An Exploratory Evaluation of State Road Provision to Commuters and Shippers using Data Envelopment Analysis and Tobit Regression

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Abstract

Due to mounting fiscal pressures over the last few years, the federal government as well as many state and municipal governments in the United States (U.S.) have had to re-examine their transportation policies and programs. Tax increases and/or spending cuts which aim to trim budget deficits are major preoccupations of most policy makers and legislative bodies nowadays. With regard to the task of building new or rehabilitating bridges, highways, and toll gates, cost-benefit analysis and economic impact studies are often undertaken by various government entities to rank and prioritize spending in the hopes of maximizing fiscal efficiency and road usage benefits. Since most highway construction and maintenance expenditures are absorbed by state governments, it is mostly up to state policy makers to decide transportation priorities. However, no research to date has been conducted to evaluate the comparative efficiency of state road provision to commuters and shippers. Such research would be useful to a state government's budgetary allocation and spending plans. This paper is one of the first to assess and rank the comparative efficiency of all 50 states in the U.S. by using data envelopment analysis and then to explain variations in efficiency ratings by using Tobit regression analysis.

Keywords: *data envelopment analysis, Tobit regression, road provisions, toll pricing, mass transit*

JEL Classification: R41, R52

INTRODUCTION

The time it takes people to commute to work or for businesses to ship goods has very important implications for workers' quality of life and the ability of businesses to get goods to customers. Both commuting and shipping times also have important public policy implications, because they can dictate what motor vehicle owners and shippers should pay in taxes and fees each year for road/highway/bridge/mass transit construction, maintenance, debt service, and so forth. That is to say, local business competitiveness may rest heavily on commuting and shipping times that are affected by basic transportation infrastructure such as roads, highways, transit rails, and bridges (roads for short hereafter). Nevertheless, the United States (U.S.) investment in the preservation and the development of basic transportation infrastructure lags so far behind that of China, Russia and European countries that it may lead to a steady erosion of the social and economic foundations for American prosperity in the long run (Halsey III, 2010). To make matters worse, the ongoing worldwide economic crisis coupled with severe government budget shortfalls continue to limit the U.S. government's effort to increase its spending on infrastructure development and maintenance. In order to align its public transportation policy with economic goals, the federal, state, and municipal governments in the U.S. actively have sought ways to generate more revenue streams by increasing toll fees, gasoline and property taxes, mass transit fares, and road-congestion prices. However, these revenue generating ideas may backfire since they can further increase the financial burdens of cash strapped citizens and businesses.

At the same time, while trying to minimize commute time to work and goods shipment times, states must also provide roads that have the capacity to serve resident-commuters as well as trucking firms that deliver consumer products and provide jobs to constituents. A transportation system must serve constituents adequately in their journey to work by providing access for enough commuters. Trucking firms must have roads with enough room to allow a sufficient number of trucks to move safely and to make deliveries at various points within a region. For this reason, road provision must not only try to minimize commute and delivery times but also allow access to all consumers of road services who have paid taxes for road provision, although such access creates congestion and road maintenance problems. The tensions between providing maximum access and at the same time reasonable commute times without delays or congestion present many challenges to policy makers.

As such, there is a growing concern over road provision, especially when the government spends its budget excessively on certain construction projects or wastes its resources on less prioritized (i.e., "pork barrel") projects. To ease this concern, public policy makers (especially state and municipal government authorities) should justify their actions on road provision for their constituents, since road provision is mostly financed by state governments with some projects partially funded with federal government aid, although road projects receiving federal funding are usually locally identified and prioritized (U.S. Department of Transportation 2011a). As state and municipal governments face financial problems that have persisted after the conclusion of the latest economic recession, the efficiency and effectiveness of all governmental programs including road provision have come under closer scrutiny. If commuters and shippers are facing more delays in their travels and suffering from higher transportation costs despite rising road spending, there is a need for a systematic study which can examine and then evaluate road provision policies (Texas Transportation Institute, 2011). In response to such a need, this paper aims to examine ways that state governments in the U.S. provide transportation infrastructure through road provision so as to help policy makers (state and federal) develop road provision strategies to improve efficient long-term road investment plans. In addition, this paper identifies factors that may significantly influence road provision and infrastructure investment decisions.

RELEVANT LITERATURE

Since approximately 70 percent of road provision decisions regarding highway construction and maintenance spending are made by state governments, it is mostly up to state policy makers to decide transportation budget priorities (U.S. Department of Transportation, 2010). Despite the significance of road provision on state fiscal plans and regional economic development, the research for this paper has found no study to date that has been conducted to compare the 50 states with respect to their efficiency in providing road services to commuters and shippers. Though not directly related to state road provision issues, Deller and Nelson (1991) assessed the economic efficiency of a sample of Midwestern (Illinois, Minnesota, and Wisconsin) township governments in providing low-volume, rural road services. Their empirical test revealed that the local government's separate, small scale operations were less efficient and more costly than multiple local governments' consolidated but larger scale operations due to economies of scale. This finding implied that road provision decisions have to be made at the state government level as opposed to the local township level.

Extending the concept that the efficient allocation of financial resources by the government could affect the quality of road services, Min and Lambert (2006) attempted to compare a group of states on their abilities to raise and spend tax dollars with regard to their road provision. Although their study was one of the first to measure the comparative efficiency of state governments' highway expenditures and road finances relative to their peers and previous years of performances using data envelopment analysis (DEA), it was still confined to the comparison of only 11 states.

Its other shortcoming was the failure to identify exactly what environmental factors might have caused the inefficiency.

Later, De la Garza, Triantis, and Fallah-Fini (2009) attempted to measure the relative efficiency of highway maintenance operations undertaken by the state department of transportation and its private contractors. Their study also tried to assess the effects of environmental variables such as climate, geographic conditions, pavement conditions, and privatization on road maintenance efficiency. This study, however, was limited to the comparison of local highways within 200-250 miles of Virginia's interstate highways. In other words, this study neither provided any cross-state comparison, nor discussed any state road provision implications of highway maintenance.

To overcome the aforementioned shortcomings of prior studies on road provision, this paper measures the comparative efficiencies of all 50 states in the U.S. using DEA and then uncovers the main sources of relative efficiency or inefficiency of state road provision using a series of Tobit regression analyses.

RESEARCH METHODOLOGY

To gauge the efficiency of many different organizations and institutions, data envelopment analysis (DEA) is employed in this paper. DEA is a special application of linear programming based on the frontier methodology of Farrell (1957). In general, DEA is a nonparametric modeling or estimation method that uses a linear programming technique to construct a production possibility frontier based on common inputs and common outputs used by similar "decision making units (DMUs)". DMUs refer to the collection of private firms, non-profit organizations, departments, administrative units, and groups with the same (or similar) goals, functions, standards and market segments. The frontier represents the optimal amounts of output given various combinations of inputs, and DMUs are ranked relative to one another according to how close they come to reaching an optimal level of output on the frontier with a score of 1.0 representing efficiency, which means a DMU has matched an optimal point on the frontier (Cook and Zhu, 2005). It establishes a "relative" benchmark standard. Also, DEA production techniques can have either constant returns to scale (CRS) or variable returns to scale (VRS), while the analysis of DMUs can be approached from either an input minimization or output maximization orientation as one is a dual of another.

DEA can be employed for measuring the comparative efficiency of any entities including banks (Casu and Molyneux, 2003), hospitals (Ferrier and Valdmanis, 2004; Anderson et al., 2008), municipal services (Moore, Nolan and Segal, 2005), transit agencies (Nolan, Ritchie, and Rowcroft, 2001), trucking firms (Min and Joo, 2006), third party logistics (3PL) providers (Min and Joo, 2006), hotels (Min et al., 2008), national economies (Leibenstein and Maital, 1992; Lovell, Pastor, and Turner, 1995; Margaritis, Fare, and Grosskopf, 2007; Afonso, Schuknect and Tanzi, 2010), paratransit systems (Min and Lambert, 2011) and many other different types of DMUs.

The general DEA model can be mathematically expressed as (Charnes, et al., 1978; Fare et al., 1994; Nolan et al., 2001):

$$\text{Maximize Efficiency score } (jp) = \frac{\sum_{r=1}^{t} u_r y_{rjp}}{\sum_{i=1}^{m} v_i x_{ijp}} \tag{1}$$

$$\text{Subject to} \quad \frac{\sum_{r=1}^{t} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1, \quad \mathrm{j} = 1, \ldots, n, \tag{2}$$

$$u_r, v_i \geq \varepsilon, \qquad \forall r \text{ and } i, \tag{3}$$

where

y_{rj} = amount of output r produced by DMU j,

x_{ij} = amount of input i used by DMU j,

u_r = the weight given to output r,

v_i = the weight given to input i,

n = the number of DMUs,

t = the number of outputs,

m = the number of inputs,

ε = a small positive number.

The fractional, non-linear programming model described above can be converted to a linear programming (LP) model without much difficulty. A major assumption of LP is a linear relationship among variables. Therefore, an ordinary LP for solving DEA often utilizes a constant returns-to-scale so that all observed production combinations can be scaled up or down proportionally (Charnes et al. 1978). On the other hand, by using a piecewise LP, DEA can consider a non-proportional returns-to-scale including increasing or decreasing returns-to-scale (Banker et al. 1984).

The aforementioned DEA model was utilized to compare the relative efficiency of providing road services to commuters, mass transit riders, and trucking shipper based on the following input and output secondary data (US Department of Transportation, FHWA, OHPI 2007, 2008, and 2009):

1. Average of Total Tax Receipts for Highways in thousands, 2007 to 2009. Since state tax revenue was invested for highway maintenance and construction, this data is categorized as an input in the delivery of road services to **commuters, trucking shippers, and transit riders**.
2. Average of Total Disbursements for Highways, Operating and Capital Expenditures, in thousands, 2007-2009. Since this comprises and represents a major source of road provision, this is also regarded as an input to the delivery of road services to **commuters, trucking shippers, and transit riders**.
3. Average of Total Tax Receipts and Disbursements for State Mass Transit Projects, in thousands, 2007 to 2009. Since revenues and disbursements for each state for state mass transit projects were identical (matched) for each year, just two inputs were combined into one here. Some states did not spend any financial resources on mass transit projects during this time period, and so these states were not included in the mass transit DEA. Spending by local governments and/or aid from the state or from the federal government are not included.[1] These amounts are used as inputs for the delivery of **mass transit** services.
4. Total Urban and Rural Lane Miles, 2009. Total urban and rural lane miles are used as an input for road provision to **commuters, trucking shippers, and transit riders** (US Department of Transportation, FHWA 2011b).
5. Average of Construction Cost Index, 1997-2005 (1987 base year prices). This index measures how much costs have increased from one year to the next for each state for road maintenance and construction projects that have received federal highway funding. Some

[1] Not all states spent money during this time period on state mass transit projects, so only the 42 states spending money on projects were used for analysis in the DEA and Tobit models. Road lane miles are used for all three groups including mass transit service since most mass transit in the US is conducted by bus systems and since data on commuter rail line miles are not available or not aggregated at the state level. We could not find much data on rail line miles at the local municipal level either.

states have seen more rapid and higher increases in costs than others. (US Department of Transportation, FHWA 2011b). Thus, this index affects the efficiency of road provision and is treated as an input for road provision to commuters, shippers and transit riders.

For DEA outputs, the following data are used:

1. Average Time to Work in minutes for those not working at home and using Car, Truck or Van, 2007-2009 (US Census Bureau, American Community Survey, 2007-2009). Since commuting time reflects the efficiency of road provision, this data is regarded as an output for **commuters**.
2. Estimated Number of Commuters Driving Alone or Carpooling (US Census Bureau, American Community Survey, 2007-2009). This is used as an output for **commuters** and reflects the total capacity or access that states must offer to motor vehicle operators.
3. Average Time to Work in minutes for those not working at home using Mass Transit, 2007-2009 (US Census Bureau, American Community Survey, 2007-2009). Taking into account those who commute to work using the mass transit system, this data is also viewed as an output for **transit riders**.
4. Estimated Number of Mass Transit Riders (US Census Bureau, American Community Survey, 2007-2009). This is a capacity and output measure for mass **transit riders**.
5. Average Score on Estimated Trucking Congestion (1=weak, 2=moderate, 3=strong). Since most "choke points" are in the urban metropolitan areas, the average score on estimated trucking congestion is calculated primarily based on the extent of traffic jams and bottlenecks in the selected urban metropolitan areas representing the state (e.g., Detroit in the state of Michigan; Chicago in the state of Illinois; Indianapolis in the state of Indiana). Given that no statewide estimates of traffic congestion exist, we used maps showing chronic

bottlenecks in the urban metropolitan areas throughout the U.S. as the surrogate traffic congestion measure of each state (US Department of Transportation, FHWA, 2011c). Those states which had metro areas that had severe bottlenecks (often more than an hour of delays) received a score of 3, whereas those that showed no metro areas displaying bottlenecks received a score of 1. Those that displayed moderate traffic delays scored a 2. This was used as an output for **trucking shippers**.

6. <u>Ton Miles of Truck Shipment Per State in Millions</u> (US Department of Transportation, Federal Highway Administration, Freight Facts and Figures 2009 (2011d)). For **trucking shippers** this was used as an output to reflect the capacity that states have to offer to commercial shippers. This includes shipments leaving, entering, and passing through the state as well as local and within state shipments.

Since DEA constructs a production frontier based on output maximization, the reciprocals of the values for outputs 1, 3, and 5 above are used to make smaller the longer commuting or shipping times. For example, in comparing average commuting times of 10 minutes and 20 minutes as outputs, maximizing output would indicate that 20 is a better score for commuting time rather than 10, although shorter commute times are preferred to longer ones. Therefore, these outputs are transformed into 0.10 for 10 minutes and 0.05 for 20 minutes so that outputs are scaled correctly.

The descriptive statistics for the preceding input and output variables are summarized in Table 1, and the scores of the constant returns to scale (CRS) and variable returns to scale (VRS) generated by DEA for each form of travel are displayed in Tables 2, 3 and 4. CRS efficiency assumes that there is a constant or fixed increase in output for each equivalent increase in inputs. For instance, under this scale, a 10% increase in inputs should yield a 10% increase in output. VRS efficiency is slightly different from CRS efficiency in that it assumes that any increases in output due to increases in inputs are variable. For example, under this scale, a 10% increase in inputs can yield a 5%, 10%, or 20% increase in output. VRS efficiency may perhaps be a more realistic assumption for many production settings, especially those involving large economies of scale.

In examining the CRS and VRS efficiency scores in Tables 2 to 4, Hawaii is the one state that scores 1.0 either under CRS or VRS efficiency for all the three forms of transportation. Only a handful of states score a 1.0 for both CRS and VRS efficiency with regard to mass transit, and all of them are states with large urban populations with the exception of Alaska. With regard to truck shipping and commuting by car, truck or van, those states which score 1.0 under both types of efficiency are varied with regard to geographic location, degree of urbanization, and median household income. California, Florida, Mississippi, Tennessee, and West Virginia are states that score 1.0 on both types of efficiency scores for both truck shipping and commuting by car, truck, or van.

[Insert Tables 1 through 4 around here.]

To further identify the main sources of efficiency or inefficiency of road provision, we paired these DEA scores against a set of independent variables using a special form of regression analysis called Tobit regression. In general, Tobit regression is intended for analyzing continuous data that are censored, or bounded at a limiting value. The Tobit regression model is well suited to measure the transformed efficiency such as DEA efficiency scores, when dependent variables have sensible partial effects over a wide range of independent variables (see, e.g., Amemiya, 1985; Breen 1996; Wooldridge, 2006 for details of Tobit regression). A Tobit regression model assumes that the dependent variable has its value clustered at a limiting value, usually zero. But, in the DEA model that is proposed in this paper, the dependent variable is right censored at 1.0, and the model can be written in terms of the underlying or the latent variable that is mathematically expressed as:

$$y_i^* = X_i\beta + \varepsilon_i$$

and $\varepsilon_i \sim N(0,\sigma^2)$. In our sample, we observe y (=y*) only when $y_i^* < c$ (right censored). The values of Y are censored to the right at 1, and thus we need to estimate

$$E(y_i \mid y_i < c, x_i) = E(y_i \mid \varepsilon_i \le c - x_i\beta_i)$$

The probability that $\varepsilon_i \le c$ is

$$\Phi\left[\frac{c}{\sigma}\right] = \int_{-\infty}^{c/\sigma} \frac{1}{\sqrt{2\pi}} \exp(-t^2/2)dt$$

The expected value is

$$E(y_i \mid y_i < c, x_i) = x_i^{'}\beta - \sigma\frac{\phi(c)}{\Phi(c)}$$

$$= x_i^{'}\beta - \sigma\hat{\lambda}_i(c), \text{ where } c = \frac{c - x_i^{'}\beta}{\sigma}$$

It should be noted that the Tobit model accounts for truncation. A regression of the observed '*y*' values on '*x*' will lead to an unbiased estimate of β (or the independent variables). While the Tobit regression analysis does not yield a measure of variation in the dependent variable as opposed to the coefficient of determination (r-squared) in ordinary least squares regression, it does yield a log-likelihood statistic that indicates the explanatory power of the model employed, and the larger the absolute value of the log-likelihood statistic, the greater the explanatory power of a model.

The following variables were used as independent variables to predict the DEA efficiency scores for each form of travel for each state:

1. Climate. Since extreme temperatures and/or the extent of precipitation can lead to sub-optimal road provision, the state's climate is regarded as an explanatory or environmental variable (Ladd, 1992; Garcia-Sanchez, 2006). For example, the greater the precipitation, the slower the traffic movement (i.e., greater commuting or shipping time). The US National Oceanic and Atmospheric Administration provides data for average temperatures, precipitation, and other weather conditions within the US at the city level but not at the state level (NOAA 2011). Because weather can vary so much within some states, an attempt to provide such data would be very problematic, yet some attempt to account for weather variation must be made since weather (temperature and precipitation especially) is such an important factor in road construction and rehabilitation costs/expenditures. This paper used a dummy variable where northern states (northeastern, mid-western, north central and northwestern states including Alaska) were coded with a "1" and southern states (southeastern, south central, and southwestern states including California and Hawaii) were coded with a "0". This dichotomy was based mostly upon differences in precipitation and temperature, where southern states usually have warmer year round temperatures and in some cases less precipitation. This dichotomy is not perfect, but is the best that can be done absent other data. The hypothesis is that colder states with more precipitation should have lower DEA scores because of higher maintenance costs due to their having more rain, ice, and freezing weather.
2. Average of State Median Household Income, 2007-2009 (US Census Bureau, American Community Survey, 2007-2009). This is used as a proxy for a state's ability to raise the tax revenues necessary to carry out road construction and maintenance projects. In other

words, we made a premise that higher income states, *ceteris paribus,* can afford to invest more in their road infrastructure because they have better tax bases and greater financial resources (Lambert and Meyer, 2008). The state resident's income level is also highly correlated with the State Growth Domestic Product (GDP), another measure of state tax capacity. The rationale being that greater financial capacity would lead to higher efficiency scores since wealthier state residents can afford to pay more for roads.

3. Urban Population as a Percentage of the State's Population, 2009 (US Census Bureau, American Community Survey, 2007-2009). Since the majority of a state's labor force lives and works in metro areas and most trucking bottlenecks occur in metro areas according to the FHWA (US Department of Transportation, 2011c), the urban composition of a state is essential for gauging the state's road provision efficiency. The rationale being that greater urbanization is associated with greater traffic congestion, which would lead to lower DEA efficiency scores, although urbanization may provide greater economies of scale in road provision, which could lead to higher DEA scores.
4. Land Area of each state in square miles (US Census Bureau). Obviously, the larger the land mass of the state, the more it has to spend on roads, so this variable is used as a control variable that can account for road expenditures. Also, it is noted that the sheer size of the state may help to create economies of scale that can influence road provision efficiency.

Tables 5 to 7 show the results of the Tobit regression analysis used to assess the DEA scores for the three types of travel using roadways.

[Insert Tables 5 to 7 around here.]

RESULTS AND DISCUSSIONS

The results of the three different sets of Tobit models show that only two explanatory variables at the most are statistically significant at $\alpha = 0.05$ in most models. The Tobit regression models explain only small amounts of variation in the dependent variable due to the low log-likelihood scores. In Table 5, the average median household income of state residents and climate are the strongest predictors of CRS road provision efficiency with regard to car, truck or van commuters (carpooling or driving alone). Apparently, the greater the financial resources of a state resulting from a higher income tax base, the more it can spend to build and maintain road infrastructure. Additionally, warmer weather is a benefit to a state—those states in the south, southwestern and western parts of the US scored higher on CRS efficiency than other states. These factors may explain why some wealthier and warm weather states such as Hawaii, California, and Florida did relatively well on the CRS and VRS DEA scores for commuters using car, van or truck. Hawaii ranked 5th, California ranked 8th, and Florida ranked 22nd in median household income in 2007 (US Census Bureau 2009).

No variables worked well with regard to predicting commuter VRS efficiency scores. Average median household income is statistically significant at alpha = 0.10, again implying that higher income states have the resources to provide road services efficiently. VRS efficiency provides a lower threshold for a DMU to demonstrate efficiency, and so more states can attain efficiency under VRS conditions. Therefore, it is probably more difficult to pinpoint specific conditions under which VRS efficiency holds.

In Table 6, median household income is also good predictor for both types of mass transit efficiency scores. Again, this is used as a proxy for a state's tax base, and the results show that the greater this is, the more efficient transit provision is in a state. More financial resources can be used to provide greater access to those not traveling to work by motor vehicle and to try to minimize commuter congestion problems through providing mass transit alternatives. In looking back at Table 3, Georgia, Illinois, New York are among the states receiving efficiency scores of 1.0 under both CRS and VRS conditions. Although the urban population variable is not significant in either model in Table 6, each of these states has substantial rail networks to serve transit riders, and each of these states had median household rankings in the upper half of the rankings for all states with Georgia ranked 23rd, Illinois ranked 16th, and New York ranked 18th for 2007.

Next, in Table 7, climate is the only variable in the models that impacts truck shipping. The warm weather states have higher efficiency scores on average probably due to the ease of maintaining roads in parts of the country that have less cold weather and precipitation, which in turn makes it easier for goods to move easily in these area. Also, less precipitation means fewer shipping delays due to possible inclement weather which can include heavy snow during part of the year. State median household income is not a factor with regard to truck shipping efficiency unlike in the other two sets of models. Under CRS conditions, the urban population variable is statistically significant at $\alpha = 0.10$ and has a negative sign. This implies that more urbanized states are less efficient in accommodating truck shipping, all else held constant, because of their greater congestion problems.

Many public services such as road provision can gain efficiencies from the economies of scale that urban areas often provide. In our models, the percentage of a state's population that is urban had no impact on any of the efficiency scores with maybe the exception of the truck shipping CRS scores. This finding is somewhat parallel with that of an earlier study conducted by Winston and Langer (2006) which showed that road infrastructure investment in highly urbanized areas tended to be inefficient, even when the investment was made for new road construction that attempted to alleviate traffic congestion and provide greater access to motor vehicle commuters. According to Winston and Langer (2006), every dollar in urban road spending yields less than a dollar in benefits because the congestion relief is only temporary—as new roads are built to relieve traffic congestion in one part of an urban area, these new roads later become other choke points as drivers see them as good alternatives to old ways of traveling. Also, the authors believe that there will never be any way for road construction to keep up with annual increase in the total number of vehicles on the roadways. Instead, they recommended peak travel time or congestion pricing for major roadways during peak usage times, such as rush hour traffic. Such pricing could take the form of tolls with shippers probably willing to pay a little more to prevent delays. On the other hand, they suggest that exemptions to the peak load pricing, or tolls, should be granted to mass transit providers or to commuters that carpool in order to relieve traffic congestion in the urban settings.

CONCLUDING REMARKS

To the best of our knowledge, this paper is one of the first to comprehensively measure and benchmark the comparative efficiency of state road provision in the U.S., while identifying the factors (e.g., resident income, urbanization) most influential for road provision efficiency. In most of the models tested, either the greater the level of state resident income and/or the warmer the weather, the higher the road or mass transit provision efficiency on average. We also found that greater urbanization in a state provided few efficiencies with respect to road provision. This finding is contradictory to the notion that more dense development in an urban environment usually accompanies economies of scale in providing some public services such as road or mass transit provision, although some scholars point out that certain population thresholds have to be reached first before mass transit provision is viable (Hirsch, 1973 and 1984; Ladd, 1992; Carruthers and Ulfarsson, 2003; Garcia-Sanchez, 2006; O'Sullivan 2007). With regard to mass transit specifically, the population density of most US metro areas is not considered dense enough to provide enough ridership to make it economically viable unless large subsidies are provided (O'Sullivan 2007).

Overall, Hawaii is the clear benchmark after it registered perfect CRS and VRS efficiency scores of one in each category. Hawaii's success is unique in that it is isolated from the mainland, and thus its transportation access for those coming in from outside the islands is limited to a non-surface mode of transportation such as air carriers, cruise ships, and ferries. Since a lack of transportation access could undermine Hawaii's tourism industry, which is a major economic engine for Hawaii, the state government of Hawaii has made a conscious effort to properly maintain transportation infrastructure and alleviate increased traffic congestion on state and county roads and highways. These efforts include: The Statewide Transportation Improvement Program which includes the improvement of overall ground transportation services, a $20 million investment for a commuter rail project in Honolulu, and the construction of a $3.7- $6 billion rail system in Honolulu. Hawaii's success in road provision is peculiar since its budget health was ranked one of the lowest (47 out of all 50 states) and it suffered from a budget deficit of $214 million in 2011 after state tax collections dropped by 0.9% in 2010 (Zimmerman, 2011; State Budget Solutions, 2011, http://statebudgetsolutions.org/state/detail/hawaii). This finding implies that budget shortfalls alone cannot be a legitimate excuse for road provision inefficiency.

Since state income is so important to efficient road provision, the need for a continued federal role to help poorer states provide better roads and mass transit systems is verified somewhat by the results presented in this paper. Some have pointed out that some states receive less back in federal gasoline taxes collected in their jurisdictions whereas others receive more (Winston and Langer 2006), yet with income being a key to efficient state road provision, some form of redistribution by the federal government of gasoline tax revenues from wealthier to poorer states appears to be justified. Lower income states do not have the tax base to raise motor vehicle taxes and other road user fees too high in the first place in order to boost their efficiency in road provision.

This exploratory study is far from being perfect due in part to its reliance on a limited time frame (three year period) and surrogate measures extracted from secondary data available in the public domain. To overcome some of the shortcomings of this study, future research efforts can be geared toward:

- Expansion of time-series data across multiple time periods;
- Examination of both short-term and long-term effects of states' budget health, transportation budget, and highway maintenance patrols on road provision;
- Investigation of the impact of major road infrastructure developments (i.e., rapid rail systems) on road provision;
- A comparison of road provision efficiency at the international level (e.g., U.S. versus Australia).

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Table 1—Descriptive Statistics

Variable	Mean	St. Dev.
CRS Efficiency Commuters	0.854	0.117
VRS Efficiency Commuters	0.890	0.115
CRS Efficiency Mass Transit	0.356	0.326
VRS Efficiency Mass Transit	0.409	0.336
CRS Efficiency Truck Shipping	0.778	0.200
VRS Efficiency Truck Shipping	0.836	0.167
Climate	0.6	0.4949
Percent Population Urban 2009	69.62	14.2
Median Household Income, 2007-2009	$51,124	8476
Land Area of State in Square Miles	70748	85987

Inputs for DEA, Commute to Work, Mass Transit, and Truck Shipping Efficiency:

Variable	Mean	St. Dev.
Avg. Total Receipts , 2007-2009, thousands	$2,738,668	2,927,361
Avg. Total Disbursements, 2007-2009, thousands	$2,565,914	2,717,528
Total Urban and Rural Lane Miles, 2009	169,609	114,036
Avg. Receipts and Disbursements, Mass Transit, 2007-2009, thousands	$77,097.3	195,119.5
Average of Construction Cost Index, 1997-2005	146.25	40.3

Outputs for DEA, Commute to Work, Mass Transit, and Truck Shipping Efficiency:

	Mean	St. Dev.
Avg. Time to Work in Minutes for those not working at Home 2007-2009	23.35	3.5
Estimated Number of Commuters Driving Alone/Carpool, 2007-2009	2,418,522	2,552,572
Avg. Time to Work in Minutes Using Mass Transit, 2007-2009	42.47	6.81
Estimated Number of Commuters Mass Transit, 2007-2009	156,544	394,402
Avg. Score on Trucking Congestion (1=weak, 2=moderate, 3=strong)	2.06	0.89
Ton Miles of Truck Shipment Per State in Millions	42,279	38,288

Table 2—DEA Scores for Commuting to Work Using Car, Truck or Van

Inputs

Construction Cost Index Avg 1997-2005, 1987 base year prices

Avg total receipts, all sources, used for hwys 2006-2008

Avg Total Disbursements for hwys, 2006-2008

Total Lane Miles, Urban and Rural

Outputs

Reciprocal of Avg time to work * 100, car truck or van, 2007-2009

Commuters, carpool or drive alone

DMU Name	*VRS Efficiency*	*CRS Efficiency*
Alabama	0.81612	0.80806
Alaska	1.00000	0.92854
Arizona	0.88060	0.87030
Arkansas	0.86280	0.84518
California	1.00000	1.00000
Colorado	0.89391	0.88676
Connecticut	1.00000	1.00000
Delaware	1.00000	0.78872
Florida	1.00000	1.00000
Georgia	1.00000	0.99376
Hawaii	1.00000	1.00000
Idaho	0.84771	0.77110
Illinois	0.77509	0.77388
Indiana	0.82343	0.81740
Iowa	0.70423	0.69651
Kansas	1.00000	0.78562
Kentucky	0.76727	0.75020
Louisiana	0.71321	0.70099
Maine	0.74164	0.71772
Maryland	1.00000	0.96540
Massachusetts	0.95163	0.94198
Michigan	1.00000	1.00000
Minnesota	0.74259	0.74126
Mississippi	1.00000	1.00000
Missouri	0.65070	0.65061
Montana	0.66798	0.64281
Nebraska	1.00000	0.64605
Nevada	1.00000	0.91399
New Hampshire	0.85538	0.83022
New Jersey	1.00000	1.00000
New Mexico	0.85034	0.78231
New York	1.00000	0.87887

North Carolina	0.93202	0.93082
North Dakota	0.77639	0.73128
Ohio	0.97436	0.91764
Oklahoma	0.77275	0.76992
Oregon	0.82415	0.80122
Pennsylvania	0.77803	0.74880
Rhode Island	1.00000	1.00000
South Carolina	1.00000	1.00000
South Dakota	1.00000	0.93562
Tennessee	1.00000	1.00000
Texas	0.88360	0.80459
Utah	0.83939	0.79861
Vermont	1.00000	1.00000
Virginia	0.87550	0.85699
Washington	0.66119	0.66050
West Virginia	1.00000	1.00000
Wisconsin	0.92581	0.90825
Wyoming	0.73566	0.71383

Table 3—DEA Scores for Commuting to Work Using Mass Transit

Inputs	**Outputs**
Avg Total Receipts & Disbursements 2007-2009	Reciprocal of Avg Time to Work Using Mass Transit
Total Lane Miles, Urban and Rural	Commuters using mass transit (estimate)

DMU Name	*VRS Efficiency*	*CRS Efficiency*
Alaska	1.00000	1.00000
Arizona	0.12806	0.11904
Arkansas	0.13430	0.10309
California	0.23383	0.23362
Colorado	0.08272	0.07805
Connecticut	0.29492	0.26933
Delaware	0.80551	0.71537
Florida	0.75151	0.75065
Georgia	1.00000	1.00000
Hawaii	1.00000	1.00000
Idaho	0.29608	0.19939
Illinois	1.00000	1.00000
Iowa	0.39487	0.12517
Kansas	0.10808	0.10180
Kentucky	0.16705	0.07338
Louisiana	0.20073	0.17199
Maryland	0.43792	0.42515
Massachusetts	0.46747	0.46335
Michigan	0.05358	0.04590
Minnesota	0.10550	0.05683
Mississippi	0.13934	0.12030
Montana	0.16381	0.14690
Nebraska	0.16351	0.15867
New Hampshire	0.55115	0.40419
New Jersey	0.57966	0.56682
New Mexico	0.09048	0.07018
New York	1.00000	1.00000
North Dakota	1.00000	0.23373
Ohio	0.46734	0.46600
Oklahoma	0.10293	0.10130
Oregon	0.30394	0.29253
Pennsylvania	0.14485	0.14445
Rhode Island	0.70436	0.63493
South Carolina	0.13509	0.12547

South Dakota	0.37428	0.15049
Tennessee	0.08615	0.06611
Texas	0.04654	0.04385
Vermont	0.79343	0.70795
Washington	0.28103	0.27474
West Virginia	0.27254	0.24461
Wisconsin	0.13268	0.12561
Wyoming	1.00000	0.95406

Table 4—DEA Scores for Truck Shipping Efficiency

Inputs	Output
Construction Cost Index Avg 1997-2005, 1987 base year	Reciprocal Truck Freight Congestion
Avg total receipts, all sources, used for hwys. 2006-2008	Total Ton Miles of Truck Shipments
Avg Total Disbursements for hwys., 2006-2008	
Total Lane Miles, Urban and Rural	

DMU Name	*VRS Efficiency*	*CRS Efficiency*
Alabama	0.84454	0.82960
Alaska	0.95138	0.95138
Arizona	0.92199	0.83477
Arkansas	1.00000	0.99696
California	1.00000	1.00000
Colorado	0.53896	0.37444
Connecticut	0.89596	0.50625
Delaware	1.00000	0.76109
Florida	1.00000	1.00000
Georgia	0.91150	0.90374
Hawaii	1.00000	1.00000
Idaho	0.85357	0.85357
Illinois	0.87352	0.87174
Indiana	0.90884	0.89902
Iowa	0.59870	0.59870
Kansas	0.64365	0.64365
Kentucky	0.89900	0.85233
Louisiana	0.77751	0.68999
Maine	0.70118	0.70118
Maryland	0.88994	0.71663
Massachusetts	0.63533	0.38038
Michigan	0.73417	0.73318
Minnesota	0.42223	0.28715
Mississippi	1.00000	1.00000
Missouri	0.58869	0.56727
Montana	0.80862	0.80862
Nebraska	0.60524	0.60524
Nevada	0.71730	0.71730
New Hampshire	0.75251	0.75251
New Jersey	0.79830	0.61390
New Mexico	1.00000	1.00000
New York	0.55122	0.47173
North Carolina	0.75301	0.72303
North Dakota	0.86784	0.86784

Ohio	0.96704	0.96464
Oklahoma	0.96307	0.96160
Oregon	0.74500	0.65039
Pennsylvania	0.79638	0.78609
Rhode Island	1.00000	0.47949
South Carolina	0.98849	0.85182
South Dakota	1.00000	1.00000
Tennessee	1.00000	1.00000
Texas	1.00000	1.00000
Utah	0.81630	0.65818
Vermont	1.00000	1.00000
Virginia	0.98795	0.94677
Washington	0.41460	0.40948
West Virginia	1.00000	1.00000
Wisconsin	0.65799	0.65403
Wyoming	1.00000	1.00000

Table 5—Commuter Travel Efficiency Car, Truck or Van

Response Variable: CRS Efficiency Scores for Commuting by Car, Truck or Van

Predictor	Coefficient	Std. Error	Z	P-value
Intercept	0.5883	0.1274	4.6200	0.0000
Climate	-0.1274	0.0461	-2.7600	0.0060
Land Area of State in Sq. Miles	0.0000	0.0000	-1.5000	0.1340
Avg. Median Household Income, 2007-09	0.0000	0.0000	2.5400	0.0110
Pct. Pop Urban 2009	-0.0011	0.0019	-0.5700	0.5710

Log-Likelihood = 12.299

Response Variable: VRS Efficiency Scores for Commuting to Work by Car, Truck or Van

Predictor	Coefficient	Std. Error	Z	P-value
Intercept	0.5522	0.1769	3.1200	0.0020
Climate	-0.0904	0.0626	-1.4500	0.1480
Land Area of State in Sq. Miles	0.0000	0.0000	-0.4200	0.6710
Avg. Median Household Income, 2007-09	0.0000	0.0000	1.8400	0.0660
Pct. Pop Urban 2009	-0.0001	0.0025	-0.0500	0.9620

Log-Likelihood = -5.609

Table 6—Commuter Travel Efficiency, Mass Transit

Response Variable: CRS Efficiency Scores for Mass Transit

Predictor	Coefficient	Std. Error	Z	P-value
Intercept	-0.6702	0.3143	-2.1300	0.0330
Climate	-0.0625	0.1215	-0.5100	0.6070
Land Area of State in Sq. Miles	0.0000	0.0000	0.5500	0.5800
Avg. Median Household Income, 2007-09	0.0000	0.0000	2.4200	0.0150
Pct. Pop Urban 2009	-0.0003	0.0047	-0.0700	0.9450

Log-Likelihood = -16.001

Response Variable: VRS Efficiency Scores for Mass Transit

Predictor	Coefficient	Std. Error	Z	P-value
Intercept	-0.3980	0.3517	-1.1300	0.2580
Climate	0.0169	0.1358	0.1200	0.9010
Land Area of State in Sq. Miles	0.0000	0.0000	0.4000	0.6880
Avg. Median Household Income, 2007-09	0.0000	0.0000	2.2000	0.0280
Pct. Pop Urban 2009	-0.0042	0.0053	-0.7900	0.4310

Log-Likelihood = -21.447

Table 7—Truck Shipping Efficiency

Response Variable: CRS Efficiency Scores for Truck Shipping

Predictor	Coefficient	Std. Error	Z	P-value
Intercept	1.2777	0.1900	6.7300	0.0000
Climate	-0.1920	0.0690	-2.7800	0.0050
Land Area of State in Sq. Miles	0.0000	0.0000	1.3600	0.1730
Avg. Median Household Income, 2007-09	0.0000	0.0000	-0.1800	0.8590
Pct. Pop Urban 2009	-0.0049	0.0029	-1.7200	0.0850

Log-Likelihood = -2.162

Response Variable: VRS Efficiency Scores for Truck Shipping

Predictor	Coefficient	Error	Z	P-value
Intercept	0.9444	0.1514	6.2400	0.0000
Climate	-0.1457	0.0556	-2.6200	0.0090
Land Area of State in Sq Miles	0.0000	0.0000	0.0300	0.9780
Avg. Median Household Income, 2007-09	0.0000	0.0000	0.7600	0.4450
Pct. Pop Urban 2009	-0.0026	0.0023	-1.1300	0.2580

Log-Likelihood = 14.297