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Benchmarking and evaluating the comparative efficiency of urban paratransit systems in the United States: A data envelopment analysis approach

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BENCHMARKING AND EVALUATING THE COMPARATIVE EFFICIENCY OF URBAN PARATRANSIT SYSTEMS IN THE UNITED STATES: A DATA ENVELOPMENT ANALYSIS APPROACH

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ABSTRACT

The Americans with Disabilities Act (ADA) of 1990 encouraged public transit authorities to reassess the way they serve aging populations and physically-handicapped individuals requiring door-to-door services. As the demand for paratransit services rose dramatically the last few years due to a growing number of aging baby-boomers and injured Iraq-Afghanistan War veterans, many public transit authorities have been faced with the dilemma of meeting the growing demand while controlling costs in times of ongoing budget crises. To help public transit authorities better cope with such a dilemma, this paper evaluates the comparative operating efficiency of 75 selected paratransit agencies in the United States using data envelopment analysis (DEA) and then identifies the best-practice paratransit systems. Lagging paratransit agencies can use such systems as benchmark reference points to evaluate their performance against other systems. Finally this paper develops a profile of both efficient and inefficient paratransit agencies to discern a host of factors influencing the operating efficiency of paratransit systems.

INTRODUCTION

The Americans with Disabilities Act (ADA) of 1990 required each public transit agency operating a fixed route system to provide physically or mentally disabled individuals with paratransit services that are comparable to the level of services provided to the general public without disabilities (ADA Paratransit Handbook, 1992). This service requirement includes door-to-door pickup/delivery services with a fare scheme comparable to regular transit. Due to the rapid growth of aging baby boomers and disabled Iraq-Afghanistan War veterans, the demand for paratransit services is expected to rise substantially over the next few decades. In response to the increased demand for paratransit services, public transit authorities have attempted to incorporate paratransit services as an integral part of the mass-transit system. Paratransit services aim to increase the mobility in an area where existing mass-transit systems fail to satisfy the regional demand and/or the specific needs of users with disabilities (mostly handicapped or elderly people) for public transportation (Tuydes and Ozen, 2009). In general, paratransit services refer to pre-scheduled, demand-responsive public transportation services that provide curb-to-curb access for people who are unable to use fixed-route mass transit services due to their mental or physical disabilities. These disabilities include:

- Passengers who are unable to get on, ride, or get off an accessible public transit vehicle without others' help;
- Passengers who are unable to get an accessible public transit vehicle because it does not have a lift;
- Passengers who are unable to get around bus stops or subway stations on their own due to their physical or cognitive handicaps.

The important benefits of paratransit services are to: (1) increase travel choices; (2) improve mobility; (3) enhance community environments; (4) impose a market discipline on public transportation; (5) make poor neighborhoods more accessible; and (6) help stimulate advanced transportation technologies (Cervero, 1997). In contrast with the fixed route/schedule based public transportation system, paratransit is more expensive on a per-passenger basis due to its customized service requirements for user-specified origin/destination and time.

According to the American Public Transit Association (APTA), the total operating expense of paratransit services in the United States surpassed $1.2 billion with a meager $173 million collected in fares (American Public Transit Association, 2009). APTA also reported that paratransit ridership made up 2% of mass transit ridership nationwide but 13% of operating costs in 2008 (Kern, 2009). As such, controlling paratransit operating costs as well as meeting service demand remains the greatest challenge for public transit authorities and paratransit service providers.

Considering the significant impact of paratransit services on public well-being and government budgets, a growing number of regional and local government officials have attempted to find ways to improve paratransit services, while better utilizing resources (e.g., drivers, dispatchers, maintenance crews, vehicles, equipment, depots) required for paratransit services under tight budget constraints. These attempts include the assessment of past and current paratransit service quality in terms of their efficiency (e.g., greater access to paratransit services, less waiting time for paratransit services).

Since the paratransit service efficiency may hinge on the community setting (i.e., the density of housing development, urban sprawl) and municipal size, a majority of the published literature regarding public services (Kain, 1967; Real Estate Research Corporation, 1974; Ladd, 1992 and 1994; Rosen, 1992; Carruthers and Ulfarsson, 2003; Moore et al., 2005; Garcia-Sanchez 2006; O'Sullivan, 2007) has focused on the discussions of appropriate municipal size and its potential impact on the efficiency of public services such as paratransit services. For example, in densely populated urban areas, distances paratransit vehicles must travel are short, but heavy traffic can cause delays, whereas sparsely populated suburban areas may involve longer travel times.

Moore et al. (2005) argued that larger urban cities were not efficient in the provision of local public services due to public sector unionism and layers of the bureaucracy which led to decreasing returns to scale in the provision of public services. On the contrary, others such as Ladd (1992 and 1994) and Rosen (1992) contended that increasing or constant returns to scale were common for making public service delivery in large cities due to dense population settlement and good road/transportation infrastructure networks. Their rationale is that costs be spread over a large population, which usually minimizes per capita tax liabilities, despite the fact that too large of a jurisdiction in terms of population or a jurisdiction growing too quickly or with too much population density can lead to decreasing returns to scale (Carruthers and Ulfarsson, 2003; Garcia-Sanchez, 2006; O'Sullivan, 2007). In particular, Ladd (1992 and 1994) observed that metro counties exceeding a population density of 250 per square mile tended to experience diseconomies of scales for providing public safety protection. Similarly, O'Sullivan (2007) found that an upper limit of a total population of 100,000 could be a cutoff point before diseconomies appeared for some local public goods like police, fire, and schools.

In contrast with the large urban metropolitan setting, sparsely populated suburban areas pose challenges for offering adequate paratransit services because dispersed populations limit access to paratransit services. Also, limited financial resources, communication gaps, and a lack of skilled drivers in suburban or satellite city areas may compound the problem of delivering paratransit services to their residents. Thus, the small satellite city setting can adversely influence the efficiency of paratransit services.

RELEVANT LITERATURE

Despite a growing interest in paratransit services among the general public, the published literature evaluating the efficiency of paratransit services has been scant. However, some attempts have been made to assess the efficiency of paratransit services from financial or administrative perspectives. For instance, Jackson (1982) compared the real costs of service provided by major subsidized paratransit operations to that of for profit private-sector run operations in the New England region. He discovered that cost figures per passenger trip by non-profit and publicly-owned paratransit services were seriously underestimated and did not truly reflect the actual costs or the cost-efficiency of paratransit services provided.

From a different perspective, Bower (1991) investigated the impact of an automated paratransit routing/scheduling system called COMSIS on the operating cost and service quality of paratransit services. As expected, COMSIS turned out to be useful for reducing scheduling errors, reducing the cost of generating schedules, and identifying traffic patterns. Thus, Bower (1991) concluded that COMSIS improved the overall efficiency of paratransit service quality. Similarly, Chira-Chavala and Venter (1997) analyzed the impact of automated vehicle and passenger scheduling methods on the operating costs of paratransit systems. They found that such methods lowered unit paratransit transportation cost by 13%.

Further extending the earlier works of Chira-Chavala and Venter (1997), Pagano et al. (2002) assessed the impact of the computer-assisted scheduling and dispatching (CASD) systems on the service quality of paratransit services in central Illinois. They found that CASD systems allowed passengers to experience less riding time and greater on-time services at both pickups and drop-offs and subsequently enhanced their overall satisfaction with the paratransit services. On the other hand, the use of CASD to promote higher vehicle productivity resulted in slightly longer ride times. In addition, callers to the system experienced being put on hold more often. Overall, they concluded that the quality of service was positively affected by the implementation of the CASD system.

More recently, Fu et al. (2007) evaluated efficiency levels of individual paratransit systems in Canada with the specific objective of identifying the most efficient paratransit systems and the sources of their efficiency using data envelopment analysis (DEA). Through identification of the most efficient paratransit systems along with the key influencing factors such as automated scheduling methods, they developed new paratransit service policies and operational strategies for improved resource utilization and quality of services. In order to improve the efficiency of paratransit vehicle schedules, Shioda et al. (2008) proposed a computerized tool including a data mining technique that developed paratransit performance metrics reflecting the interests of paratransit stakeholders such as passengers, drivers, and municipal governments.

These performance metrics include: number of passengers per vehicle per hour, dead-heading time, passenger wait time, passenger ride time, and degree of zigzagging. This computerized tool turned out to be useful for improving the overall paratransit service quality. Though not directly tied to paratransit services, Paquette et al. (2009) conceptualized and defined quality of services in dial-a-ride operations intended for people with limited mobility. In particular, they identified various service dimensions and attributes used to measure quality of services in dial-a-ride operations. Most recently, Min (2010) developed a profile of paratransit riders and identified the key determinants of paratransit service quality.

As discussed above, a majority of these prior studies focused on the efficiency of particular paratransit systems (e.g., automated paratransit scheduling and routing) in terms of their cost saving opportunities and service deliveries. However, none of these prior studies but Fu et al. (2007) attempted to evaluate the relative efficiency of paratransit services in comparison to other public transit systems. Fu et al. (2007) employed DEA to create an overall ranking of cities according to their provision of paratransit services, yet their sample size is relatively small in assessing overall city service performances. In fact, their evaluation of paratransit services used a sample of 32 cities in Canada. Their analysis also only used three inputs (total number of paratransit employees, total fuel expenses, and total number of vehicles used for paratransit services) and a single output measurement (revenue vehicle kilometers) to benchmark paratransit services among 32 Canadian cities. Despite such shortcomings, their study is the only one to date that has attempted to measure the comparative efficiency of municipalities relative to other comparable communities with respect to paratransit services. Indeed, studies measuring paratransit service efficiency are still lacking, although there are a significant number of studies that develop benchmarks for other public services (e.g., Nolan et al., 2001; Magd and Curry, 2003; Northcott and Llewellyn, 2005; Wynn-Williams, 2005; Braadbaart, 2007; Vagnoni and Maran, 2008).

Considering the paucity of paratransit service benchmarking studies, this paper is intended to measure the relative efficiencies of 75 U.S. paratransit systems in terms of their capability to minimize paratransit costs, while handling a certain volume of paratransit service requests under multiple inputs and outputs. In addition, this paper identifies which exogenous variables, such as population size, resident profiles, housing density, and local weather conditions significantly impact the relative paratransit service efficiency of these cities.

THE DEVELOPMENT OF THE DATA ENVELOPMENT ANALYSIS MODEL

As a way of comparatively assessing and benchmarking the efficiencies of paratransit systems, this paper proposes a data envelopment analysis (DEA) model with an input-oriented ratio form under both constant returns to scale (CRS) and varying returns to scale (VRS). In general, DEA is referred to as a linear programming (non-parametric) technique that converts multiple incommensurable inputs and outputs of each decision-making unit (DMU) into a scalar measure of operational efficiency, relative to its competing DMUs. Herein, 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. DEA can be employed for measuring the comparative efficiency of any entity including paratransit systems, which has inputs and outputs and is homogeneous with peer entities in an analysis. Therefore, DEA can be applied to the wide variety of DMUs such as paratransit systems in a certain municipality without much restriction as long as DMUs satisfy the basic requirements of inputs and outputs summarized in Table 1.

DEA is designed to identify the best practice DMU without *a priori* knowledge of which inputs and outputs are most important in determining an efficiency measure (i.e., score) and assessing the extent of inefficiency for all other DMUs that are not regarded as the best practice DMUs (e.g., Charnes et al., 1978). Since DEA provides a relative measure, it differentiates between inefficient and efficient DMUs relative to each other. Due to its capability to discern inefficient DMUs from efficient DMUs, DEA can be useful for developing benchmark standards (e.g., Min et al., 2008). The proposed DEA model can be mathematically expressed as (Charnes, et al., 1978; Fare et al., 1994; Nolan et al., 2001):

Solving the above equations, the efficiency of a DMU (jp) is maximized subject to the efficiencies of all DMUs in the set with an upper bound of 1 (Min and Lambert, 2006). DEA solves a linear program for each DMU in order to calculate a relative efficiency score that measures how well each DMU uses its inputs to produce its output

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

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

$$u_r, v_i \ge \varepsilon, \qquad \forall r \text{ and } i, \qquad (3)$$

where

= 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.

when compared to the "best" DMU, which produces the greatest output using the least amount of input. Often the best DMU is a composite and may not necessarily exist, yet all DMUs are compared against the performance of this best DMU. A score of 1.0 indicates that a DMU is efficient (or matches the composite producer/DMU), whereas a score less than 1.0 indicates inefficiency (Anderson et al., 1999). A DMU with a score of 1.0 is on the frontier of a plane which relates inputs and outputs where those with a score of less than 1.0 are on the interior of the frontier.

From the paratransit system perspective, an efficiency score represents a system's ability to transform a set of inputs (given resources) into a set of outputs. Herein, the paratransit systems that were evaluated under study represent mostly city owned public/non-profit ones. For our analysis, we make the conservative assumption that the paratransit system is provided with constant returns to scale because efficiency scores based on variable returns to scale tend to raise or inflate the scores (Garcia-Sanchez, 2006).

The DEA analysis is conducted by applying the above equations to actual data of regional paratransit systems serving 75 municipalities in the US. From these data sets, two different sets of DEA scores were calculated and then regressed against a set of independent (environmental) variables using Tobit regression which expresses observed responses in terms of latent variables. 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 analyses).

In general, a Tobit regression model assumes that the dependent variable has its value clustered at a limiting value, usually zero. But, in our model, the dependent variable is right censored and the model can be written in terms of the underlying or the latent variable that is mathematically expressed as:

where å$_i$ ~ N(0,ó^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 å$_i$ d" 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

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

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

TABLE 1
INPUT AND OUTPUT VARIABLES IN THE DEA MODEL

Variables used in Data Envelopment Analysis	Mean	Standard Deviation
Outputs:		
1 Total amount of annual fare received	$1,724,745	$2,299,117
2. Annual revenue vehicle hours (in thousands)	377.9149	293.7305
3. Annual revenue vehicle miles (in thousands)	5,947.493	5,148.653
Inputs:		
1. Number of vehicles used	259.96	286.5005
2. Operating expenses	$20,757,960	$23,080,150
3. Annual passenger miles (in thousands)	7,068.223	5,067.616
4. Annual unlinked trips (in thousands)	771.908	481.0856
Variables used in Tobit Regression	**Mean**	**Standard Deviation**
Dependent variables:		
1. VRS efficiency score	0.8127927	0.17754198
2. CRS efficiency score	0.672887	0.179733
Independent variables:		
1. Density-traffic congestion index	.0007	1.00069
2. Median household income	$47,258.253	$6,171.40548
3. Percentage of residents below the poverty line	11.764121.8%	2.3246412%
4. Percentage of population aged 65 or older and disabled population	28.959463%	4.3153984%
5. Average January temperature	38.929	14.8864
Average July temperature	76.020	6.4709
6. Annual precipitation in inches	35.3439	14.00035

Thus, the Tobit model accounts for truncation. A regression of the observed 'y' values on 'x will lead to an unbiased estimate of â (or the independent variables).

DEA INPUT-OUTPUT MEASURES AND RELATED VARIABLES

Columns 3 and 4 in Table 2 shows the DEA efficiency scores of the 75 paratransit systems in terms of their total amount of annual fare revenues, annual revenue vehicle hours, and annual revenue vehicle miles given the following inputs (US National Transit Database, 2005):

- The Number of Vehicles Used by the Paratransit System. Since the number of vehicles used for paratransit services represents resources invested in the paratransit system and indicates how well these resources are utilized for paratransit operations, this measure should be regarded as an input.

- Operating Expenses. These expenses incur in carrying out the paratransit authority's day to day operations. They include driver payroll, employee benefits, pension contributions, depreciation of equipment, utilities, and vehicle repair and maintenance costs. Since these expenses can affect the paratransit authority's revenues and their subsequent service offerings, they will be regarded as one of the inputs.

● Annual Passenger Miles Driven. Route miles or a related measure have been frequently used as a way to evaluate the efficiency of mass transit systems (Viton, 1997; Nolan et al., 2001). Indeed, annual passenger miles driven by the paratransit vehicle can reflect the utilization rate of that vehicle and the subsequent paratransit efficiency. As such, we viewed annual passenger miles driven as the input.

● Annual Unlinked Trips. An annual unlinked trip refers to the number of trips made by paratransit riders on a paratransit vehicle each year, regarding each transfer between public bus routes or between bus and rail/subway as an individual trip (www.statemaster.com/.../trn_pub_tra_ann_unl_pas_tri_percap-**unlinked-passenger-trips**-per-capita). Since paratransit riders are counted each time they board paratransit vehicles no matter how many vehicles they use to make a trip from their origin to destination, annual unlinked trips should be regarded as an input regardless of whether an individual fare is collected for each leg of trip.

Both CRS (constant returns to scale where inputs are assumed to be infixed proportions, e.g., each bus has the same operating expense) and VRS (variable returns to scale, e.g., operating expenses are allowed to vary per bus) efficiency scores were then used as dependent variables in a Tobit regression and regressed against the following independent variables, which are also used to identify factors significantly influencing the paratransit efficiency.

● Density-Congestion Index. Since traffic congestion increases vehicle travel time, it can cause the delay of paratransit services and thus increase fuel consumption of the paratransit vehicles. If this is correct, we can expect an inverse relationship between the extent of traffic congestion and average paratransit operating efficiency in terms of paratransit vehicle run times and utilization, everything else held constant. On the other hand, greater population and housing density decrease commuting time for drivers. If this is correct, then we can expect a positive relationship between density and paratransit efficiency, everything held constant. It should be noted that this index is not readily available from the published sources. As a surrogate measure, we developed this index by combining the distance-weighed population/housing density with a percentage of residents who spent 30 minutes or more for their daily commutes through factor analyses.

● Median Household Income. This is used as a proxy for a municipality's ability to adequately fund a paratransit system. In other words, we made a premise that higher income cities, *ceteris paribus*, can afford to better support their paratransit systems because they have better tax bases and greater financial resources (Lambert and Meyer, 2008).

● Percentage of Household below the Poverty Line. Min (2010) discovered that a vast majority (more than 80% of his surveyed respondents) of the paratransit riders were people who were well below the federal poverty threshold (annual income less than $10,830 for one-person household; $14,570 for two-person household). That is to say, the paratransit system has become an important means of transportation for low-income people who cannot afford to use other more expensive means of transportation. As discussed above, since the concentration of low-income residents can influence the utilization of paratransit services, a percentage of the households below the poverty line in the municipality may be used as a proxy for the municipality's ability to better utilize the paratransit services and its subsequent paratransit operating efficiency.

● Percentage of Population aged 65 or older and Disabled Population aged 5 or older in the Municipality. Min (2010) found that nearly half

TABLE 2.
EFFICIENCY SCORES OF PARATRANSIT SERVICES IN MAJOR U.S. MUNICIPALITEIS USING DEA

DEA Efficiency Scores

No. City	Input- oriented variable return to scale (VRS) efficiency	Input-oriented constant-to return scale (CRS) efficiency	RTS Score	Input-Oriented RTS
1 Allentown, PA	0.73711	0.51211	0.57795	Increasing
2 Atlanta, GA	0.96707	0.75047	0.51930	Increasing
3 Austin, TX	0.74393	0.58357	0.40614	Increasing
4 Baltimore, MD	0.79504	0.78890	0.89731	Increasing
5 Barnstable Town, MA	1.00000	0.64835	0.40305	Increasing
6 Boston, MA	0.96480	0.75929	2.21786	Increasing
7 Bremerton, WA	0.71403	0.38818	0.31503	Increasing
8 Charlotte, NC	1.00000	0.60358	0.38518	Increasing
9 Chicago, IL CTA	1.00000	0.59768	3.11619	Increasing
10 Chicago, IL Pace	1.00000	0.67708	2.99027	Decreasing
11 Cleveland, OH Laketran	0.84862	0.53270	0.37114	Increasing
12 Cleveland, OH GCRTA	0.71273	0.51671	0.44178	Increasing
13 Dallas, TX ATC/VANCOM	0.73426	0.70944	1.21076	Decreasing
14 Dallas, TX Fort Worth	1.00000	0.83730	0.33127	Increasing
15 Daytona Beach, FL	1.00000	0.82222	0.75489	Increasing
16 Denver, CO	0.66524	0.64624	1.23626	Decreasing
17 Detroit, MI	1.00000	1.00000	1.00000	Constant
18 Flint, MI	0.58047	0.55732	0.75478	Increasing
19 Florence, SC	1.00000	1.00000	1.00000	Constant
20 Grand Rapids, MI	0.81879	0.44402	0.44572	Increasing
21 Hartford, CT	0.61661	0.52206	0.69368	Increasing
22 Honolulu, HI	0.50435	0.49820	0.90571	Increasing
23 Houston, TX	0.88308	0.60071	2.10770	Decreasing
24 Indianapolis, IN	0.98281	0.62199	0.45404	Increasing
25 Jacksonville, FL	1.00000	1.00000	1.00000	Constant
26 Kansas City, MO	0.76288	0.33157	0.32894	Increasing
27 Kennewick, WA	0.58204	0.40949	0.38195	Increasing
28 Lancaster, PA	0.95469	0.51862	0.34182	Increasing
29 Lansing, MI	0.77687	0.53058	0.40638	Increasing
30 Las Vegas, NV	0.59370	0.59342	0.98963	Increasing
31 Leominster, MA	0.66914	0.65845	0.94434	Increasing
32 Los Angeles, CA Access	1.00000	0.71126	3.11116	Decreasing
33 Los Angeles, CA LA DOT	0.49739	0.49569	0.81620	Increasing
34 Los Angeles, CA LACMTA	0.40586	0.40466	0.92469	Increasing
35 Los Angeles, CA OCTA	0.78857	0.69069	1.60731	Decreasing

36 Louisville, KY	1.00000	1.00000	1.00000	Constant
37 Madison, WI	1.00000	0.47732	0.31115	Increasing
38 Miami, FL Advanced Trans	1.00000	0.85629	1.88899	Decreasing
39 Miami, FL Board of County	1.00000	0.95648	1.50529	Decreasing
40 Miami, FL Broward County	1.00000	0.81280	2.11858	Decreasing
41 Milwaukee, WI	0.48061	0.44533	1.20009	Decreasing
42 Minneapolis, MN Mobility	0.78736	0.72561	1.39856	Decreasing
43 Minneapolis, MN Metro Tran	0.46856	0.41717	0.82278	Increasing
44 New York, NY American Tran	0.94294	0.93000	1.21959	Decreasing
45 New York, NY Atlantic Tran	1.00000	0.96411	1.73681	Decreasing
46 New York, NY MTA	1.00000	0.80962	0.65197	Increasing
47 New York, NY NYCT	1.00000	1.00000	1.00000	Constant
48 New York, NY NJ Transit	0.71872	0.67501	1.39505	Decreasing
49 Orlando, FL	0.81430	0.80970	1.04221	Decreasing
50 Palm Bay, FL	0.71780	0.67084	0.91940	Increasing
51 Philadelphia Delaware Count	0.75081	0.74918	1.02637	Decreasing
52 Philadelphia SEPTA	1.00000	0.72521	2.88384	Decreasing
53 Phoenix, AZ	0.74895	0.72349	0.79450	Increasing
54 Pittsburgh, PA	1.00000	0.61521	2.73780	Decreasing
55 Port Huron, MI	1.00000	0.84664	0.38497	Increasing
56 Portland, OR	0.54401	0.52130	1.27007	Decreasing
57 Providence, RI	0.67493	0.67251	0.90932	Increasing
58 Riverside, CA	0.65850	0.61469	0.52816	Increasing
59 Sacramento, CA	1.00000	0.72908	0.44889	Increasing
60 Salt Lake City, UT	0.73903	0.68685	0.75275	Increasing
61 San Antonio, TX	0.60450	0.60441	0.93101	Increasing
62 San Diego, CA	0.61210	0.48058	0.59563	Increasing
63 San Francisco, CA Vanc.	0.68373	0.68129	1.04545	Decreasing
64 San Francisco, CA ATC	0.52083	0.41320	1.36381	Decreasing
65 San Fran., CA San Mateo Cty	0.97428	0.75300	0.50291	Increasing
66 San Jose, CA	0.59798	0.59246	1.26706	Decreasing
67 Seattle, WA King County Metro	0.58737	0.46390	2.00364	Decreasing
68 Seattle, WA Pierce	0.77437	0.51806	0.41023	Increasing
69 Spokane, WA	0.71290	0.48830	0.43658	Increasing
70 Springfield, MA	0.85733	0.58661	0.52775	Increasing
71 St. Louis, MO	0.85103	0.84853	0.52873	Increasing
72 Tucson, AZ	0.83643	0.63902	0.54830	Increasing
73 Wash., DC Montgomery Cty	1.00000	1.00000	1.00000	Constant
74 Washington, DC WMATA	1.00000	1.00000	1.00000	Constant
75 Wichita, KS	1.00000	1.00000	1.00000	Constant

TABLE 3
A SUMMARY OF RESULTS FROM THE TOBIT REGRESSION ANALYSES

Predictors	Model 1	Model 2
	Dependent Variable: CRS Efficiency Score	**Dependent Variable: VRS Efficiency Score**
Density-traffic congestion index	0.0695518** (p=0.000)	0.0536784* (p=0.075)
% of senior or disabled population	0.0111974**(p=0.016)	0.0194661** (p=0.008)
Average temperature	0.0364899* (p=0.070)	0.051167 (p=0.860)
Intercept	0.3561404* (p=0.070)	0.3032459 (p=0.150)
Log-Likelihood Ratio	14.102	-18.186
Pseudo r^2	0.28	0.27

Note: *Statistically significant at á = 0.10
**Statistically significant at á = 0.05

of his surveyed paratransit riders were senior citizens. Also, given that paratransit services are intended for physically and mentally handicapped individuals, it makes sense that we consider the potential relationship between the paratransit operating efficiency and its users' profiles in terms of senior citizenship and disability status.

- Average January and July Temperatures. Since extreme temperatures can lead to sub-optimal provision of certain municipal services such as paratransit services, it is regarded as an explanatory or environmental variable (Ladd, 1992; Moore et al., 2005; Garcia-Sanchez, 2006).

- Annual Precipitation in Inches. Holding other things constant, the greater the precipitation, the slower the average paratransit service response time and the more difficult it is to complete a greater number of vehicle runs (Moore et al., 2005). In particular, during winter times, snow removal could delay passenger pickup/delivery processes and subsequently increase vehicle travel times. In other words, large precipitation may lead to lower paratransit efficiency scores.

RESULTS AND DISCUSSION

These six independent variables were examined to see if they significantly affected the paratransit efficiency. As a paratransit efficiency measure, we considered both CRS and VRS efficiency scores. In other words, both CRS and VRS efficiency scores were used as dependent variables. The initial results of a Tobit regression model show that median household income, percentage of household below the poverty line, and annual precipitation did not significantly influence either CRS or VRS efficiency. On the other hand, the final results of a Tobit regression analysis recapitulated in Table 3 shows that the density-congestion index, percentage of senior citizens and disabled population, and temperature turned out to be significant independent variables ($p < .10$) for either Model 1 (with CRS efficiency) or Model 2 (with VRS efficiency). Correlation coefficients of these independent variables summarized in Table 3 indicates that the traffic congestion index, percentage of senior citizens and disabled population, and temperature positively influence paratransit efficiency.

To elaborate, the more densely settled the area and the more congested the traffic, the better the paratransit efficiency. This finding is somewhat surprising in that we expected an inverse relationship between density-congestion and paratransit efficiency. This unexpected result may be explained by the fact that a congested area happens to be the downtown area where many paratransit riders are concentrated and thus pickup/drop-offs of those riders require short vehicle miles. In other words, the more dense the rider population, the higher the efficiency score for a municipality's paratransit systems. This tendency has been observed by earlier urban economics studies conducted by Kvalseth and Deems (1979) and Lambert and Meyer (2006, 2008). Steele (1993) also suggested that population clusters could improve the quality of public services such as paratransit services.

The percentage of the population 65 years or older combined with the percentage of the population 5 years and over who report at least one disability is a good predictor of paratransit efficiency. Temperature works well in Model 1, but not in Model 2.

Table 2 shows both CRS and VRS efficiency scores in terms of total amount of annual fare revenues, annual revenue vehicle hours, and annual revenue vehicle miles for the municipality as the outputs. These output variables measure how well paratransit vehicles were utilized in generating revenues. The best performing municipalities with respect to both CRS and VRS efficiency scores are Detroit, Michigan; Florence, South Carolina; Jacksonville, Florida; Louisville, Kentucky; New York, New York; Washington, DC; and Wichita, Kansas. This result is somewhat surprising in that none of these cities are known to be either retirement communities or magnets for senior citizens. However, it should be noted that with an exception of Washington DC, most of these cities such as Detroit, Florence, Jacksonville, Louisville, and New York have relatively large percentages of senior citizens over 65 years old and persons with disabilities (e.g., 29.10% for Detroit; 33.64% for Florence; 29.72% for Jacksonville; 30.86% for Louisville; 31.13% for New York). In contrast, Los Angeles, California; Milwaukee, Wisconsin; Minneapolis, Minnesota performed poorly by registering the CRS and VRS efficiency scores below 0.50. As expected, these cities have relatively low percentages of senior citizens and persons with disabilities (e.g., 27.70% for Los Angeles; 27.84% for Milwaukee; 22.29% for Minneapolis).

In order to achieve efficiency, a paratransit system probably needs a critical number of threshold number or percentage of clients to serve, so perhaps a threshold of 30% of the population being 65 years or older and/or disabled is necessary for efficient operations and economies of scale. Also, we found that many west-coast cities such as Portland, Oregon; San Francisco, California; San Jose, California; San Diego, California; Seattle, Washington tended to perform poorly as compared to east-coast cities such as New York, New York; Boston, Massachusetts; Miami, Florida, which typically had more senior citizens on average than other cities.

CONCLUSIONS AND IMPLICATIONS

This paper is one of the first to comprehensively measure and benchmark the comparative efficiency of paratransit systems in U.S. municipalities using DEA analysis, while identifying the factors (e.g., city size, resident income) most influential for paratransit service efficiency. DEA is a technique that helps public policy makers identify lagging paratransit systems with respect to various performance standards (e.g., vehicle utilization, return-on-investment of financial resources) and then highlight the specific aspects of paratransit performances that should be strengthened to further improve their efficiency. In all the DEA models tested, the greater the extent of density-congestion of a city, the more efficient the paratransit operation. However, we found that the overall size of a city has no bearing on the paratransit efficiency. Congruent with O'Sullivan's assertion (2007), mega cities exceeding populations of several million, such as Los Angeles, San Francisco, San Diego, and Seattle, did not produce high efficiency scores for their paratransit systems in terms of both CRS and VRS efficiencies.

On the other hand, mega cities such as New York and Detroit were considered to be benchmarks for others to meet. Thus, the economies of scale alone did not seem to dictate the paratransit efficiency. Especially, an intriguing observation that we made is the full efficiency of the Detroit paratransit system which endured a series of more severe budget cuts. Somewhat ironically, its lack of resources created a sense of urgency for their better utilization and then might have helped the paratransit authority streamline its operations.

Also, the findings of the Tobit regression models suggest that cities with densely populated downtown areas, less geographically dispersed, and East Coast/Midwestern cities with greater percentages of senior citizens and persons with disabilities tend to be more efficient in offering paratransit services than the other cities such as those on the West Coast. As noted earlier, more dense development usually accompanies economies of scale in providing public services to a certain extent (Hirsch, 1973 and 1984; Ladd, 1992 and 1994; Carruthers and Ulfarsson, 2003; O'Sullivan, 2007; Rosen, 1992; Garcia-Sanchez, 2006). Examples of public policies to encourage dense development within a city include: establishment of urban growth boundaries; assessment of higher impact fees for the development of remote neighborhoods; limitation of building permits only to existing neighborhoods or areas next to existing neighborhoods ("fill-in" development); and enactment of zoning laws which forbid new development until certain population densities are achieved in existing areas or neighborhoods of the cities.

When it comes to multiple paratransit systems in a given city, the cities with multiple paratransit systems tended to perform poorly. For example, Los Angeles, Minneapolis, San Francisco, Seattle, and Cleveland with multiple paratransit systems registered DEA efficiency scores well below 1. The only exception is the New York metro area which has five different paratransit systems, but other than the New Jersey transit system all four performed relatively well. The possible rationale being that, despite its separate paratransit systems, its unified government often shares resources among themselves. Another case in point is that benchmark cities such as Detroit, Florence, Jacksonville, Louisville, and Wichita have single paratransit systems. Perhaps, single paratransit authority or unified city governments are meant to attain paratransit efficiency by reducing paratransit service duplications and exploiting economies of scale.

For public policy purposes, and when it comes allocating resources, federal and state governments should reward and develop those paratransit systems that have large target populations (around 30% or more elderly and disabled) and that serve densely settled areas (a population per square mile of at least 7,000 on average). More emphasis nowadays seems to be placed on encouraging city planners and local governments to develop less sprawled and denser urban environments which can increase the efficiency of some public services including paratransit services. Therefore, federal and state governments should sustain policies that encourage denser local development to enhance the efficiency of paratransit services.

Regarding lagging paratransit systems whose financial and human resources were not fully utilized, public policy makers need to consider either outsourcing their operations to private companies or streamlining their operations by creating a separate taskforce that can dedicate its efforts to the continuous improvement of paratransit efficiency.

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