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Efficiency, Effectiveness, and Management Characteristics of Rural Local Bus Services in the U.S.

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Abstract

This paper conducts semiparametric analysis of service production efficiency and service effectiveness of U.S. rural bus services, using network data envelopment analysis (NDEA) and censored regression. Production efficiency is measured by the ratio of the service provided to the resource inputs, and service effectiveness is measured by the ratio of the service consumed to the service provided. The analysis finds strong scale economies in production efficiency, while service effectiveness peaks at annual vehicle revenue hours of approximately10,000. Operators with smaller service areas have lower production efficiency because of lack of capacity, while their service effectiveness is higher due to their compact network and local knowledge. Moreover, operators in states with regional transportation planning organizations perform better than operators in states without such organizations, particularly in service effectiveness. Private operators are not performing well compared to public operators, even in production efficiency. The assessment indicates regional coordination ensures services are scaled to achieve both high production efficiency and high service effectiveness. The analysis also demands revisiting contracting schemes with private operators to improve their performance.

JEL Classification: R49, H83, M11, M38, N72
Key words: Rural transit; bus; efficiency; effectiveness; data envelopment analysis

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1. INTRODUCTION

Most public transit services in the U.S. are operated or subsidized by various levels of government. The use of public money demands objective assessment of the service performance because subsidies should be provided at the minimum required level for socially desirable services. In particular in the U.S., the Moving Ahead for Progress in the 21st Century Act (MAP-21) requires an outcome-driven, performance-based approach to decision-making processes for transportation projects in the states and metropolitan areas. Currently, the MAP-21 requirements to public transit systems are limited to asset management and safety issues. However, to set a baseline for state of practice, comprehensive performance evaluation systems for transit should be proactively prepared and strategically developed from there.

Transit performance measures are typically designed to capture two important dimensions of transit systems: efficiency and effectiveness (Fielding, 1987, Chapter 4). Efficiency is measured by comparing the volume of service provided with the resource inputs. It assesses whether the operator is making the best use of resources. Effectiveness measures consumption of transit services to evaluate social impacts of the services.

This paper examines production efficiency and service effectiveness of rural bus services in the U.S. because these services are socially important and heavily subsidized, yet insufficiently studied. Although most rural residents own and drive private automobiles in developed countries, some individuals are incapable of or cannot afford driving (National Household Travel Survey, 2009; Stommes and Brown, 2002). Rural public transit provides those transportation disadvantaged people essential access to daily needs, and are important for addressing social justice of the region (Farrington and Farrington, 2005). Moreover, rural industries, such as tourism and recreation, demand public transit service to support visitors' mobility and to provide access to low-skilled workers in surrounding regions (Brown, 2004).

Despite the importance of public transit to local rural economies and communities, low land-use density and dispersion of rural travel destinations makes it difficult to operate in these areas. In the U.S., the service coverage has declined substantially after the Bus Regulatory Reform Act of 1982, leaving many rural counties without transit services (Stommes and Brown, 2002). Remaining non-urbanized services depend heavily on subsidies, such as Section 5311(f), Transportation for Other than Urbanized Area grants.

Efficiency and effectiveness of rural local transport has attracted much less research attention than it deserves (Keeling, 2009). Literature about transit efficiency and effectiveness focuses on urban transit (Chu et al. 1992 and Karlaftis, 2004 for example), due in part to limited data availability for rural bus transit services. In the U.S., the National Transit Database (NTD) has collected urbanized transit service data since the 1980s. However, NTD rural reporting started only in 2006, and became consistent and available beginning in 2007. Moreover, the data reporting requirement is less rigorous for rural transit than for urban transit, which discourages researchers from focusing on rural transit.

The assessment employs semiparametric approach. First, efficiency of each transit service is evaluated based on network data envelopment analysis (NDEA) to evaluate overall performance of the rural bus transit, including both production efficiency and service effectiveness. Due to a data issue (described in section 3.1), the efficiency scores are calculated in the six-year pooled data, not by year. Then, Tobit regression is conducted to assess whether the differences in organization and service area have any association with operator performance calculated in the first stage. In the second stage, we use a panel data of operators and conduct a Tobit regression with individual operator random-effects.

2. METHODS AND FACTORS OF PERFORMANCE MEASURE

2.1 Data Envelopment Analysis in Public Transportation Performance Evaluation

Three types of performance measures have been developed extensively in the literature: performance indicators (PIs), stochastic frontier analysis (SFA), and data envelopment analysis (DEA). The most commonly and historically used measure is the PIs because it is simple and intuitive (Fielding et al. 1978, Meyer and Gomez-Ibanez, 1981, for example). However, using multiple PIs to measure transit performance often leads to contradictory conclusions, depending on the choice of indicators (Benjamin and Oden, 1990). The second measure, SFA, is a parametric approach to obtain a production frontier. SFA employs a specific functional form to assess production frontier, and it allows inefficiency of the operator compared to its own frontier rather than compared to a peer group. SFA is often considered to be inappropriate in transit performance analysis because the assumptions in functional form and error term distribution may be inappropriate (Charnes et al. 1996; Karlaftis and Tsamboulas, 2012, for example). Moreover, SFA allows only one output for the analysis, which makes it difficult to capture multiple dimensions of transit services.

Given the limitations of PIs and SFA, DEA attracts research attention in the analysis of performance evaluation because (1) it provides a single efficiency indicator, (2) it allows analyzing multiple inputs and outputs simultaneously, and (3) it is a nonparametric approach that does not require assumptions about functional form. DEA is developed by Farrell (1957), Charnes, Cooper, and Rhodes (1979), and Banker, Charnes, and Cooper (1984). It evaluates relative performance of each decision-making unit (DMU) by comparing its input-output ratio to production frontier composed by the best-performing DMUs. Efficiency measures may follow either constant returns to scale (CRS) or variable returns to scale (VRS) assumption.

The original DEA does not account for mechanisms of production. However, recent developments in NDEA, which is stylized by Färe and Grosskopf (2000), enable researchers to take into account the multiple production processes in the efficiency analysis. NDEA has evolved from a simple two-stage structure to a more complex structure. It relates efficiency measures of each process and the system as a whole, and reduces bias that occurs when the efficiency of each stage is measured independently (Kao, 2014).

Ample preceding research uses the DEA approach to analyze efficiency and effectiveness of public non-rural transit (see Chu, Fielding, and Lamar, 1992; Karlaftis, 2004; Yu and Lin, 2008; and Barros and Peypoch, 2010 among others), and an increasing number of studies assess transit performance using NDEA. The focus of the analysis includes returns to scale of the system (Odeck, 2003), productivity change over time (Barros and Peypoch, 2010; Viton, 1998), effects of subsidies on transit performance (Karlaftis and McCarthy, 1998), structure of transit institutional systems including privatization (Sampio, Neto, and Sampaio, 2008), efficiency of transit operators with respect to multiple types of services (Yu and Fan, 2009), and region-wide transit system efficiency (Barnum, Karlaftis, and Tandon, 2011). NDEA is preferred when researchers try to analyze transit firms with more complex production structures (Sheth, Triantis, Teodorović, 2007; Yu and Fan, 2009; Yu, 2008, among others), or combine production and consumption efficiencies in the performance evaluation (Kao, 2009; Yu and Chen, 2011; Yu and Lin, 2008).

2.2 Analyzing Efficiency and Effectiveness of Rural Bus Services in the U.S.

Transit service consists of service production and service consumption processes, and each process corresponds to the concepts of efficiency and effectiveness (Fielding, 1987, Chapter 4). Production efficiency is measured by determining the quantity of resource inputs required to generate the service volume. Typically, capital, labor, and fuel are considered as input factors, and vehicle revenue hour or vehicle revenue mile are considered as output factors (Fielding, 1987). Service effectiveness is evaluated by determining the proportion of the produced transportation service consumed by passengers. Most research employs vehicle revenue hour or vehicle revenue mile as a measure of supply, and the number of passengers or the number of unlinked passenger trips as a measure of consumption (Chu, Fielding, and Lamar, 1992; Karlaftis and Tsamboulas, 2012; Yu and Fan, 2009, among others).

To the extent of our knowledge, empirical research on transportation services focuses on urban areas or on large-scale inter-city systems, not on services in rural areas. Notably, any investigation of rural transit performance must consider the effects of institutional design, which includes factors not present in most urban areas. In the U.S. metropolitan areas, the spatial boundary of the transportation management area is determined by commuting patterns, and each metropolitan area has a metropolitan planning organization, which plans and manages transportation issues. In contrast, non-metropolitan areas (i.e., rural areas) are not required to have a regional transportation planning organization (RTPO). In states without RTPOs, departments of transportation (DOTs) have historically managed transportation issues in rural areas. Even if RTPOs exist, their organizational structures vary by state, and their spatial unit for management is defined arbitrarily because there is no obvious boundary such as a commuting shed. As a result, the spatial scale of the organization may not be appropriate, which, in turn, may affect the service provided.

3. MODEL AND DATA

3.1 Data and Analytic Approach

The data for the analysis is taken from the rural module of national transit database (RNTD) from 2007 to 2012. The RNTD summarizes the annual reports from recipients of Other than Urbanized Area Formula Program. Recipients are state DOTs, Indian tribes, and Alaska Native villages that receive the grants directly from the federal government. All the organizations that receive the grants indirectly and operate transit services are called sub-recipients. Sub-recipients are roughly categorized by whether they provide inter-city service. We focus on non-intercity service operators because intercity bus service providers report fewer data items than non-intercity services do.

Although RNTD is expected to cover existing rural transit services, it has three weaknesses in data availability. First, not all of the sub-recipient information is reported every year. This is particularly an issue in considering production frontier shift over the performance period because production frontier may easily shift by adding or removing observations. Second, operating cost is aggregated into one category, making it impossible to distinguish specific costs for vehicle operation labor, maintenance, fuel, or administration. Third, operating cost is summarized by sub-recipient, which means that there is no breakdown of operating cost by mode even if the sub-recipient operates multiple modes of transit services.

Given the data limitations, this paper conducts NDEA for the pooled data and performs semi-parametric analysis with year fixed effects to compare performance variations by year. This paper does not calculate efficiency score separately by year or conduct a Malmquist index analysis because lack of observations, as stated earlier, may contaminate the result substantially. With regard to observations included in the analysis, this paper focuses on sub-recipients who operate only scheduled, not on-demand, bus services to avoid cost allocation issues. We employ vehicle stock and aggregated operating costs as service inputs, and both revenue vehicle hour (RVH) and revenue vehicle mile (RVM) as intermediate measures (service output). Although usually either RVM or RVH is employed, with stronger preference to RVM, we posit that RVM and RVH should be considered separately. Employing RVM and dismissing RVH will place more value on inter-regional services with faster service speed than on local services with slower service speeds.

3.2 Methodology

Methodologically, this paper employs a relational model of the simple two-stage NDEA, following Kao and Hwang (2008, 2011) and Chen et al. (2013). Simple two-stage NDEA assumes that the process consists of two stages, and the products of the first stage are the only inputs of the second stage. In the analysis of public transit operation, the first stage corresponds to transit service production, and the second stage corresponds to the service consumption.

Consider N decision making units (DMUs), each of which has a simple two-stage structure. Let X_{ij}, Z_{dj}, and Y_{rj} denote ith original input (i = 1, …, m), dth intermediate measure (d = 1, …, D), and rth final output (r = 1, …, s) of DMU_j, respectively. Under the constant return to scale (CRS) assumption, a ratio form system efficiency (E^S_0) of DMU_0, divisional efficiency for stage 1 (E^1_0), and divisional efficiency for stage 2 (E^2_0) are defined as follows;

$$E_0^1 = \max \frac{\sum_{d=1}^{D} w_d Z_{d0}}{\sum_{i=1}^{m} v_i X_{i0}} \quad \text{and} \quad E_0^2 = \max \frac{\sum_{r=1}^{s} u_r Y_{r0}}{\sum_{d=1}^{D} \widetilde{w}_d Z_{d0}}$$

$$\text{s.t.} \quad \frac{\sum_{d=1}^{D} w_d Z_{dj}}{\sum_{i=1}^{m} v_i X_{ij}} \le 1 \qquad (1)$$

$$\frac{\sum_{r=1}^{s} u_r Y_{rj}}{\sum_{d=1}^{D} \widetilde{w}_d Z_{dj}} \le 1$$

$$u_r, v_i, w_d, \widetilde{w}_d \ge \varepsilon, \quad j = 1, \dots, N$$

where v_i, u_r, w_d, $\widetilde{w}_d$ are virtual multipliers and ε is a non-Archimedean number. In a relational model, the variables w_d are set equal to $\widetilde{w}_d$ so that two-stage system-wide efficiency can be defined as $E^1_0 * E^2_0$, which is equal to $E_0^S = \frac{\sum_{r=1}^{s} u_r Y_{r0}}{\sum_{i=1}^{m} v_i X_{i0}}$ (Kao and Hwang, 2008; Kao and Hwang, 2011; and Chen et al., 2013).

The system-wide efficiency E^S_0 can be calculated by following the linear program;

$$E_0^S = \max \sum_{r=1}^{s} u_r Y_{r0}$$

$$\text{s.t.} \quad \sum_{r=1}^{s} u_r Y_{r0} - \sum_{d=1}^{D} w_d Z_{d0} \le 0 \qquad (2)$$

$$\sum_{d=1}^{D} w_d Z_{d0} - \sum_{i=1}^{m} v_i X_{i0} \le 0$$

$$\sum_{i=1}^{m} v_i X_{i0} = 1$$

After the calculation of system efficiency, divisional efficiencies can be obtained by decomposing system efficiency (Kao and Hwang, 2008). The combination of E^1_0 and E^2_0 may not be unique. The uniqueness can be tested by comparing maximum and minimum achievable values of the combination (Liang et al. 2008). Maximum achievable value of E^1_0 (E^{1+}_0) can be obtained by

$$E_0^{1+} = \max \sum_{d=1}^{D} w_d Z_{d0}$$

$$\text{s.t.} \quad \sum_{r=1}^{s} u_r Y_{r0} = E_0^S \qquad (3)$$

$$\sum_{r=1}^{s} u_r Y_{r0} - \sum_{d=1}^{D} w_d Z_{d0} \leq 0$$
$$\sum_{d=1}^{D} w_d Z_{d0} - \sum_{i=1}^{m} v_i X_{i0} \leq 0$$
$$\sum_{i=1}^{m} v_i X_{i0} = 1$$

The maximum value of process 1 CRS stage efficiency (E^{1+}_0) provides the minimum value of process 2 CRS stage efficiency (E^{2-}_0), which is given by $E^{2-}_0 = E^S_0 / E^{1+}_0$. Using the same method as above, maximum value of E^2_0 (E^{2+}_0) can be calculated. And in turn, the minimum value of E^1_0 (E^{1-}_0) can be calculated as $E^{1-}_0 = E^S_0 / E^{2+}_0$. If E^{1+}_0 is equal to E^{1-}_0, E^{2+}_0 is equal to E^{2-}_0. In such cases, the combination of E^1_0 and E^2_0 is uniquely determined. If E^1_0 and E^2_0 are not uniquely determined, Kao and Hwang (2008) propose to prioritize one of them in maximization, depending on which process is more important.

Kao and Hwang (2011) proposed a method to calculate efficiency under the variable return to scale (VRS) condition, that is, a method that decomposes CRS efficiencies into technical efficiencies and scale efficiencies. Let $T_0^S, T_0^1,$ and T_0^2 denote technical efficiencies of the whole system, stage 1, and stage 2 (efficiencies under VRS condition). And let $S_0^S, S_0^1,$ and S_0^2 denote scale efficiencies of the whole system, stage 1, and stage 2. As in the conventional DEA, scale efficiencies are defined as the ratio of technical and system efficiencies (i.e., $S_0^1 = T_0^1/E_0^1$ and $S_0^2 = T_0^2/E_0^2$, the first stage efficiencies are input-oriented and the second stage efficiencies are output-oriented). The technical and scale efficiencies of the system are the products of process efficiencies ($T_0^S = T_0^1 * T_0^2$ and $S_0^S = S_0^1/S_0^2$), which is consistent with the idea of a relational model.

Input-oriented VRS technical efficiency of stage 1 is calculated using a multiplier model, following Kao and Hwang (2011).

$$T_0^1 = \max \sum_{d=1}^{D} \widehat{w}_d Z_{d0} - \widehat{w}_0$$
$$\text{s.t.} \quad \sum_{i=1}^{m} v_i X_{i0} = 1$$
$$\sum_{d=1}^{D} \widehat{w}_d Z_{d0} - \widehat{w}_0 - \sum_{i=1}^{m} v_i X_{i0} \leq 0$$
$$\sum_{r=1}^{s} u_r Y_{rj} - E_0^S \sum_{i=1}^{m} v_i X_{ij} = 0 \qquad r = 1,\ldots, s \qquad (4)$$
$$\sum_{d=1}^{D} w_d Z_{dj} - \sum_{i=1}^{m} v_i X_{ij} \leq 0 \qquad j = 1,\ldots, \mathrm{N}$$
$$\sum_{r=1}^{s} u_r Y_{rj} - \sum_{d=1}^{D} w_d Z_{dj} \leq 0$$
$$v_i, w_d, \widehat{w}_d, u_r \geq \varepsilon, \quad i = 1, \ldots, m, \quad d = 1, \ldots, D, \quad r = 1, \ldots, s$$
$$\widehat{w}_0 \quad \text{is unrestricted in sign}$$

Equation 4 suggests that the technical efficiency for process 1 (T_0^1) can be independently calculated as a conventional input-oriented VRS DEA model because the last three conditions are not related to T_0^1 (Chen et al., 2013).

Output-oriented VRS technical efficiency of stage 2 is calculated using multiplier model as follows (Kao and Hwang, 2011; Chen et al., 2013):

$$T_0^2 = Max. \sum_{r=1}^{s} u_r Y_{rj}$$
$$\text{s.t.} \quad \sum_{d=1}^{D} \overline{w}_d Z_{d0} + \overline{w}_0 = 1$$
$$\sum_{r=1}^{s} u_r Y_{r0} - \sum_{d=1}^{D} \overline{w}_d Z_{d0} - \overline{w}_0 \leq 0$$
$$\sum_{r=1}^{s} u_r Y_{rj} - E_0^S \sum_{i=1}^{m} v_i X_{ij} = 0 \qquad r = 1,\ldots, s \qquad (5)$$
$$\sum_{d=1}^{D} w_d Z_{dj} - \sum_{i=1}^{m} v_i X_{ij} \leq 0 \qquad j = 1,\ldots, \mathrm{N}$$
$$\sum_{r=1}^{s} u_r Y_{rj} - \sum_{d=1}^{D} w_d Z_{dj} \leq 0$$
$$v_i, w_d, \overline{w}_d, u_r \geq \varepsilon, \; i = 1, \ldots, m, \; d = 1, \ldots, D, \; r = 1, \ldots, s$$
$$\overline{w}_0 \quad \text{is unrestricted in sign}$$

As seen in Equation 4, the last three conditions are unrelated to the calculation of the technical efficiency for process 2 (T_0^2). Thus, T_0^2 can be calculated by a conventional output-oriented VRS DEA model that considers only stage 2. After calculating technical efficiencies of process 1 and 2, scale efficiencies for each process can be calculated as $S_0^1 = T_0^1/E_0^1$ and $S_0^2 = T_0^2/E_0^2$.

4. OPERATIONAL EFFICIENCY OF RURAL BUS SERVICES

4.1 Service Characteristics

Table 1 summarizes descriptive statistics of sub-recipient characteristics. The first column shows the number of unique operators (DMUs) observed in the category, and the second column shows the total number of observations. Between 2007 and 2012, 354 operators provided 1077 observations. Among the 333 operators that reported their operator type, 276 are public organizations, of which the vast majority, 216, are not state DOT or tribal (hereafter, we call them general public organizations), four are state DOTs, and 56 are tribal organizations. The remaining 57 operators are private organizations, of which 51 are not-for-profit and 6 are for-profit. With regard to the service area, 151 operators serve only a single county,[1] 69 operators serve a region that consists of multiple counties, and 58 operators serve only a municipality. Thirty-six operators serve Native American reservations (hereafter "reservations"), which mostly, but not perfectly, overlap with tribal operators (of the 36 operators serving reservations, 32 are tribal operators).

Columns adjacent to the number of observations summarize inputs, intermediate measures (service output), and outputs (service consumption). Generally, the service inputs, intermediate measures, and outputs peaked around 2008 and 2009, and have decreased since 2010. The increase in the resource input between 2007 and 2008 seems to have increased the annual vehicle miles, while keeping the average annual vehicle hours relatively constant. In contrast, the decrease in fleet size and operating cost between 2010 and 2012 reduced both annual revenue vehicle hours and annual revenue vehicle miles. The resulting ridership responded to the increase in the service volume provided between 2007 and 2008, but then decreased gradually after 2008.

When the operation size is compared between operator types, public operators spend more on operating cost than private operators do, while their fleet sizes are comparable. With higher operating costs, public operators seem to produce more intermediate outputs (revenue vehicle hours and revenue vehicle miles) and more final outputs (unlinked passenger trips) than private operators. Among the public operators, tribal transit operators are the smallest in all aspects. Comparatively, tribal operators are approximately a half to two-thirds in fleet size, operating costs, vehicle hours, and vehicle miles, and only one-fifth of the ridership.

The inputs and intermediate measures of the services become greater as the service area becomes larger, while the ridership does not follow the trend. Municipal services enjoy high ridership, although their service outputs are smaller than those of single or multiple county level services. The service for reservations appears to be smaller than for municipalities.

[1] Hereafter, "county" and "counties" include independent cities. Independent cities exist mostly in Virginia, have historically functioned like counties and are treated as county-equivalents in public statistics.

TABLE 1 Descriptive Statistics

			Inputs		Intermediate measures		Outputs	Service characteristics		
	Number of DMUs	Number of observa tions	Avg. Fleet Size	Avg. Operating Costs ($)	Avg. Annual Vehicle Hours	Avg. Annual Vehicle Miles	Avg. Annual Unlinked Passenger Trips	Avg. Speed	Avg. Passenger per VH	Avg. Passenger per VM
All the observations	354	1077	11.1	824,144	16,106	283,554	128,048	17.6	7.95	0.45
2007	176	176	10.9	672,650	16,607	261,967	114,143	15.8	6.87	0.44
2008	177	177	11.5	904,192	16,829	291,750	148,144	17.3	8.80	0.51
2009	181	181	11.8	845,811	16,319	280,930	143,142	17.2	8.77	0.51
2010	192	192	11.4	878,667	16,423	303,441	131,060	18.5	7.98	0.43
2011	185	185	11.0	816,461	15,902	291,753	119,207	18.3	7.50	0.41
2012	166	166	9.9	821,201	14,529	272,012	112,236	18.7	7.73	0.41
Operator type										
Public	276	809	11.1	916,056	15,874	337,466	111,062	21.3	7.00	0.33
Not State DOT or Tribal	216	698	12.0	977,999	18,077	310,336	169,963	17.2	9.40	0.55
State DOT	4	7	15.7	1,290,694	17,710	406,921	87,327	23.0	4.93	0.21
Tribal	56	104	7.0	475,103	8,014	204,629	30,659	25.5	3.83	0.15
Private	57	167	11.1	472,067	12,668	227,739	45,238	18.0	3.57	0.20
Not for profit	51	138	11.3	502,705	14,345	234,478	52,590	16.3	3.67	0.22
For profit	6	29	8.8	326,274	10,505	217,355	35,198	20.7	3.35	0.16
Others / Not Reported	21	101	8.5	657,657	14,548	252,953	71,906	17.4	4.94	0.28
Service area										
Municipality	58	215	8.7	629,817	11,907	158,970	145,889	13.4	12.25	0.92
Single county	151	540	11.0	889,843	17,356	296,518	126,765	17.1	7.30	0.43
Multi counties	69	219	15.6	990,943	21,033	424,316	148,204	20.2	7.05	0.35
Reservation	36	65	5.6	444,412	6,529	169,510	29,470	26.0	4.51	0.17
Other/Not Reported	40	38	8.1	646,129	9,993	182,222	97,533	18.2	9.76	0.54
RTPO in the state										
Yes	250	798	10.0	839,447	15,714	263,291	124,640	16.8	7.93	0.47
No	93	264	14.3	795,065	17,512	347,971	139,168	19.9	7.95	0.40
State not reported	11	15	13.7	569,669	13,963	249,459	132,486	17.9	9.49	0.53

4.2. System Efficiency, Production Efficiency, and Service Effectiveness of Operators

Using the pooled data, we calculate CRS system efficiency scores (E_s), CRS process efficiency scores for the first and second stages (E_1 and E_2), technical efficiency scores (i.e., VRS process efficiency scores, T_1 and T_2), and scale efficiency scores (S_1 and S_2).[2]

The top part of table 2 is a histogram of efficiency scores that shows the number of observations and the cumulative distributions. The second part of table 2 shows the average efficiency scores for each observation year, and the bottom part shows the correlation between efficiency scores of stage 1 and stage 2.

The first column shows that E_s is very low; E_s is less than 0.1 for 96.3% of the observations. This occurs because both E_1 and E_2 are low for most of the cases. When the average scores are compared by observation year, E_s increases between 2007 and 2008, and

[2] Underlying assumption is that the base prices of inputs are comparable. Although large variance in gas prices may have affected the scores as an exogenous factor, we do not consider the impact in this section. In the following section, we assess the price-index difference effects as a part of the year fixed-effect.

between 2010 and 2012. E_s increases during these periods because E_1 increases, while E_2 remains stable.

TABLE 2 Efficiency Score Distributions

	Es		E1		E2		T1		T2		S1		S2	
	Count	Cum. Distrib.	Count	Cum. Distrib.	Count	Cum. Distrib.	Count	Cum. Distrib.	Count	Cum. Distrib.	Count	Cum. Distrib.	Count	Cum. Distrib.
0 − 0.1	1037	96.3%	497	46.1%	571	53.0%	54	5.0%	478	44.4%	55	5.1%	1	0.1%
0.1 − 0.2	29	99.0%	422	85.3%	260	77.2%	375	39.8%	303	72.5%	117	16.0%	5	0.6%
0.2 − 0.3	2	99.2%	88	93.5%	120	88.3%	212	59.5%	114	83.1%	119	27.0%	2	0.7%
0.3 − 0.4	5	99.6%	17	95.1%	49	92.9%	161	74.5%	82	90.7%	123	38.4%	8	1.5%
0.4 − 0.5	3	99.9%	14	96.4%	35	96.1%	110	84.7%	24	92.9%	134	50.9%	17	3.1%
0.5 − 0.6	0	99.9%	13	97.6%	14	97.4%	41	88.5%	24	95.2%	152	65.0%	42	7.0%
0.6 − 0.7	1	100%	5	98%	9	98%	19	90%	14	96%	135	78%	104	17%
0.7 − 0.8	0	100%	6	99%	9	99%	10	91%	9	97%	94	86%	210	36%
0.8 − 0.9	0	100%	6	99%	6	100%	9	92%	12	98%	66	92%	369	70%
0.9 − 1	0	100%	4	100%	3	100%	20	94%	11	99%	77	100%	318	100%
1	0	100%	5	100%	1	100%	66	100%	6	100%	5	100%	1	100%
Average score for each year														
2007	0.014		0.108		0.140		0.280		0.189		0.480		0.782	
2008	0.016		0.112		0.146		0.291		0.180		0.499		0.796	
2009	0.018		0.120		0.153		0.297		0.184		0.496		0.811	
2010	0.017		0.120		0.143		0.286		0.171		0.501		0.823	
2011	0.020		0.135		0.146		0.328		0.180		0.484		0.822	
2012	0.050		0.264		0.149		0.517		0.173		0.487		0.859	
Correlations between stage 1 and state 2			E1 and E2		0.0718		T1 and T2		−0.0846		S1 and S2		−0.0486	

Figure 1 illustrates a relationship between E_1 and E_2: the horizontal axis shows E_1, the vertical axis shows E_2, and each observation is plotted with different symbols by year. As shown in the table 2, most observations are low in both E_1 and E_2. Some observations are high E_1 (E_1 higher than 0.7, for example), but most observations with high E_1 have E_2 lower than 0.2. Some other observations are high in E_2 (E_2 higher than 0.7), but most have E_1 lower than 0.3. Only a few observations in 2012 show relatively high scores for both E_1 and E_2. Although there is virtually no correlation between E_1 and E_2 (table 2), it seems difficult to attain both high production efficiency and high service effectiveness.

The large variations in E_1 and E_2 originate mostly from the variations in technical efficiencies (T_1 and T_2), not from scale efficiencies (S_1 and S_2). More than 80% of observations have T_1 and T_2 scores lower than 0.5, suggesting that a few high-performing operators construct or are close to the VRS efficiency frontier line (table 2). Comparing T_1 and T_2, the gap between high- and low-performing operators is greater for service effectiveness than for production efficiency. Average score for T_1 is approximately 0.3 between 2007 and 2010, and then increases to 0.517 in 2012. In contrast, the average score for T_2 hovered around 0.18 throughout the observation period.

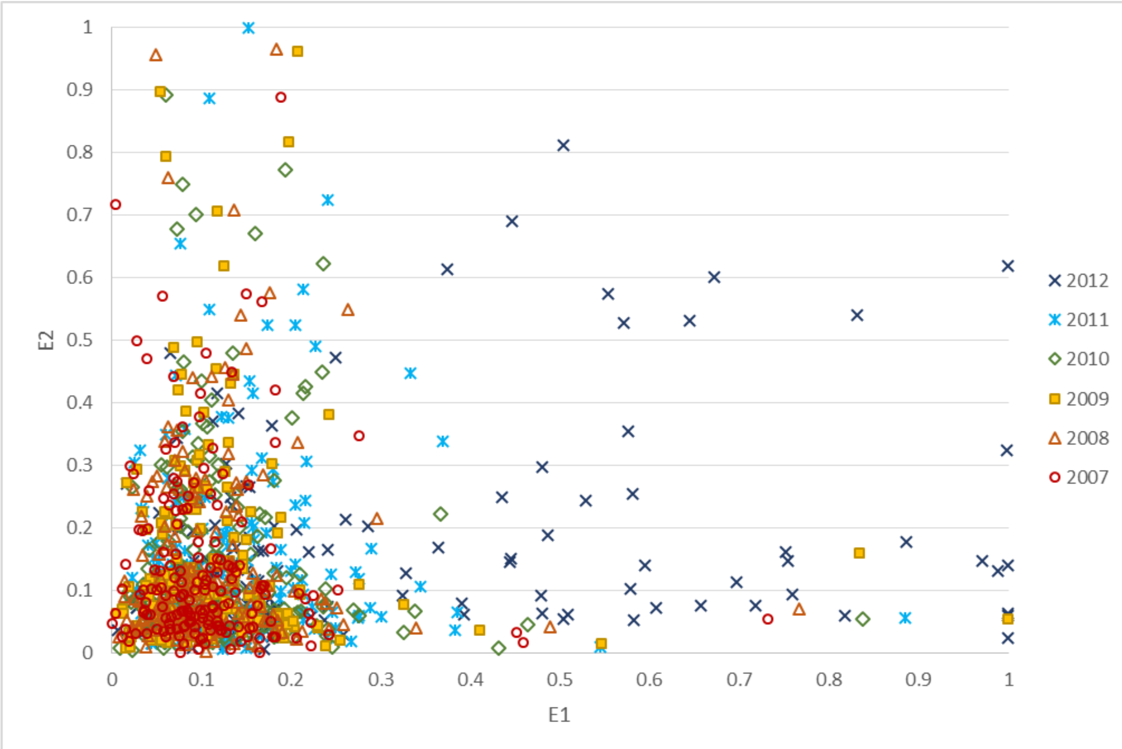

FIGURE 1 CRS efficiency for service production (E_1) and service consumption (E_2)

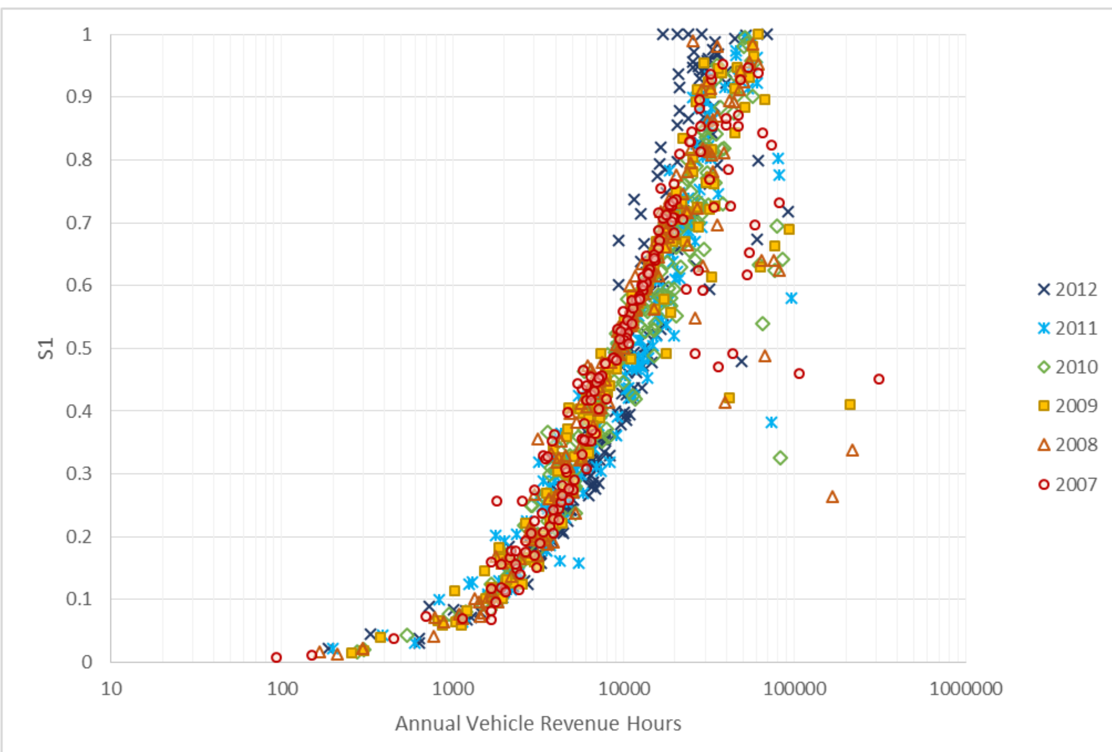

FIGURE 2 Scale efficiency in production and annual vehicle revenue mile

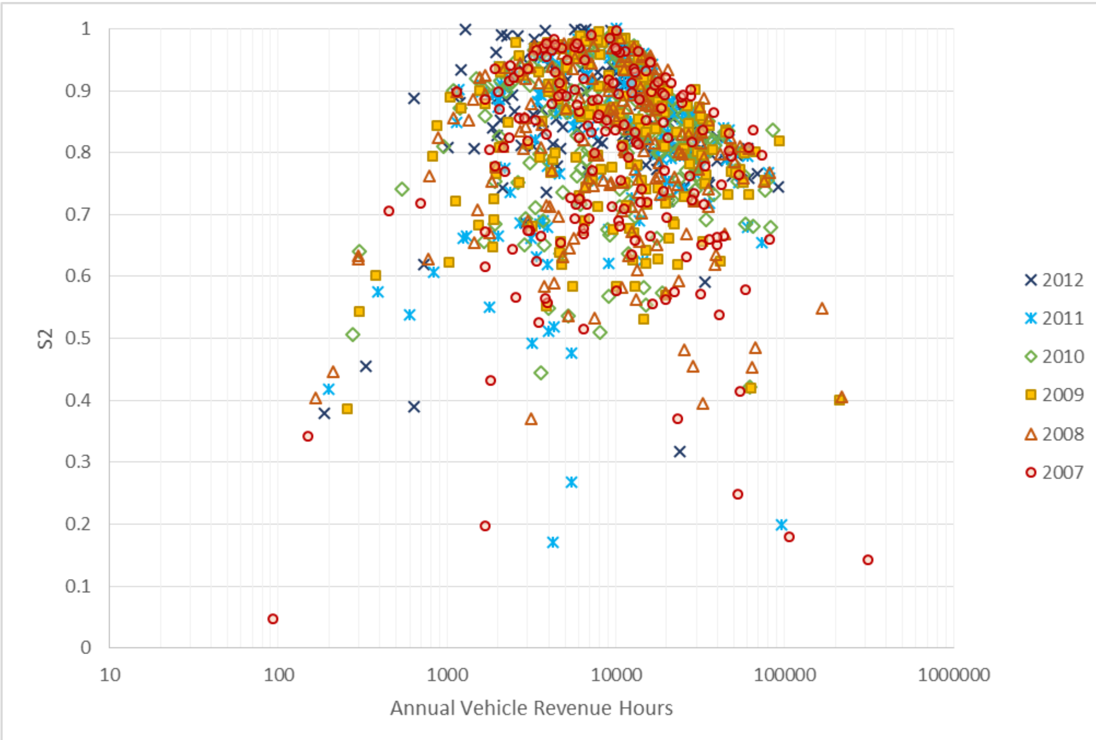

FIGURE 3 Scale efficiency in service consumption and annual vehicle revenue mile

When the scale efficiencies of the first and second stages (S_1 and S_2) are compared, S_1 has greater variation than S_2. Many observations score S_1 lower than 0.5, and as a result, S_1 averages only 0.49. In contrast, S_2 averages approximately 0.8 and trends upward through the observation years. Figures 2 and 3 show annual vehicle revenue hours in log scale in the horizontal axis, and S_1 and S_2 in the vertical axis. Scale efficiency for service production (S_1) clearly increases with vehicle revenue hours, at least up to 20,000 hours. Scale efficiency for service effectiveness (S_2) increases as vehicle revenue hours reach 5,000 hours, plateaus then decreases beyond 10,000 hours. The trend suggests that (1) it is difficult to attain very high scale efficiency scores for both S_1 and S_2, but (2) annual vehicle revenue hours near 10,000 is a desirable scale of operation, given the reasonably high S_1 and high S_2.

4.3. Operational Characteristics and Service Performance

Last, we explore the management and service characteristics that account for the efficiency scores calculated in the previous section. In the analysis, Tobit model for panel data with random specific effects is employed, an approach that accounts for the censored nature of the efficiency scores:

$$y^*_{it} = x'_{it}\beta + \varepsilon_{it} = x'_{it}\beta + \mu_i + \nu_{it}$$

$$y_{it} = \begin{cases} 0 & if\ y^*_{it} \leq 0 \\ y^*_{it} & if\ 0 < y^*_{it} \leq 1 \\ 1 & if\ 1 \leq y^*_{it} \end{cases}$$

The subscript i =1, …, N indicates the individual operators, subscript t = 1, …, T_i indicates the time period, T_i is the number of periods observed for the ith operator, μ_i is a time-invariant individual specific effect which distributes independently from x_{it}, and v_{it} is the remaining disturbance.

Operator characteristics—state DOT, tribal, and private—are represented by three dummy variables, setting the general public operators as the base case. Service area characteristics—municipality, multi-country, and reservation—are also distinguished by three dummy variables, setting single county operators as the base case. We also distinguish whether the state to which the operator belongs has RTPO as a management system, using a RTPO dummy variable (1 if the state has RTPO, 0 otherwise). Last, year dummy variables are introduced to account for annual variations in input price, wage, and other socioeconomic conditions that might affect the transit operation and ridership.

Table 3 summarizes the Tobit regression analysis for each efficiency scores: E_s, E_1, E_2, T_1, T_2, S_1, and S_2. First, private operators are less efficient than the general public operators, mainly because their effectiveness (E_2) is lower than the base-case counterpart. E_2 of the private operators is low mainly because their technical efficiency in the second stage (T_2) is significantly lower than the base case. In other words, the designed service scale of private operator bus network is appropriate, but their marketing strategies may not be appropriate in attracting passengers. With regard to the production efficiency, the scale efficiency (S_1) of private operators is significantly lower than the base case counterpart, while the technical efficiency (T_1) is not significantly different from the base case counterpart. Given that the private operators operate fleets comparable in size but with much lower operating costs than base case operators do (Table 1), the private operators may excessively cut operating cost to the extent that they undermine the scale efficiency of service production.

Differences in service area also associate with differences in production efficiency and service effectiveness, although overall system efficiency scores are not significantly different among municipal, single-county, and multi-county services. Municipal services are significantly lower in production efficiency but significantly higher in service effectiveness than single-county services, while the opposite trend is found for multi-county services. The lower production efficiency of municipal services seems to originate from lower technical efficiency, not scale efficiency, although both T_1 and S_1 are insignificant. In other words, small-size services do not have to be inefficient; however, municipalities may not have enough capacity to implement efficient service production. Service production efficiencies of multi-county services are not significantly different from those of single-county services, but the signs of E_1 and T_1 agree with the hypothesis that larger governments have better capacity for designing efficient service production.

With regard to the service consumption phase, local, geographically compact services are more effective than region-wide services. Service effectiveness of municipal services is significantly higher than that of single-county services, because of high technical and scale efficiencies (T_2 and S_2). Multi-county services are slightly lower in service effectiveness because of both low technical and scale efficiencies. The trend suggests that a smaller, geographically compact service area attracts higher ridership, and that local operators have better knowledge in designing service that attracts higher ridership.

TABLE 3 Differences in Production Efficiency by Service Characteristics

	Es	E1	E2	T1	T2	S1	S2
(Intercept)	0.0288***	0.1330***	0.1608***	0.292***	0.1829***	0.511***	0.796***
	(0.00429)	(0.0149)	(0.00665)	(0.0184)	(0.00849)	(0.0138)	(0.0152)
Agency: St DOT	−0.01113	−0.0605	0.01206	−0.0428	0.0208	−0.0241	−0.00473
	(0.0157)	(0.0524)	(0.0252)	(0.0649)	(0.0364)	(0.0532)	(0.0443)
Agency: Tribal	−0.0178**	−0.01993	−0.0303***	0.0815**	−0.0203*	−0.0275	−0.0671***
	(0.00805)	(0.0223)	(0.00928)	(0.0383)	(0.0115)	(0.0250)	(0.0197)
Agency: Private	−0.00876**	−0.0249	−0.0148***	−0.01325	−0.01745**	−0.0549***	0.01599
	(0.00370)	(0.0151)	(0.00553)	(0.0180)	(0.00695)	(0.0137)	(0.0135)
Area: Municipality	0.000748	−0.0286**	0.01613***	−0.0232	0.01888**	0.00554	0.0268**
	(0.00336)	(0.0135)	(0.00537)	(0.0195)	(0.00736)	(0.0152)	(0.0133)
Area: Multi County	−0.0008941	0.00789	−0.00771	0.00447	−0.01914***	0.00662	−0.0310**
	(0.00360)	(0.0140)	(0.00564)	(0.0164)	(0.00714)	(0.0145)	(0.0130)
Area: Reservation	−0.0165*	−0.0455*	−0.01685	0.0798*	−0.0260*	−0.1569***	0.0237
	(0.00959)	(0.0265)	(0.0131)	(0.0457)	(0.0151)	(0.0289)	(0.0265)
RTPO	0.00219	0.0216	0.01487***	0.0501***	0.01739**	−0.0425***	0.0397***
	(0.00361)	(0.0136)	(0.00533)	(0.0159)	(0.00693)	(0.0119)	(0.0134)
Y12	0.0314***	0.1347***	0.000991	0.1938***	−0.00289	0.01712	0.0324***
	(0.00335)	(0.0114)	(0.00616)	(0.0155)	(0.00782)	(0.0120)	(0.0100)
Y10	−0.00316	−0.01692	−0.00938	−0.0273*	−0.01119	0.01095	−0.001463
	(0.00319)	(0.0109)	(0.00594)	(0.0148)	(0.00748)	(0.0115)	(0.00958)
Y09	−0.00382	−0.01733	−0.00765	−0.0296*	−0.00722	0.01769	−0.01974**
	(0.00331)	(0.0113)	(0.00611)	(0.0154)	(0.00774)	(0.0120)	(0.00996)
Y08	−0.00473	−0.0218*	−0.01140*	−0.0283*	−0.01098	0.0240**	−0.0311***
	0.00337	(0.0115)	(0.00625)	(0.0158)	(0.00798)	(0.0122)	(0.0102)
Y07	−0.00716**	−0.0252**	−0.01156*	−0.0233	−0.00256	0.00291	−0.0473***
	(0.00345)	(0.0117)	(0.00634)	(0.0160)	(0.00813)	(0.0126)	(0.0103)
logSigmaMu	−3.320***	−2.419***	−1.842***	−1.502***	−1.762***	−1.549***	−2.369***
	(0.0588)	(0.0692)	(0.0166)	(0.0326)	(0.0167)	(0.0255)	(0.0561)
logSigmaNu	−3.516***	−2.278***	−2.892***	−1.996***	−2.653***	−2.244***	−2.416***
	(0.0266)	(0.0263)	(0.0227)	(0.0251)	(0.0230)	(0.0240)	(0.0263)
Log Likelishood	2021.037	751.0262	1186.826	209.5799	884.1492	489.1168	828.441
Observations	1077	1077	1077	1077	1077	1077	1077
Right-censored	0	1	1	52	5	0	1

Robust standard error in the parenthesis, *** 1% significant, ** 5% significant, and * 10% significant.

The tribal operators and/or operators that serve reservation areas suffer from significantly lower system efficiency (E_s) than general public operators or operators serving a single county. Note that the coefficients of tribal operator dummy and reservation area dummy variables are mostly in the same signs. The overlapping characteristics strongly imply that the tribal operators that serve reservations seem to suffer from both low production efficiency and low service effectiveness (E_1 and E_2). The low *system* efficiency score (E_S) of tribal operators is driven mainly by low effectiveness (E_2) that comes from low *scale* efficiency (S_2), while the low system efficiency score of the reservation area services originates from low service production efficiency (E_1) that comes from both low technical and scale efficiencies (T_2 and S_2). Overall, the service scale of tribal operators and/or reservation-area operators seems to be too small to enable efficient service production and consumption.

The positive effect of having an RTPO in the state is observed, but with some caveats. RTPO is supposed to improve efficiency and effectiveness by collecting local knowledge, developing organizational capacity, and drawing appropriate service area boundaries. The analysis supports the improvements in technical efficiency. Technical efficiencies of production efficiency and service effectiveness (T_1 and T_2) are significantly higher for operators in the states with RTPOs than those in the states without. However, the positive effect of RTPOs in improving scale efficiency is observed only for service effectiveness (S_2). Service production scale efficiency (S_1) for operators in the states with RTPO is lower than those in the states without RTPO. In addition, there remains a concern that the existence of RTPO may be endogenous to the ridership; pro-transit culture in a state may lead to both an RTPO system and high ridership.

System efficiency of rural transit has improved since 2007, particularly between 2011 and 2012. This change is a result of increased service production efficiency (E_1), and more specifically, increased technical efficiency (T_1). Since service production scale efficiency (S_1) remains stable, the use of resource seems to have improved in 2012, rather than service scale has optimized during the period. With regard to service effectiveness (E_2), a modest improving trend is observed, thanks to the scale efficiency improvements (S_2). Figure 4 reveals that improvement in the scale efficiency took place by eliminating observations that fall far behind the S_1-S_2 frontier line.

5. CONCLUSION AND FUTURE DIRECTIONS

NDEA method reveals that efficiency and effectiveness of rural transit service vary widely by service operator type and service area type, and that RTPO may improve a transit operator's technical efficiencies. Private operators do not perform more efficiently than public operators, which raises questions about current private franchising schemes. Private operators are of an inefficient size for service production and have lower technical capacity for marketing. Private service could be improved by assigning or requesting an appropriate operation scale when transit services are contracted out, and by sharing local knowledge to design a more attractive service for local riders.

The differences in service efficiency and effectiveness by service area size suggest the importance of both organizational capacity and local knowledge. Rural bus service is usually more efficient in service production when it serves larger areas, because scale economy enhances the technical efficiency of service production. Service consumption is more effective when rural services is devoted to smaller areas, because a compact network attracts more passengers, and local knowledge enables transit operators to design a more attractive bus network for passengers. However, when the service size is very small, as is the case with reservation area services, both production efficiency and service effectiveness become low because of low scale efficiencies.

The positive effects of having RTPO in the state, as observed in the analysis, supports our hypothesis that capacity building and knowledge sharing are important in improving efficiency and effectiveness of services. Although the findings about the scale efficiencies is mixed, the attempts to plan and coordinate transit network regionally seems to enable the operators to plan an efficient and effective bus service.

Last, the analysis also shows that the service production efficiency has improved between 2007 and 2012, particularly between 2011 and 2012. The improvement took place mainly in technical efficiency improvement in service production and scale efficiency improvement in service consumption. Further analysis is needed to explore whether the improvement comes from improving existing services or eliminating inefficient services, and whether the improvement is driven by any government policies or incentives. Subsequent research should also investigate sources of inefficiencies in rural bus operation, including route network design, service area land use, and socioeconomic characteristics of service area.

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