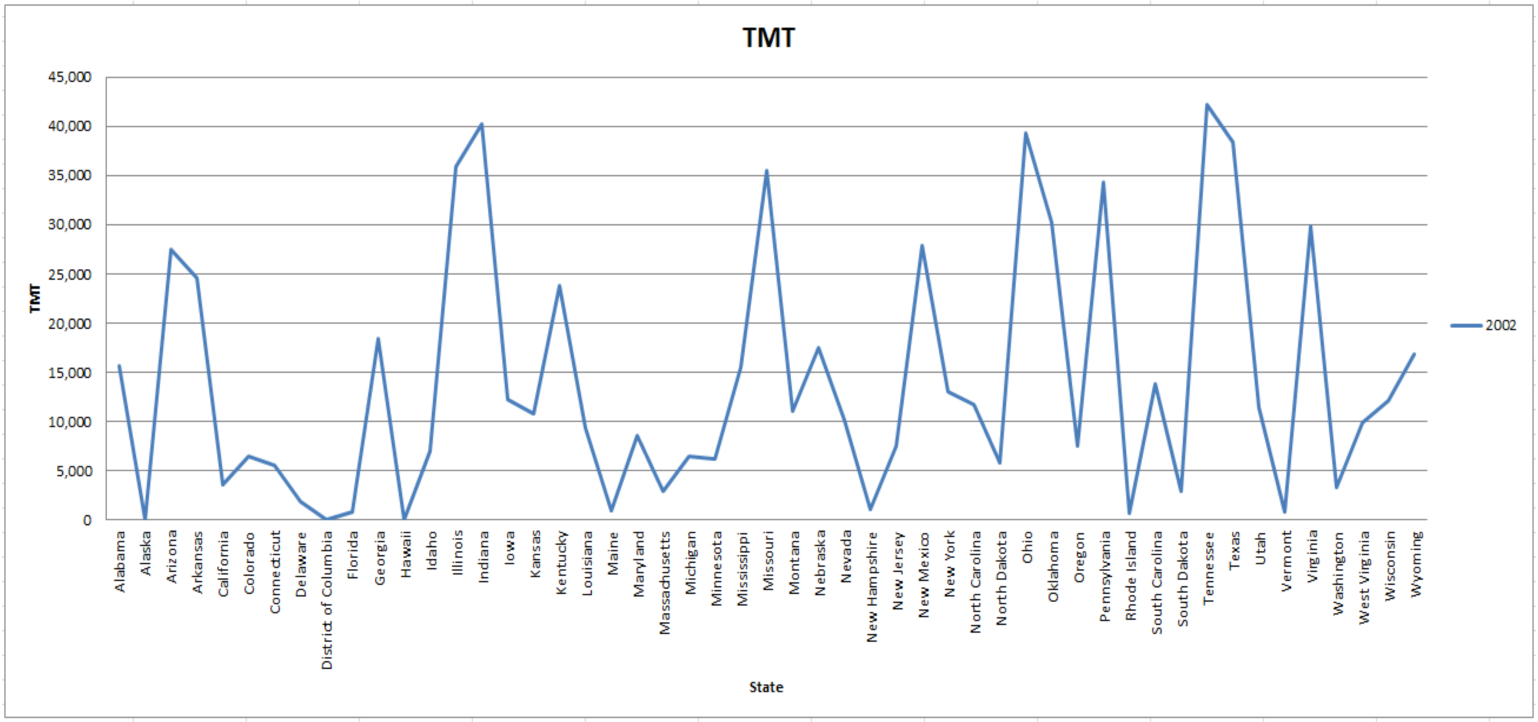

Figure C13 State-by-State Ton Miles Traveled (TMT) by Year.

Appendix D

INDIVIDUAL BOX-AND-WHISKERS PLOTS FOR VARIABLES

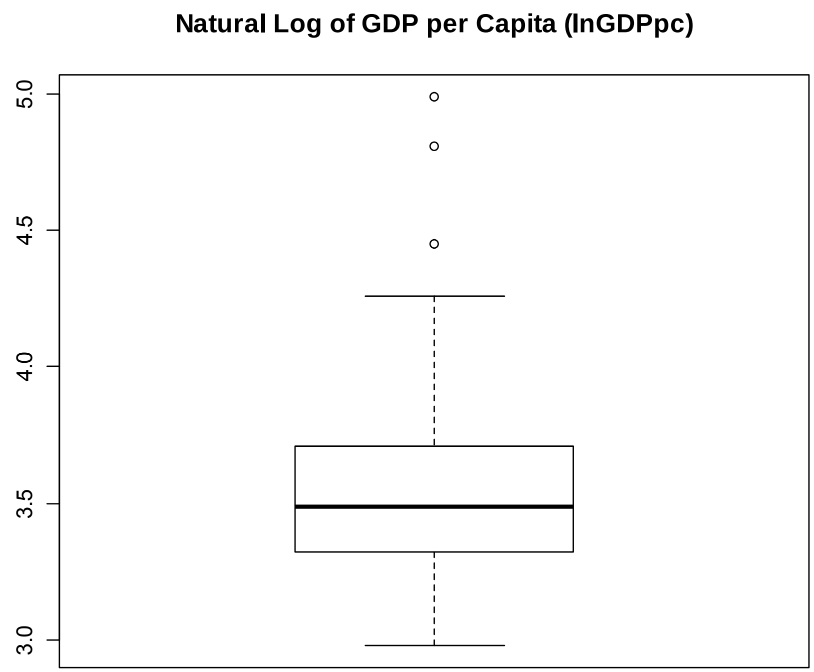

Figure D1 Natural Log of GDP per Capita for All Data Years.

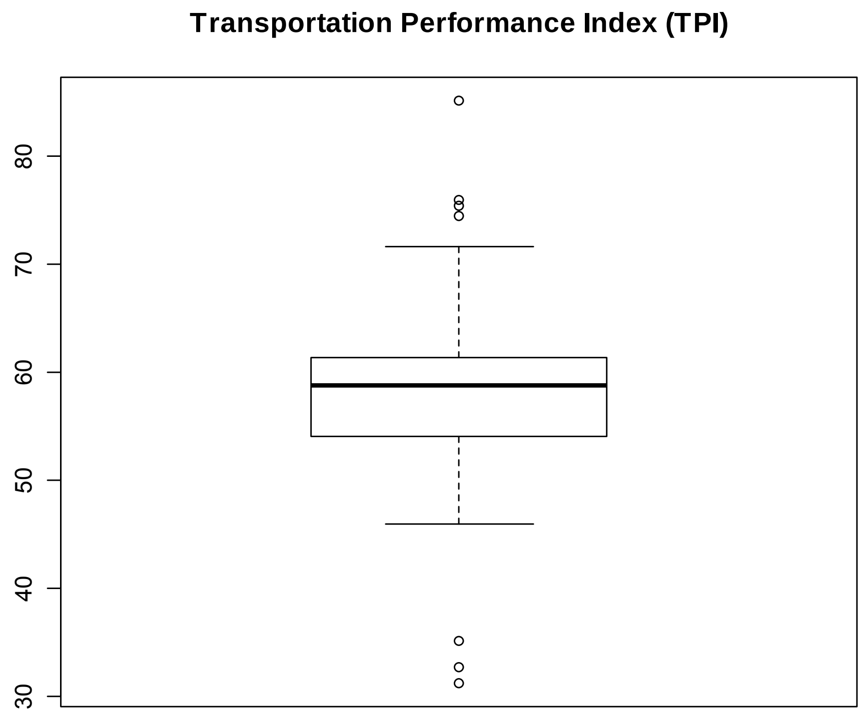

Figure D2 Transportation Performance Index for All Data Years.

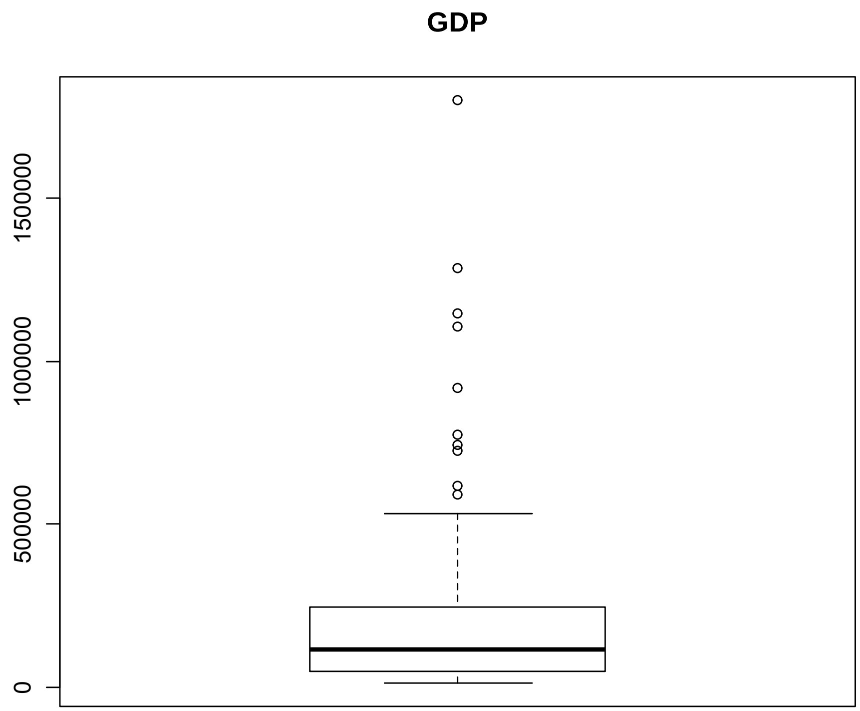

Figure D3 GDP for All Data Years.

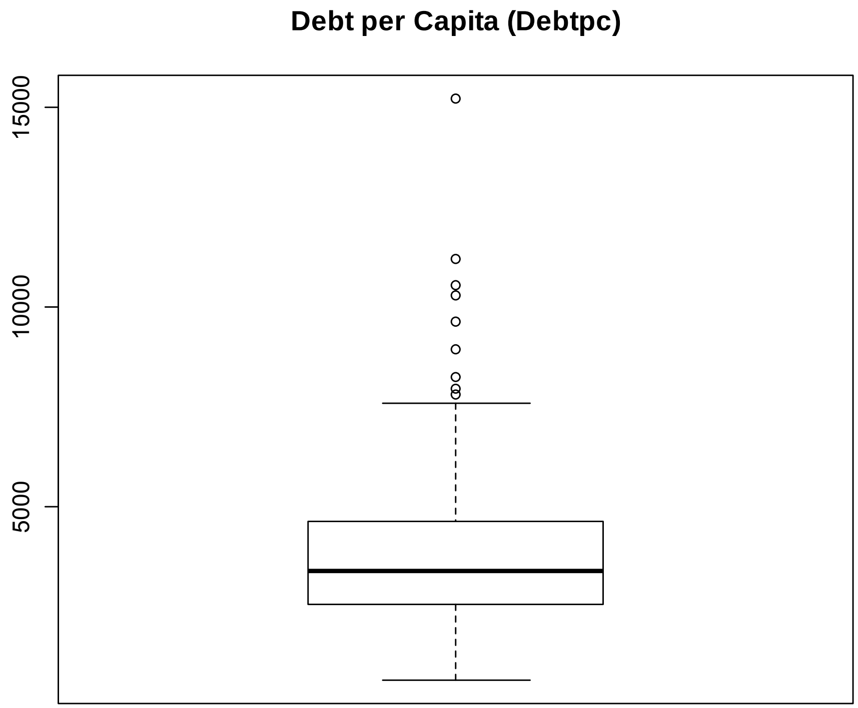

Figure D4 Debt per Capita by for All Data Year.

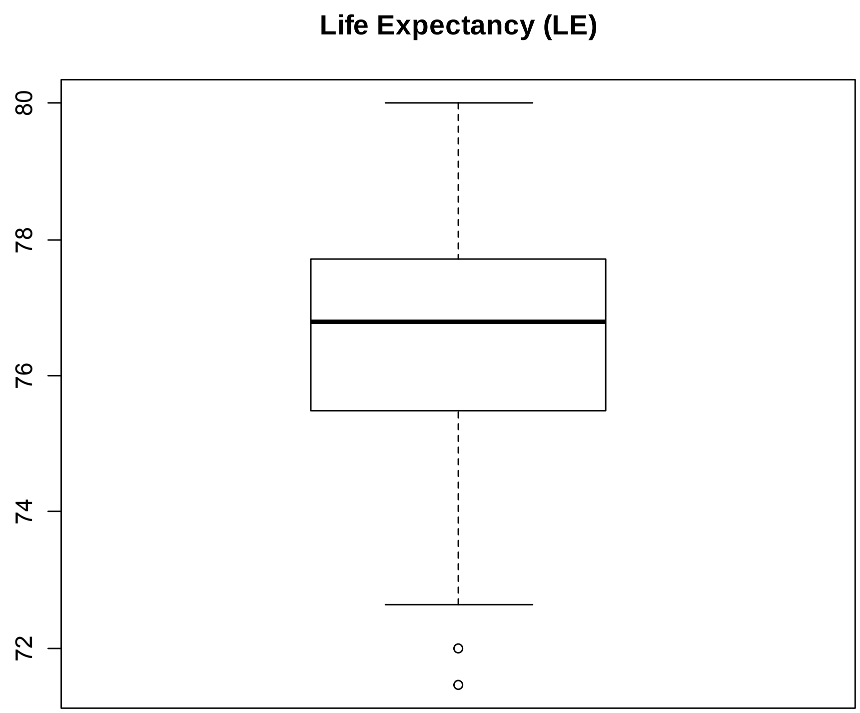

Figure D5 Life Expectancy for All Data Years.

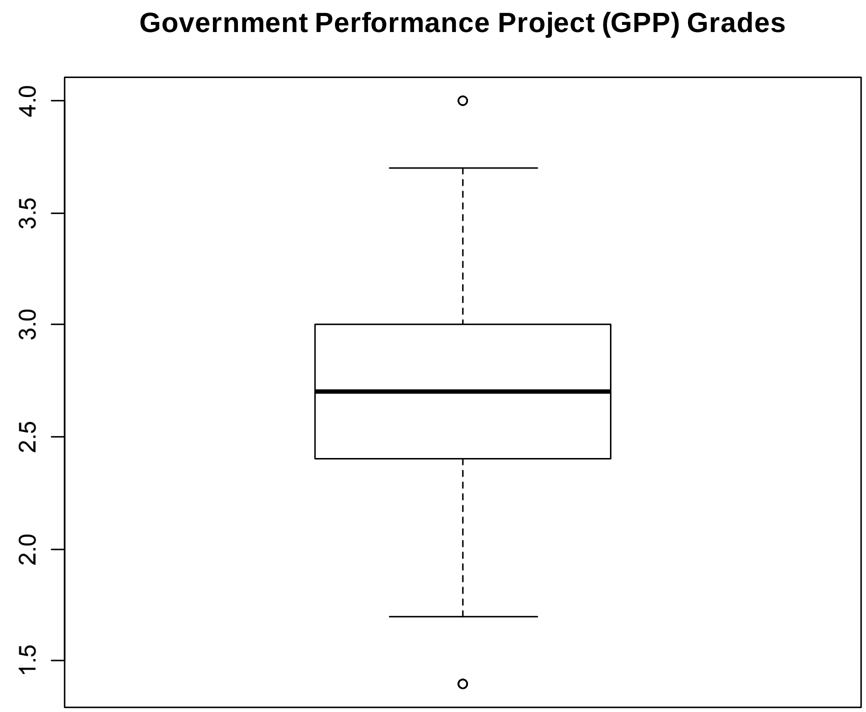

Figure D6 Government Performance Project Grades (GPP) for All Data Years.

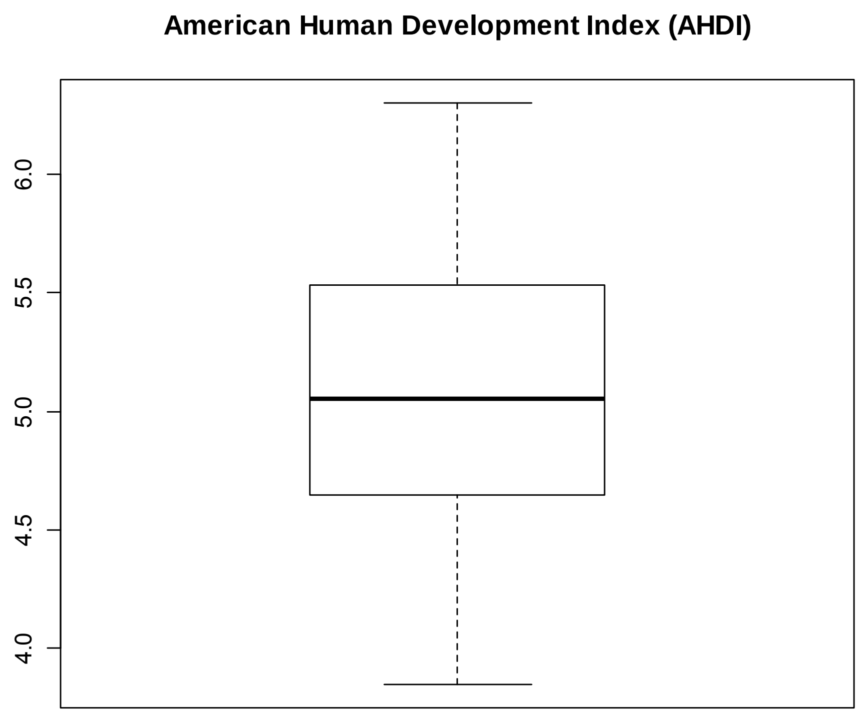

Figure D7 American Human Development Index (AHDI) for All Data Years.

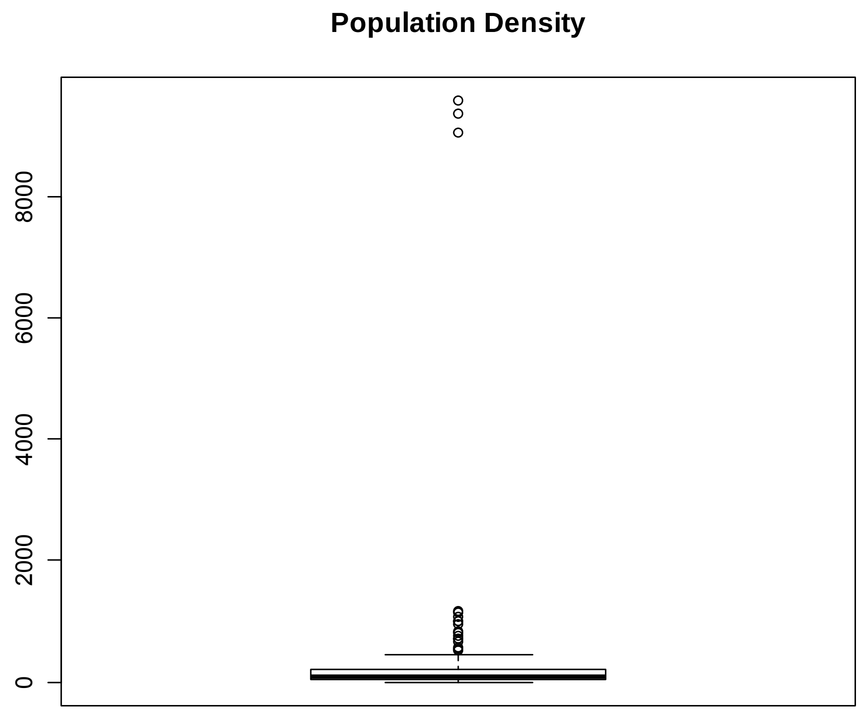

Figure D8 Population Density for All Data Years.

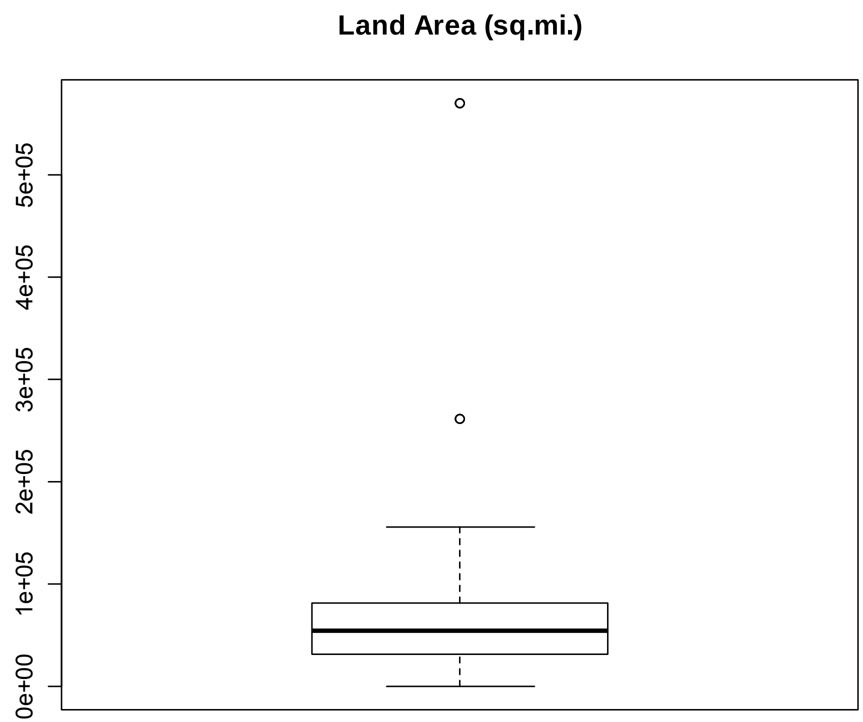

Figure D9 Land Area for All Data Years.

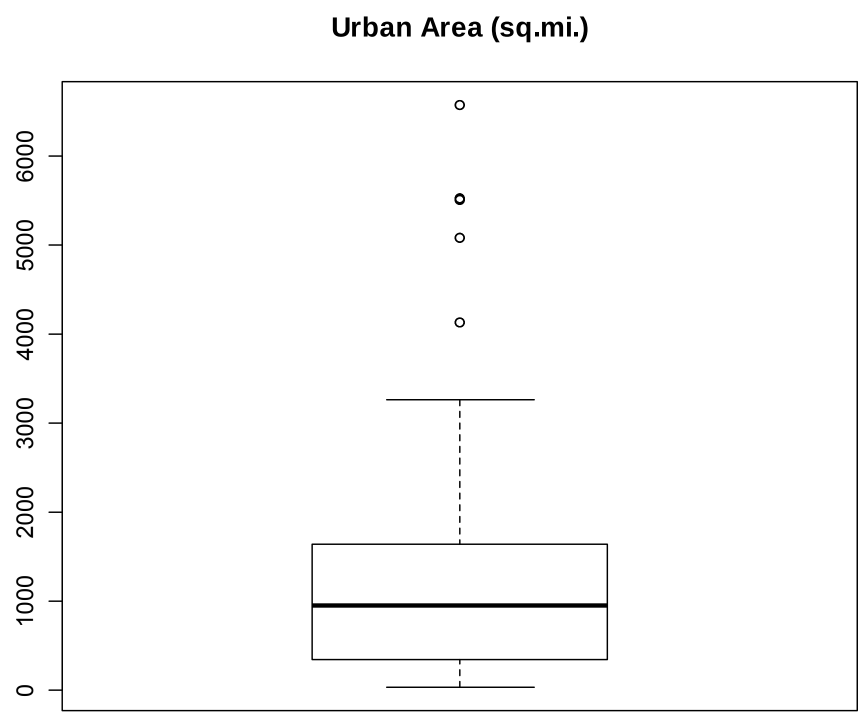

Figure D10 Urban Area for All Data Years.

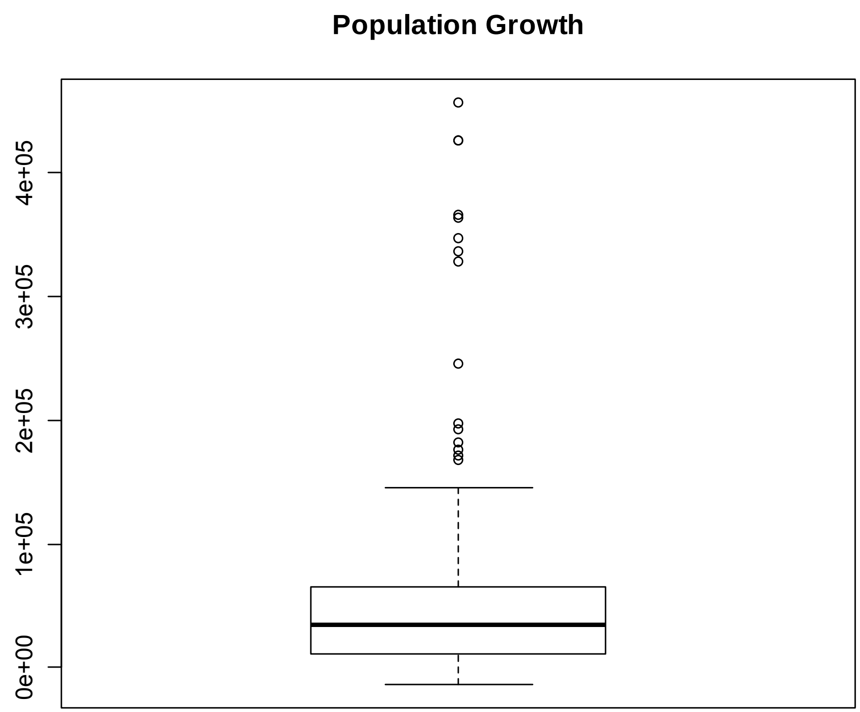

Figure D11 Population Growth for All Data Years.

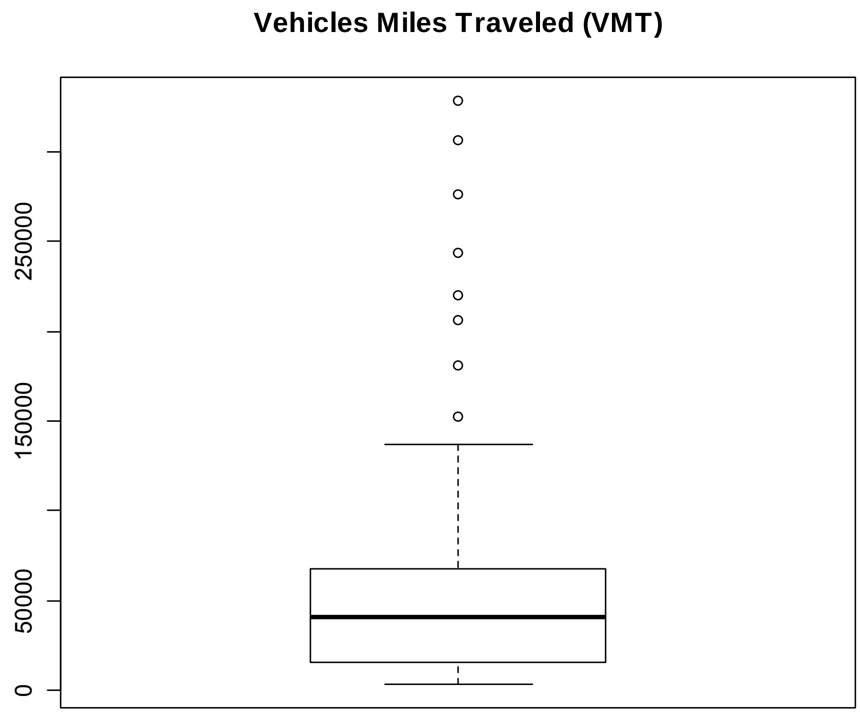

Figure D12 Vehicle Miles Traveled (VMT) for All Data Years.

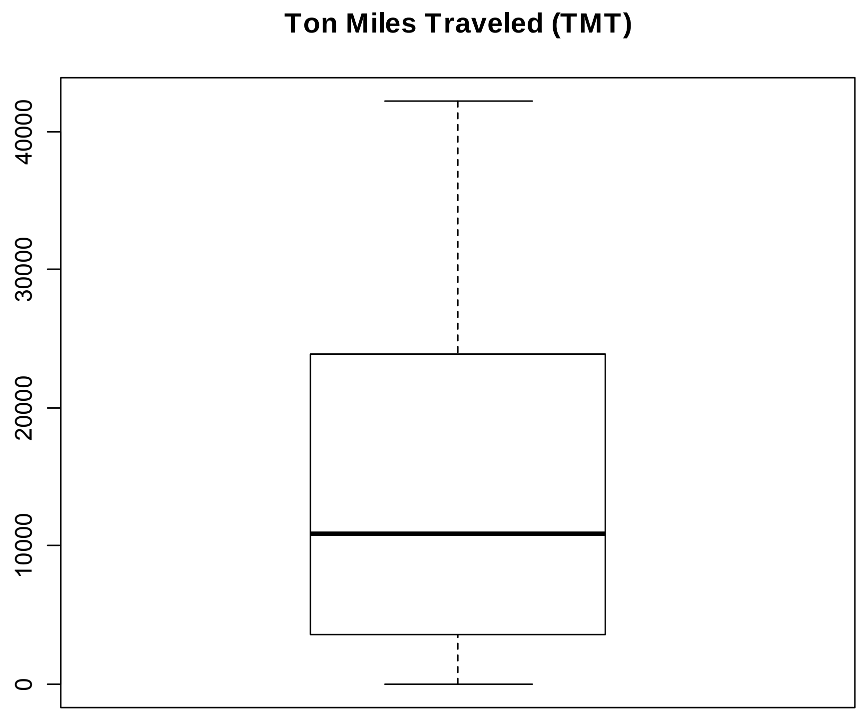

Figure D13 Ton Miles Traveled (TMT) for All Data Years.

Appendix E

DEA RESULTS FOR HP0

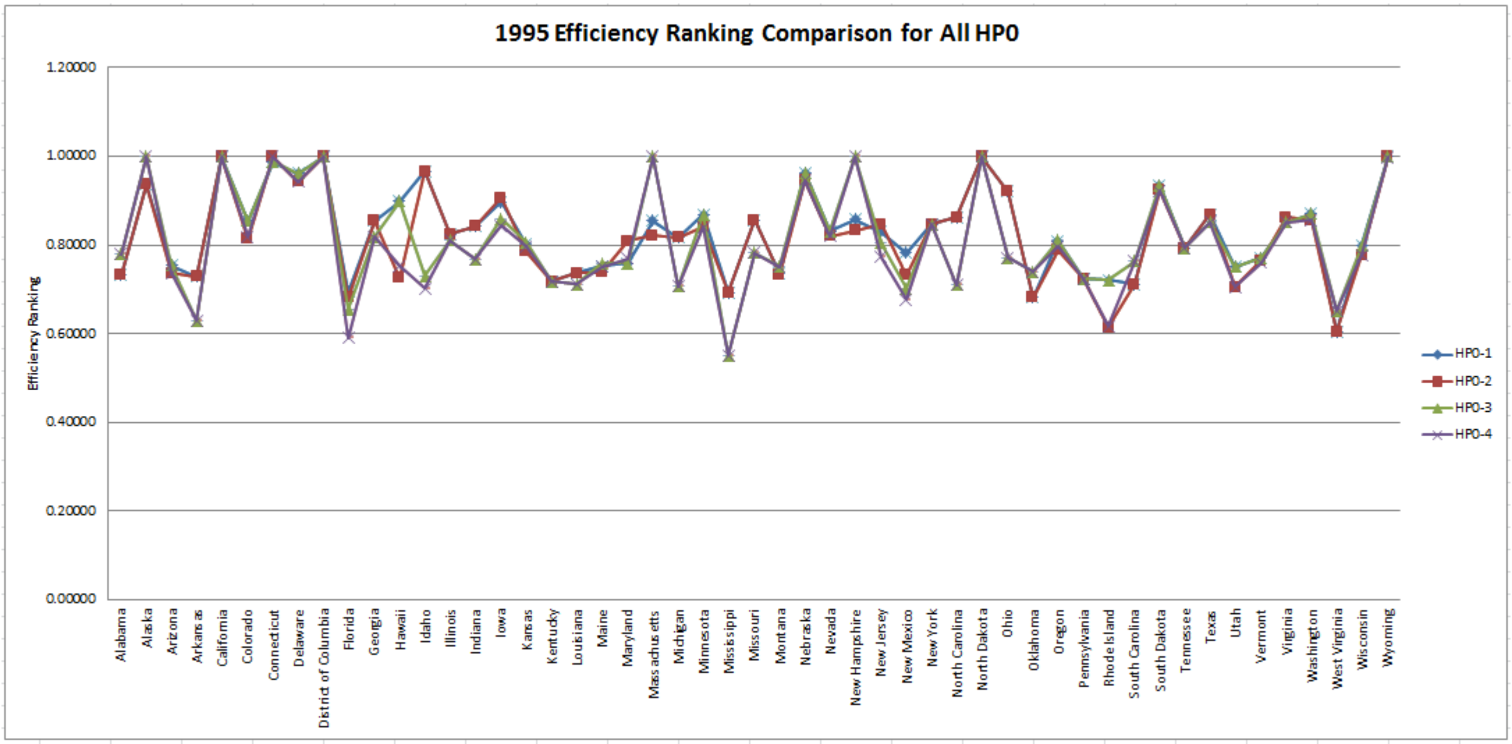

Figure E1 1995 Efficiency Ranking Comparison for All HP0.

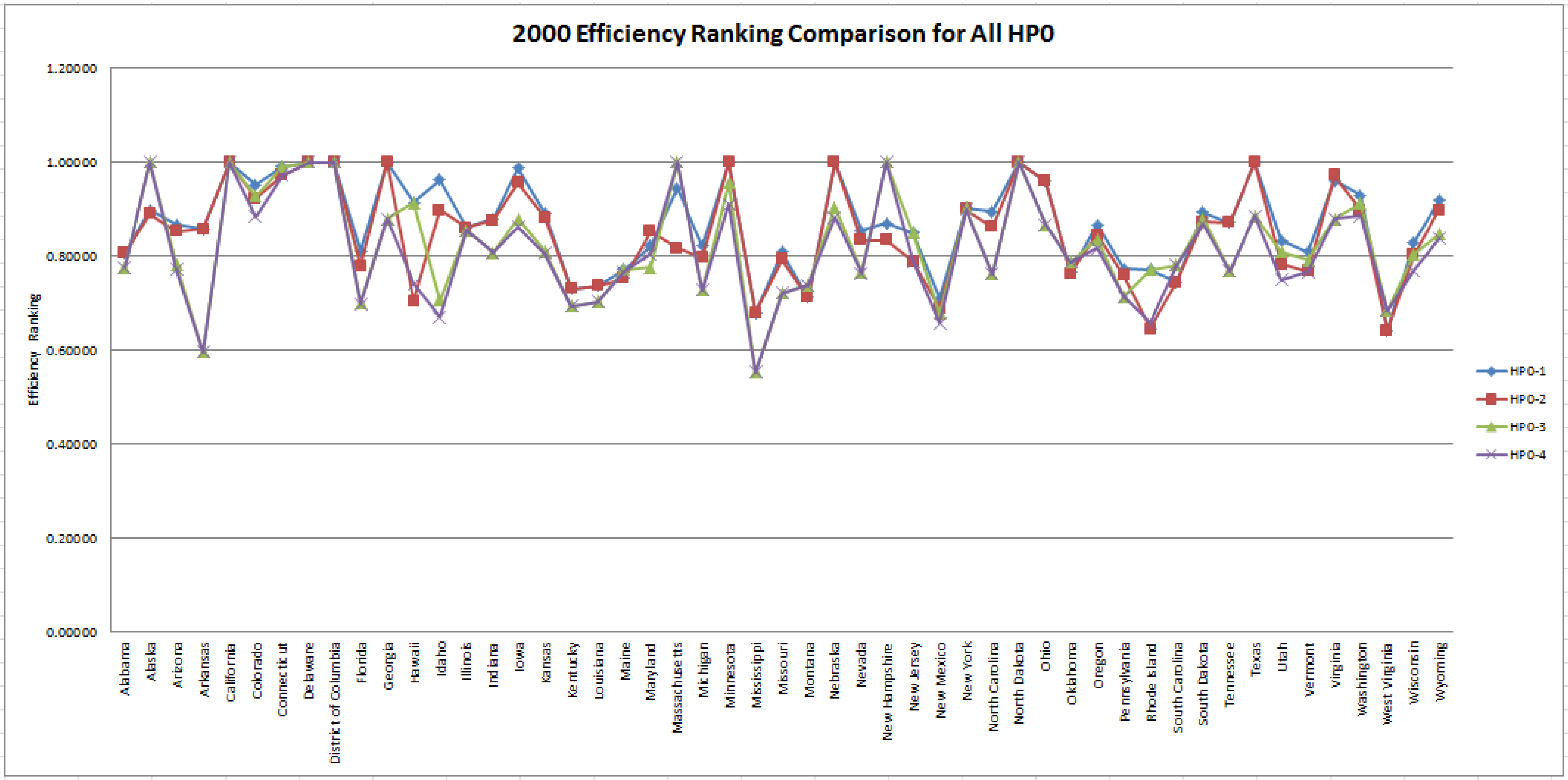

Figure E2 2000 Efficiency Ranking Comparison for All HP0.

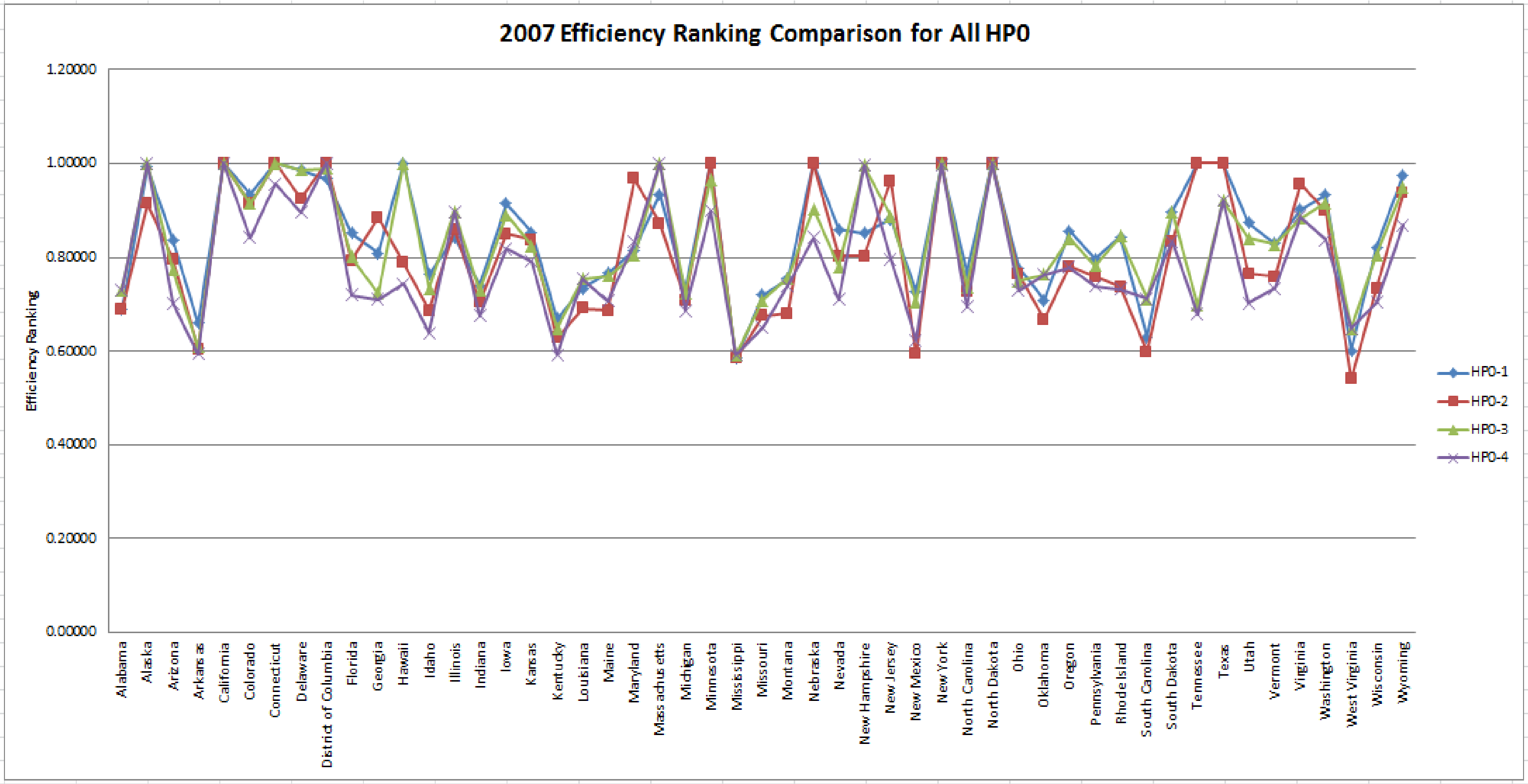

Figure E3 2007 Efficiency Ranking Comparison for All HP0.

Appendix F

DEA RESULTS FOR HPI

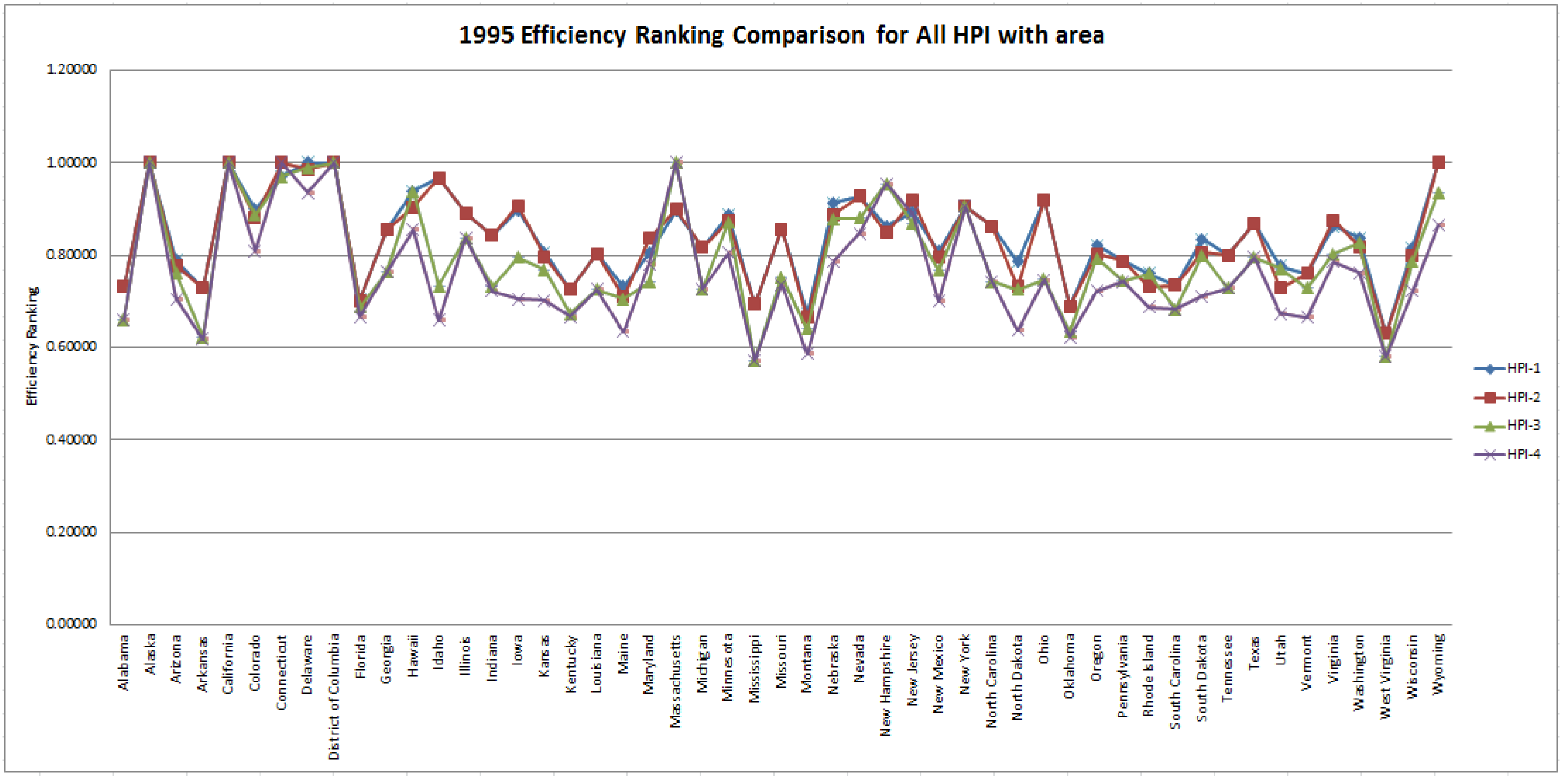

Figure F1 1995 Efficiency Ranking Comparison for All HPI with area.

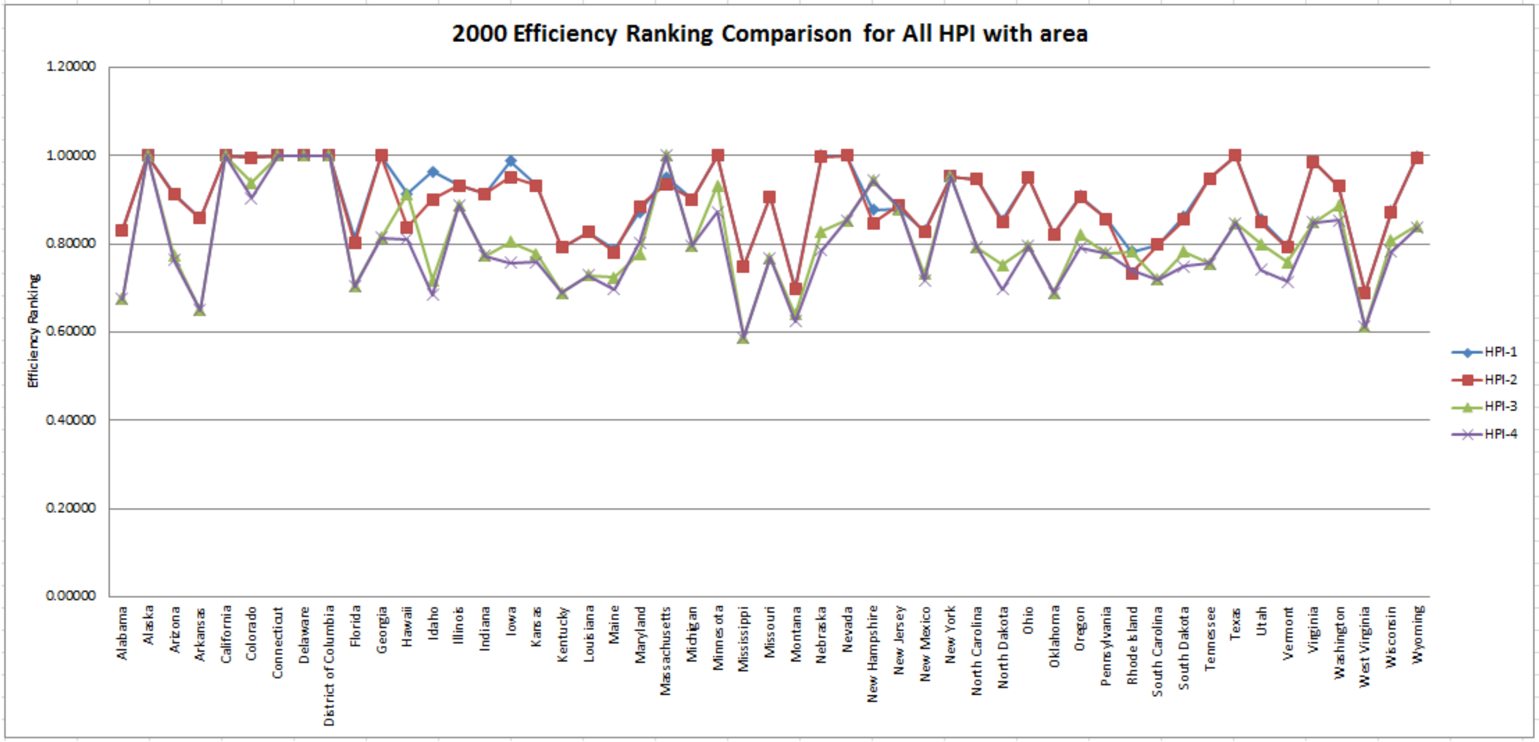

Figure F2 2000 Efficiency Ranking Comparison for All HPI with area.

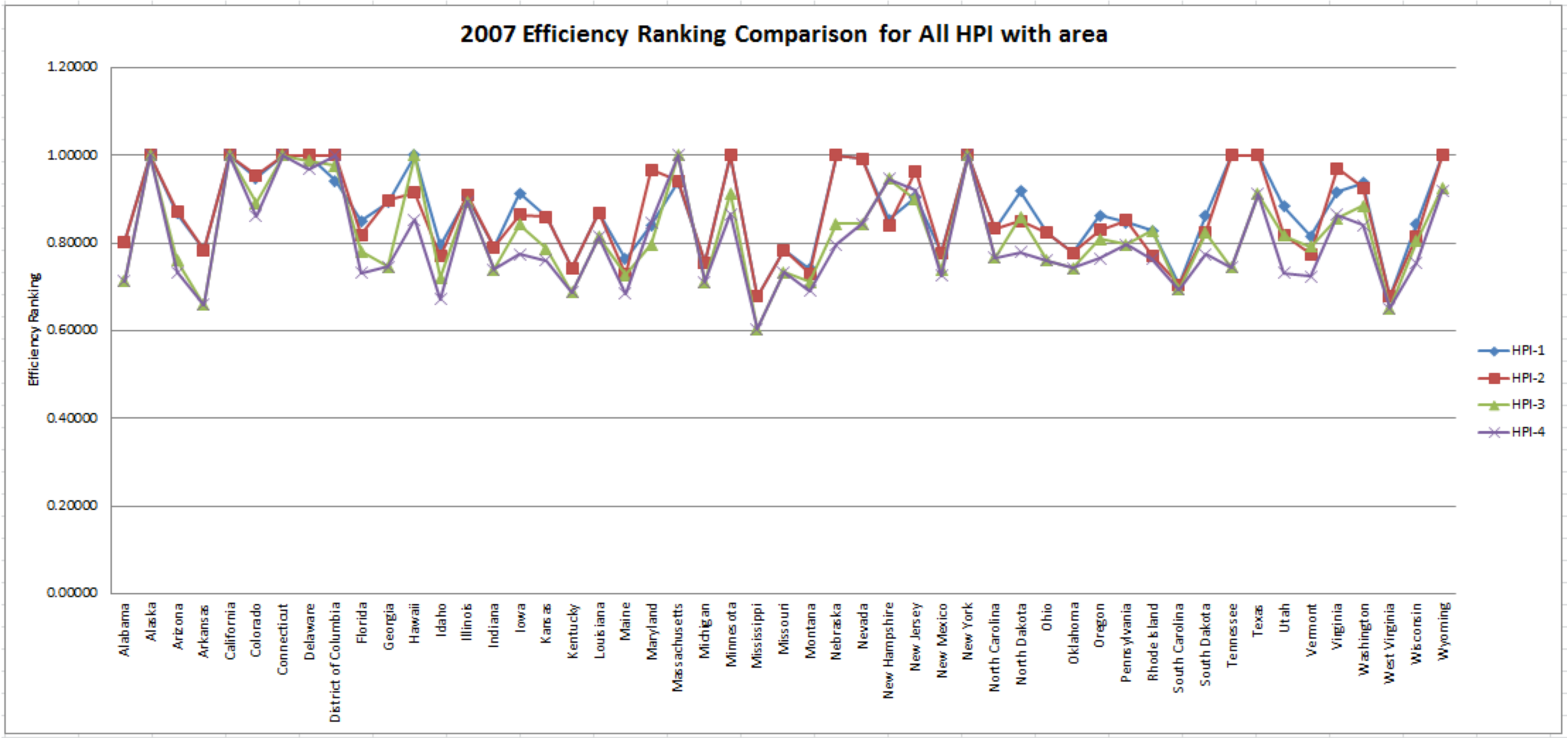

Figure F3 2007 Efficiency Ranking Comparison for All HPI with area.

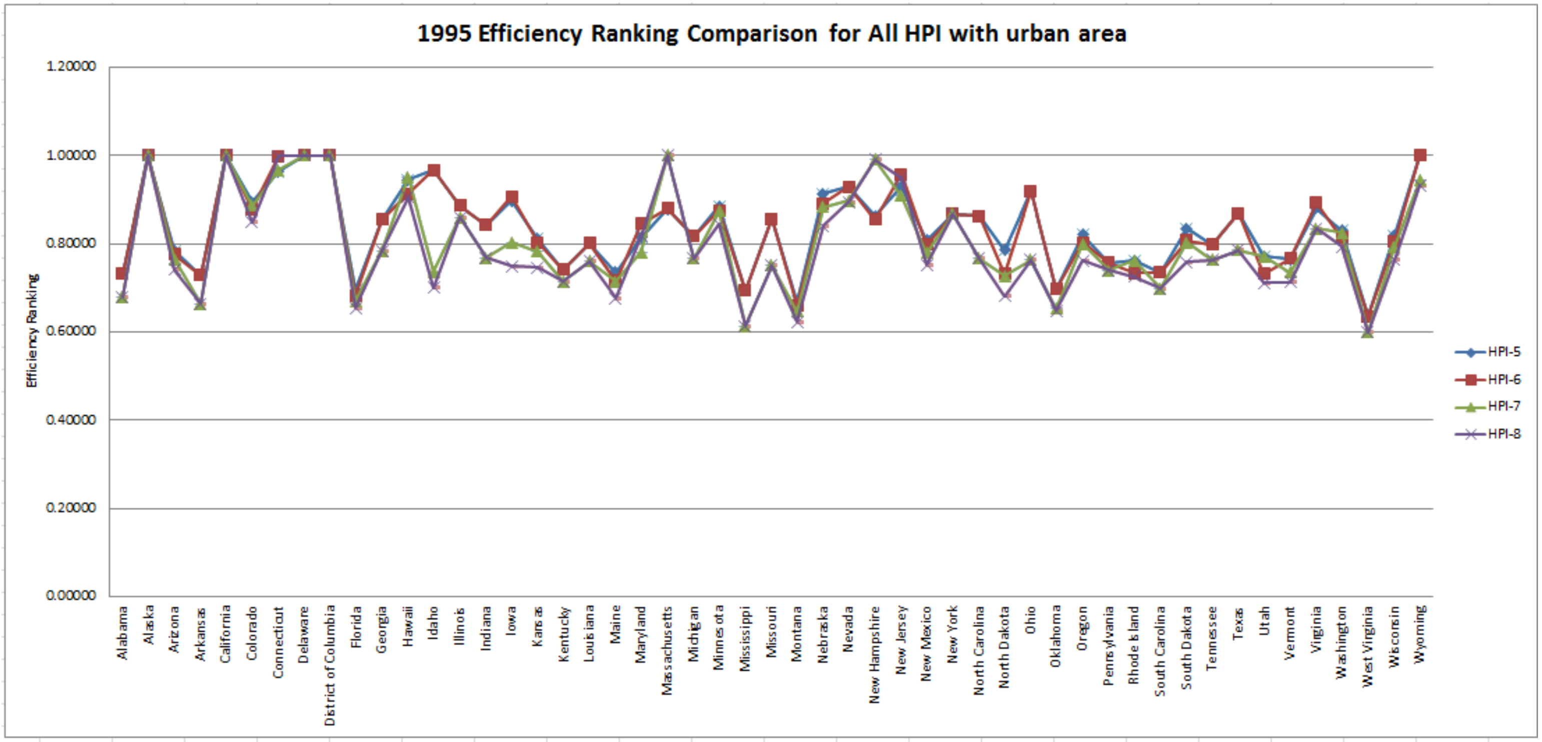

Figure F4 1995 Efficiency Ranking Comparison for All HPI with urban area.

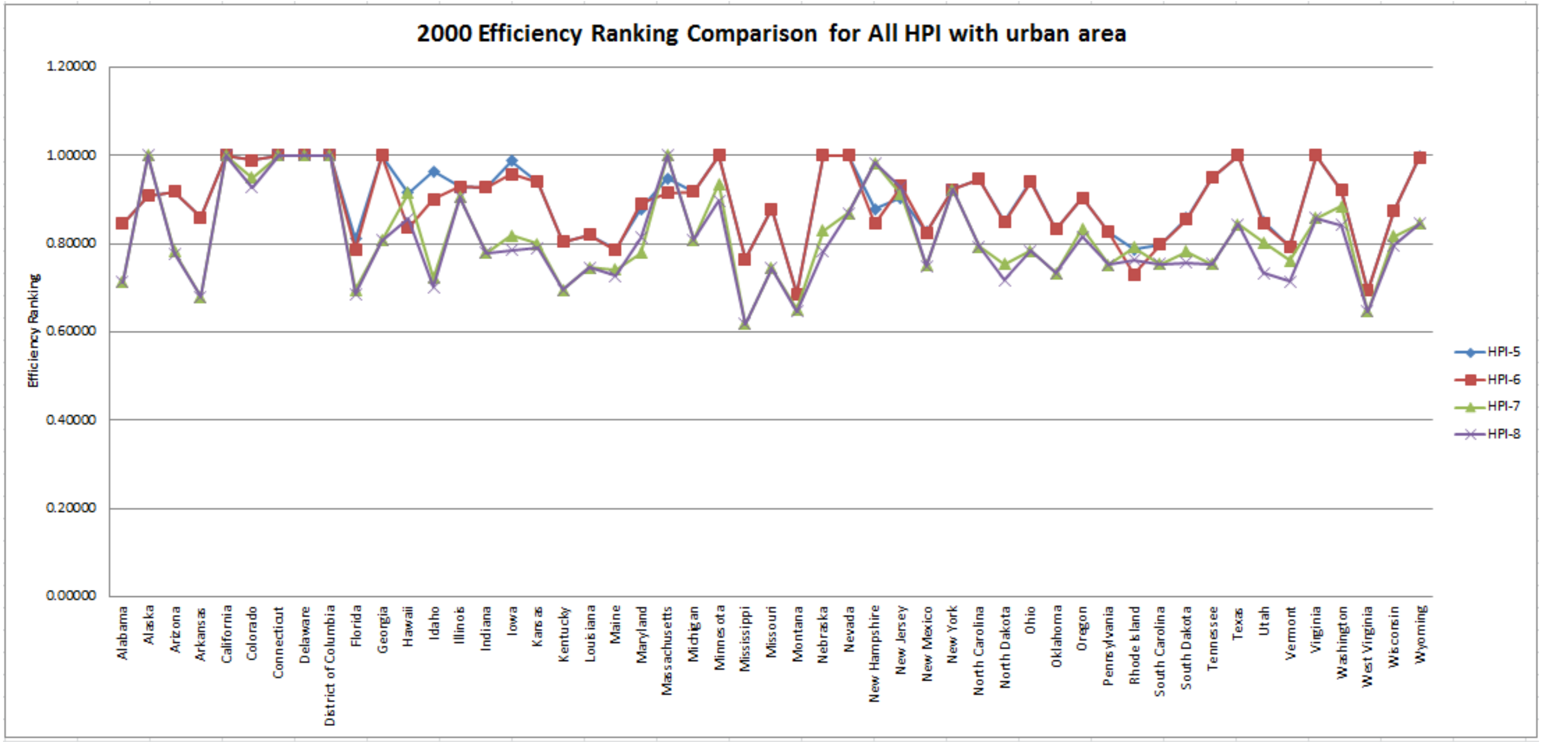

Figure F5 2000 Efficiency Ranking Comparison for All HPI with urban area.

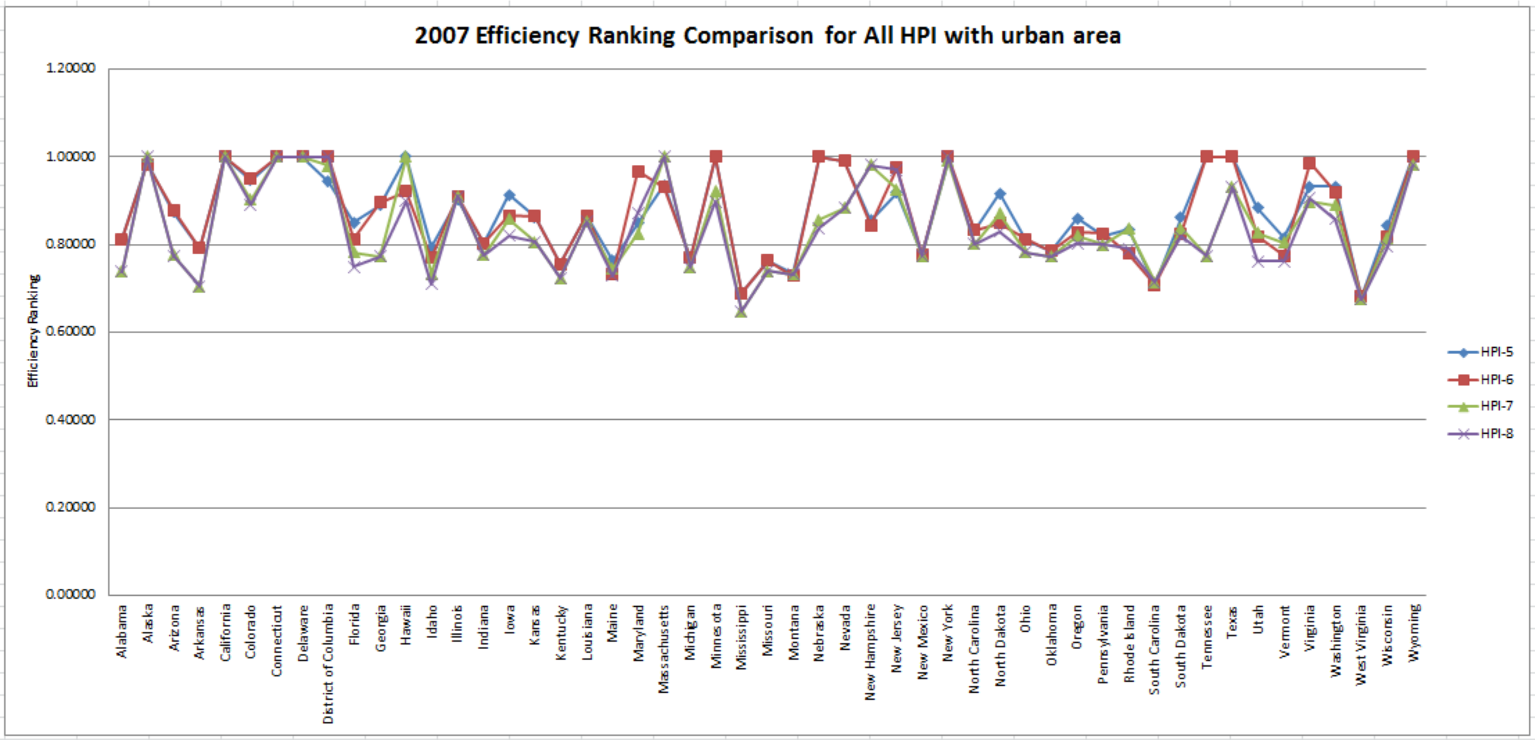

Figure F6 2007 Efficiency Ranking Comparison for All HPI with urban area.

Appendix G

DEA RESULTS FOR HPII

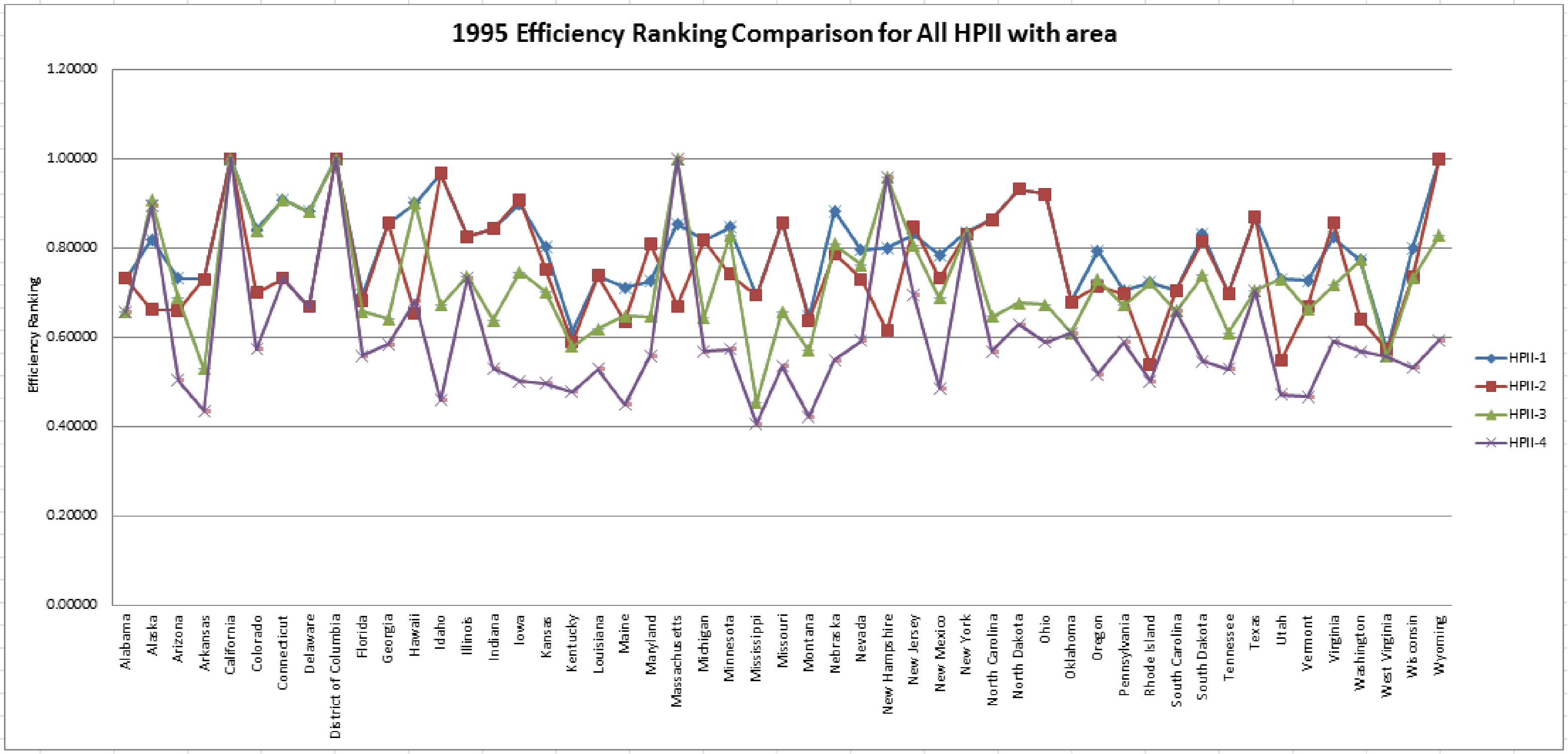

Figure G1 1995 Efficiency Ranking Comparison for All HPII with area.

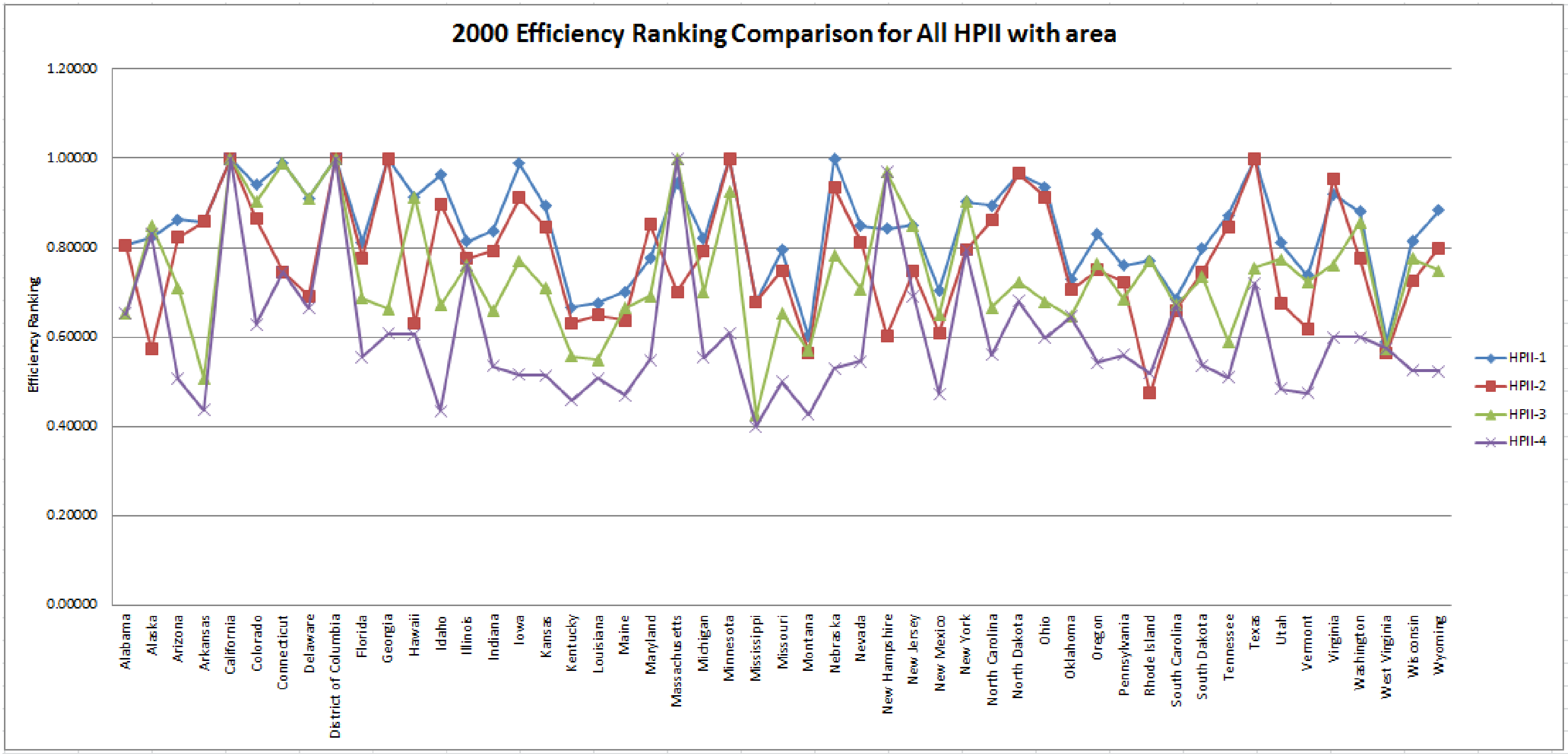

Figure G2 2000 Efficiency Ranking Comparison for All HPII with area.

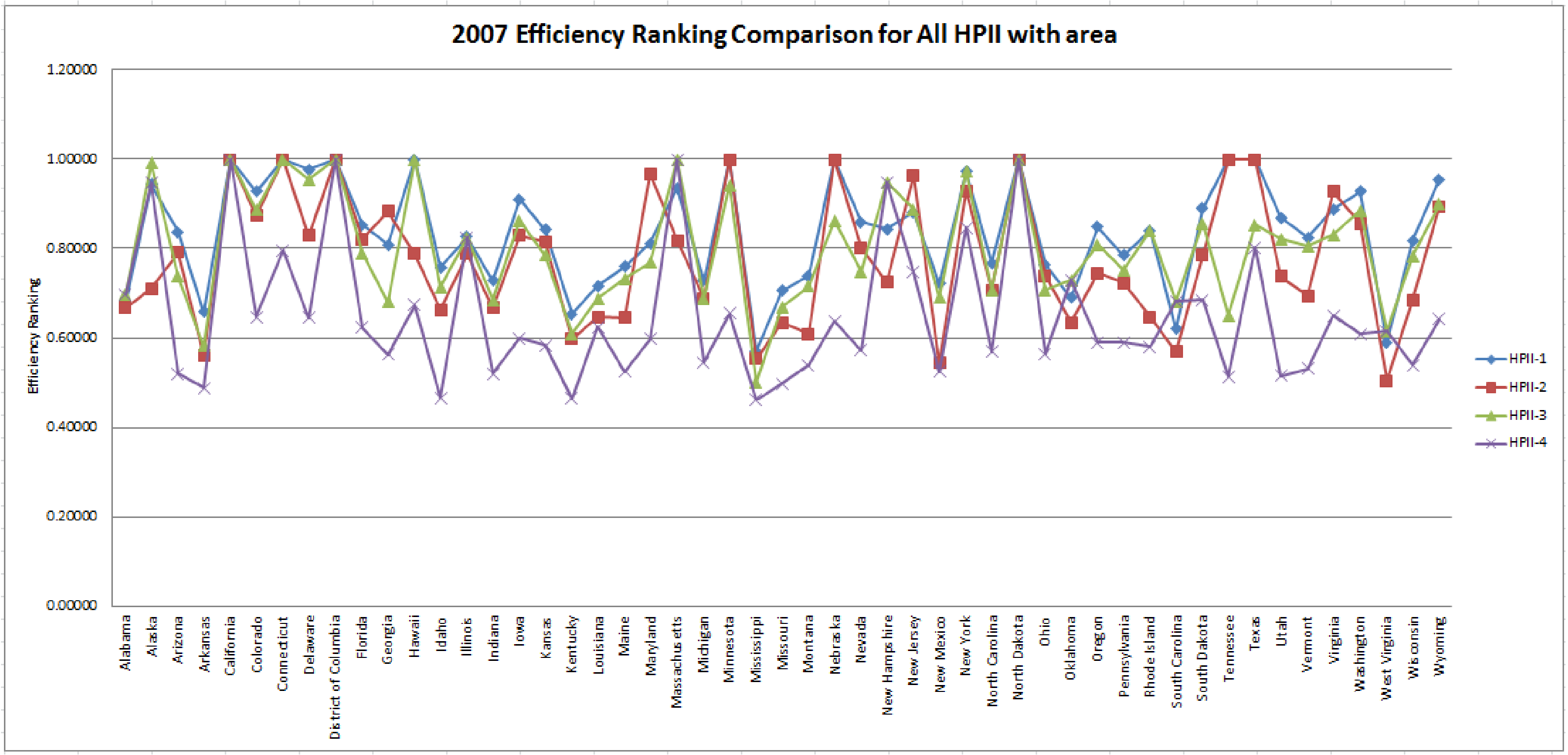

Figure G3 2007 Efficiency Ranking Comparison for All HPII with area.

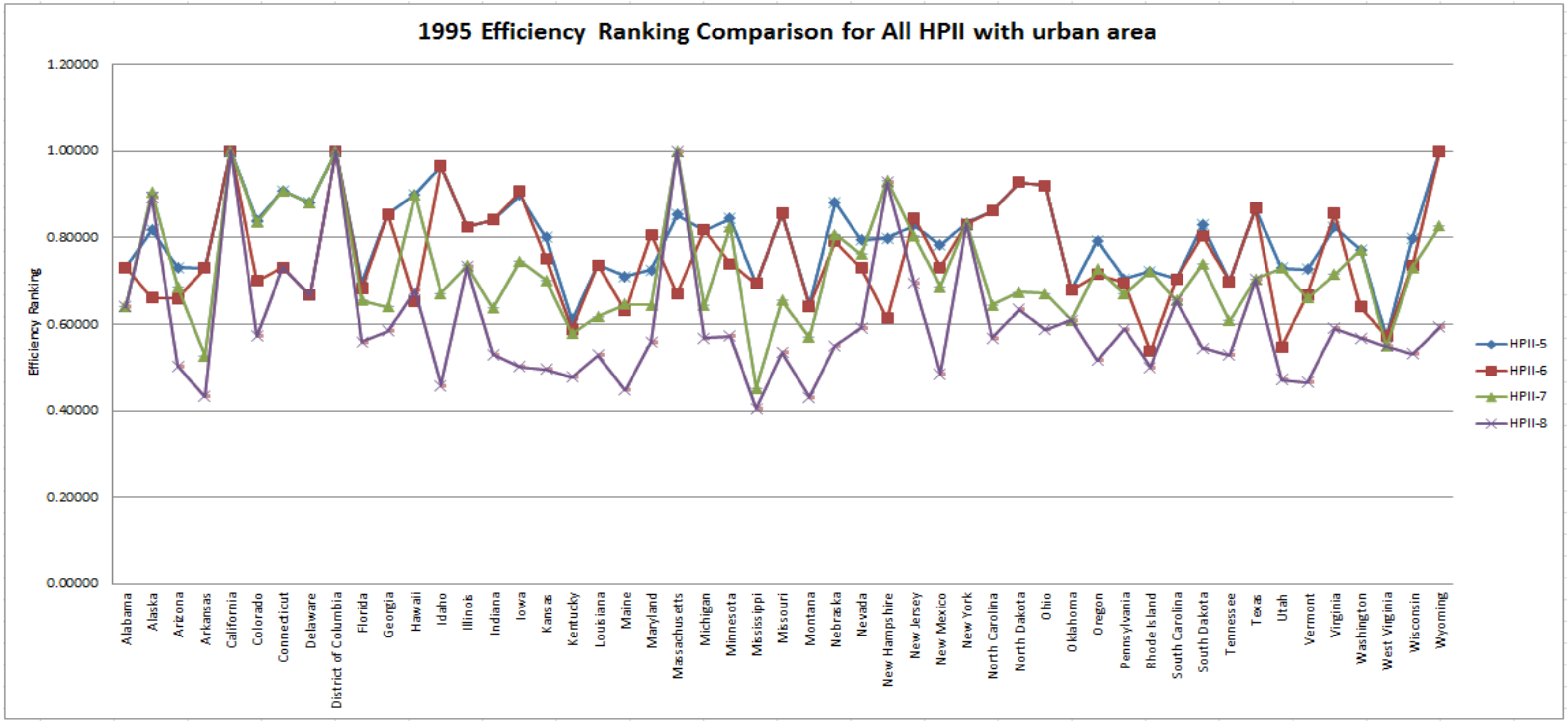

Figure G4 1995 Efficiency Ranking Comparison for All HPII with urban area.

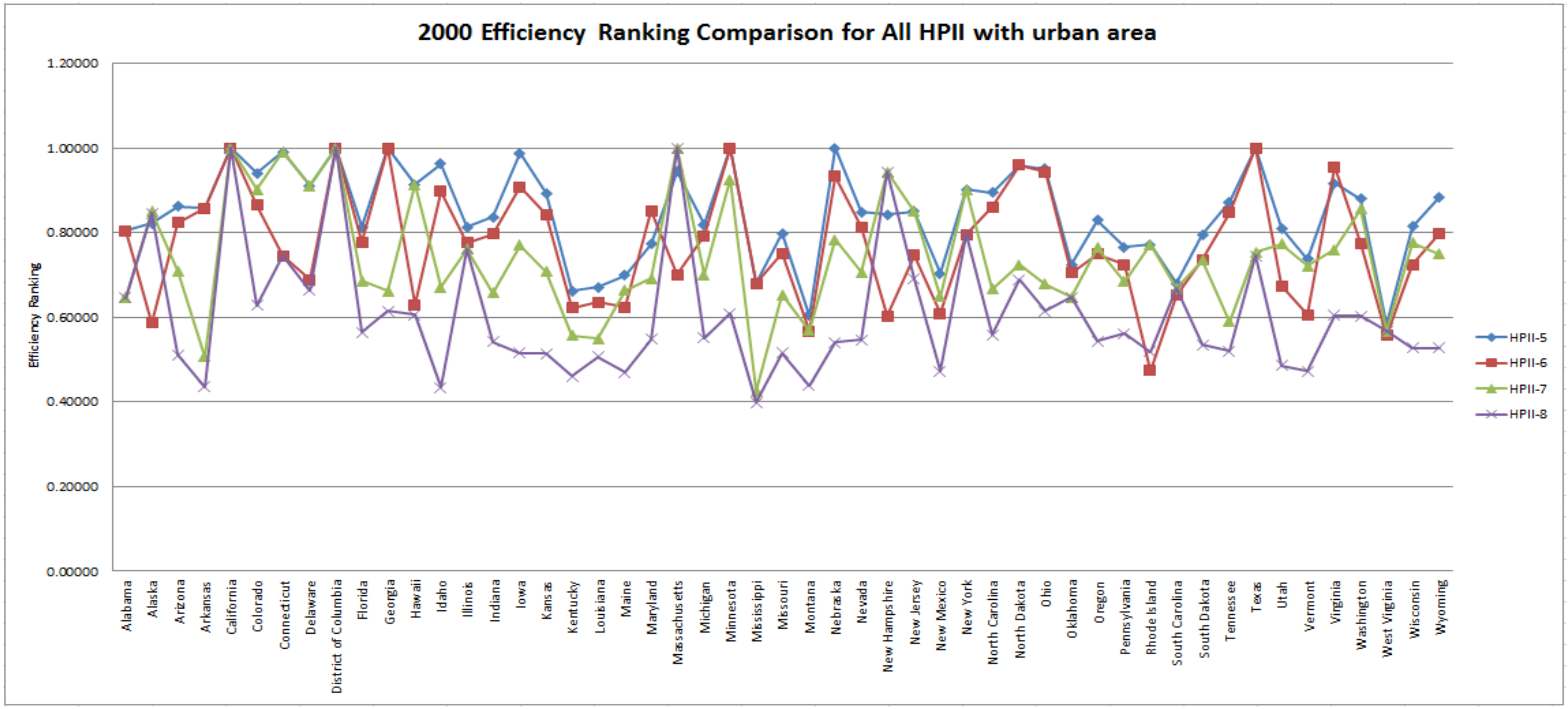

Figure G5 2000 Efficiency Ranking Comparison for All HPII with urban area.

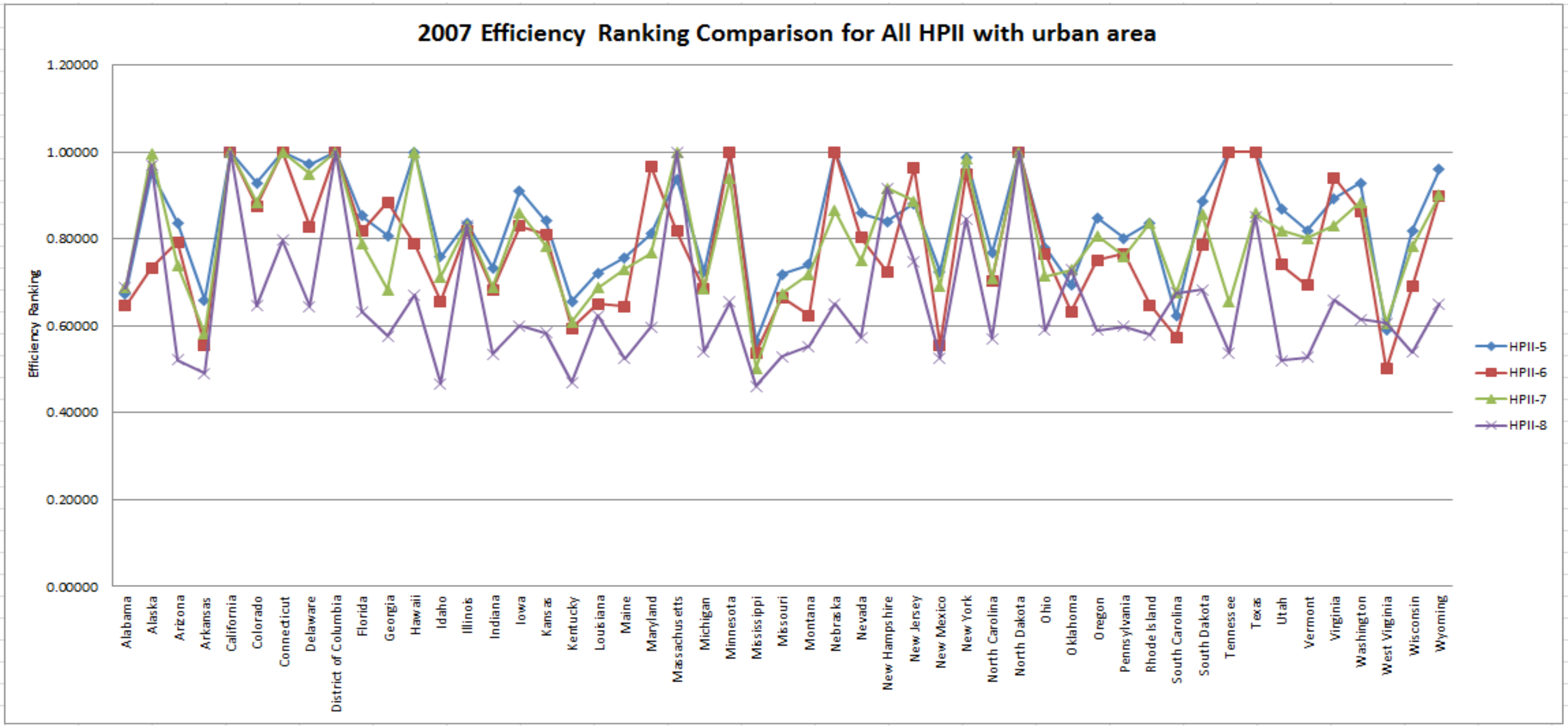

Figure G6 2007 Efficiency Ranking Comparison for All HPII with urban area.