Accessibility and Transit Performance

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Abstract

This study disentangles the impact of financial and physical dimensions of transit service operators on net transit accessibility for 46 of the 50 largest metropolitan areas in the United States. To investigate this interaction along with the production efficiency of transit agencies, two types of analysis are used: a set of linear and quadratic regressions and a data envelopment analysis. We find that vehicle revenue kilometers and operational expenses play a pivotal role in enhancing the accessibility to jobs by transit. The bivariate linear regression models indicate a 1% increase in operational expenses and vehicle revenue kilometers increase the number of jobs that can be reached within 30 minutes by 0.96 and 0.95%, respectively. The results of the quadratic functional form, also, show transit services may have both increasing and decreasing accessibility returns to scale depending on system size, and the results are sensitive to the model used. Overall, the highest system efficiency (access produced per input) is found in the New York, Washington, and Milwaukee metropolitan areas, while Riverside, Detroit, and Austin perform with the lowest efficiency.

Keywords:Public transit; Accessibility; Envelope of output; Returns to scale; Metropolitan area

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1 Introduction

Accessibility, the ease of reaching valued destinations, is an important output measure for transportation networks (Geurs and Van Wee, 2004, El-Geneidy and Levinson, 2006). Accessibility varies by time of day and between modes. For instance, Cervero and Gorham (1995) demonstrate that accessibility is significantly lower for transit commuters than auto commuters. Further, access to destinations by car is lower in rush hours than the less congested hours (Cui and Levinson, 2015). In contrast, access by transit is higher in peak hours because the increased frequency offsets the lower running speeds (Owen and Levinson, 2014).

Throughout the past decade, researchers have examined the relationship between access to valued destinations and travel behavior (Iacono et al., 2008). A recent study (Owen and Levinson, 2014), for example, found a positive correlation between transit mode share in work trips and accessibility to jobs. This share varies by metropolitan area. The New York and San Francisco metropolitan areas have the largest public transit shares, respectively, about 31 and 16%. The lowest transit usage share in work trips among the top 50 belongs to the Birmingham, Alabama metropolitan area with only 0.8%.

This article investigates the interdependency of accessibility to jobs by transit and cost dimensions of transit service operators. Furthermore, this study gives the potential performance of transit networks in metropolitan areas using accessibility as an output of the system. To this end, accessibility to jobs by transit is analyzed for 46 of the 50 largest metropolitan areas by population in the United States.

The rest of the paper unfolds as follows. The related literature is reviewed and synthesized in Section 2. The data is described in Section 3 followed by a description of methodology (Section 4) and models that are applied for analyses of the current study. The estimation results of models along with an in-depth discussion of accessibility returns to scale are represented in the analysis of results and discussion (Section 5). Finally, the paper concludes (Section 6) with scrutiny of results and recommendations for future research.

2 Literature Review

A long-standing literature investigates scale economies in urban transit systems. Many previous studies are summarized in Table 1. Notwithstanding the importance of economic return to scale, the relation of public transit costs to outputs is inconsistent. This disparity is deeply rooted in analytical and empirical sources. From the analytical methods standpoint, studies employed linear, loglinear, Cobb-Douglas, translog, and quadratic production functional forms to explore the scale economies of public transit systems. Linear models are unable to capture the economies of scale and substitution elasticities. Although the log-linear and Cobb-Douglas models allow measures of economies of scale, they are incapable of accommodating substitution elasticities.

These limitations were obviated by the introduction of the the translog function (Berndt and Christensen 1973), which has become widely used in understanding scale economies in public transportation. It is important to note, however, that this model is usually criti-

Table 1: Summary of previous studies

First Author	Data	Sample Size	Level	Functional Form	Output	Scale Economies I	D	C	Service
Johnston (1956)	UK	31	Operator	Linear, Loglinear	VM	×			Bus
Lee (1970)	UK	44	Municipality	Linear	VM			×	Bus
Koshal (1972)	US	10	Firms	Linear	VM			×	Bus
Nelson (1972)	US	85	Operator	Loglinear	VM			×	Bus
Veatch (1973)	-	66	Firms	Linear	VM	×	×	×	-
Wabe (1975)	UK	76	Operator	Linear	VM		×		Bus
Pozden (1978)	US	105	Operator	Cobb-Douglas	VM	×			Rail
Williams (1979)	US	-	-	Cobb-Douglas	VM	×			-
Viton (1981)	US	54	Operator	Translog	VM	×	×		Bus
Williams (1981)	US	-	-	Translog	VM	×	×		-
Berechman (1983)	Israel	28	Operator	Translog	PR	×			Bus
Obeng (1984)	US	-	-	Translog	VM		×		-
Obeng (1985)	US	62	Operator	Translog	PM		×		Bus
Button (1985)	UK	44	Municipality	Translog	PM	×			Bus
Gathon (1989)	Europe	60	Urban	Translog	SK	×			Bus
de Rus (1990)	Spain	101	Operator	Translog	VK	×	×	×	Bus
Levaggi (1994)	Italy	55	Operator	Translog	PK	×			Bus
Sakano (1995)	US	84	Operator	Translog	VK	×			Bus
Savage (1996)	US	22	Operator	Translog	VH	×	×		Rail
Karlaftis (1999)	US	216	Operator	Translog	VM	×	×		Bus
Odeck (2001)	Norwegian	47	Operator	Quadratic	PK	×			Bus
Karlaftis (2002)	US	295	Operator	Cobb-Douglas	VM	×			Bus
Graham (2003)	World	99	Operator	Cobb-Douglas	PM			×	Rail
Farsi (2007)	Switzerland	300	Operator	Linear	SK	×			Transit
Iseki (2008)	US	3329	Operator	Linear, Loglinear, Quadratic	VC	×	×		Bus

VM (K): Vehicle Revenue Mile (Kilometer), PM (K): Passenger Mile (Kilometer), PR: Passenger Revenue, VC: Cost per vehicle, SK: Seat Kilometer cized for several reasons.

First, the cost structure of transit system is estimated around mean production level. Second, the translog model is built on the duality theory that says a firm chooses the combination of inputs that minimizes the cost of output. In contrast with profit-seeking firms, allocated subsidies to publicly owned transit agencies affects the motivation to select prices and minimize costs. Finally, since the number of parameters escalate quadratically in the flexible form of the translog function, accommodating many variables in a model faces heterogeneity and multicollinearity problems.

In response, a few studies employed the quadratic U-shape functional form, which allows exploration of both increasing and decreasing returns to scale simultaneously. For instance, Isaki (2008) studied the scale economies of 3,329 US transit agencies, while controlling for the size of system by applying a quadratic form. He found that the quadratic form performs significantly better than linear and logarithmic forms, and thereby applying the latter forms may under- or over-estimate the performance of the transit agencies.

From a performance measurement standpoint, many studies explore the scale economies of transit systems considering vehicle revenue miles or passenger miles as the output of systems. The study of scale economies of transit system began at least as early as Johnston (1956), who investigated the performance of 31 bus operators in the UK by applying both linear and loglinear models. The results show that the bus system has increasing vehicle revenue miles returns to scale. Since then, as shown in Table 1, contradictory findings are reported regarding returns to scale. For instance, while Johnston (1956) reported increasing returns for the bus system, Lee and Steedman (1970) found a constant return to scale considering vehicle revenue miles as the output of the system.

This discussion emphasizes that all the current studies have striven to assess the efficiency of transit system by minimizing costs with respect to inputs, while vehicle revenue miles or passenger miles is considered as the output of the system. The current study introduces transit accessibility as the output.

3 Data

This study is based on two metropolitan-level major data sets. The first is accessibility to jobs by transit, estimated by the Accessibility Observatory at the University of Minnesota in 2014 for 46 of the 50 largest metropolitan areas in the US (4 of the top 50 metro areas lacked publicly available transit network data in 2014 and so accessibility could not be computed). The second: financial and physical characteristics of transit systems including, annual vehicle revenue kilometers, operational expenses, and length route of services is extracted from the publicly-available US National Transit Database (NTD) for agencies serving those metropolitan areas. These are described below.

3.1 Accessibility

The accessibility literature provides many methods of measurement. These methods might fall into one of the five major categories, namely cumulative opportunity (Ingram 1971), gravity-based (Hansen 1959), utility-based (BenAkiva1984), constraints-based, and composite accessibility. Consequently, several accessibility measurement analyses, have unfolded, frequently focusing on location accessibility (Song, 1996; Handy and Niemeier, 1997), individual accessibility (Pirie, 1979; Kwan, 1998), and the economic benefits of accessibility (Koenig, 1980; Niemeier, 1997). Pros and cons of each methods are widely discussed in previous studies. To measure the accessibility to jobs by transit, the current study employs the following method 1, accessibility for location m, say job opportunities, is weighted. In this equation, O_n is number of opportunities at location n, C_{mn} is defined as duration of travel from m to n, and $f(C_{mn})$ is a weighting function.

$$A_m = \sum_n O_n \, f(C_{mn}) \tag{1}$$

The calculation method for the weighting function plays an important role in the measurement of accessibility. Ingram (1971) proposes a binary weighting function, which is referred to elsewhere in the literature as "cumulative opportunities", as a simple and efficient method that well explains a variety of data sets. Consistent with equation 2, this method employs a binary weighting function in which t is a travel time threshold.

$$f\left(C_{mn}\right) = \begin{cases} 1\, if \;\; C_{mn} & \leq t \\ 0\, if \;\; C_{mn} & > t \end{cases} mn \tag{2}$$

The accessibility data calculation effort was undertaken in four steps for each census block by employing both visual and statistical techniques. First, a set of origins and destinations is defined as a single analysis zone in which origin-destination pairs are census blocks so that centroids fall within the zone and 60 km zone boundary, respectively. Transit travel times, then, are determined from each census block centroid pursuant to the detailed pedestrian network and transit schedule data. Followed by transit travel time computation, the number of reachable jobs from different points in space are estimated as per equations 1 and 2 for at least two iterations. Finally, to produce worker weighted accessibility, the location measure is weighted by the number of workers residing in each Census block and averaged across the entire metropolitan area. Consequently, the average weighted accessibility (i.e. cumulative opportunities) for each block over 7:00 to 9:00 morning period was calculated for ten minutes intervals. It is worth mentioning that the walk travel time distance to transit stations are considered in measuring accessibility to jobs. In this study, however, the number of reachable jobs by walk in 30 minutes threshold are subtracted from the accessibility to jobs by transit. This gives the absolute number of jobs that can be reached in 30 minutes threshold by transit exclusive of those which could be reached by walking. Since the focus of this research is on evaluating the transit system, the number of reachable jobs by transit is considered for analyses. We call this measured accessibility "net transit." For ease of reference during this study, all subsequent references to "accessibility" mean this definition.

Figure 3.1 shows how microscopic 30 minutes net transit varies from location to location for the New York and Birmingham metropolitan areas in 2014.

$$A_{nettransit,m} = A_{transit,m} - A_{walk,m} \tag{3}$$

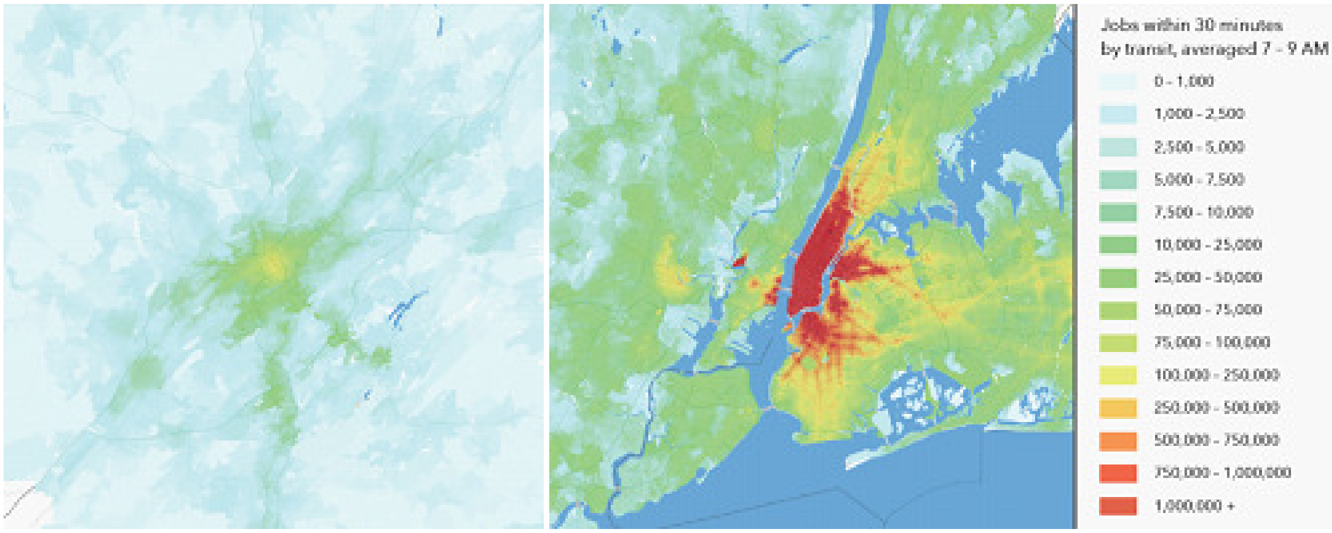

Figure 1: Jobs reachable within 30 minutes by transit (Birmingham (left), New York (right))

$$A_{nettransit,metro} = \frac{\sum_m A_{nettransit,i} \cdot Pop_m}{\sum_m Pop_m} \tag{4}$$

3.2 National Transit Database

To extract the financial and operating characteristics of transit systems, the transit agencies belonging to each metropolitan area are extracted from the 2013 NTD. The financial and operating variables, then, aggregated at the Core Based Statistical Area (CBSA). Among 85 agencies, 29 of them operate in more than one CBSA For instance, Orange County Transportation Authority operates in Los Angeles, Riverside, and San Diego. For agencies serving multiple areas, the data was allocated by the research team into the appropriate area based on the spatial distribution of service provision in each CBSA. In this vein, both the map of transit system and Core Based Statistical Area are matched; then, the length of the transit service links in each CBSA is measured. Finally, in accordance with the extracted shares, the financial and operating expenses are allocated to each metropolitan area according the share of service in each metropolitan area. For instance, the Massachusetts Port Authority officially operates in both the Boston and Providence CBSAs. However, exploring the length of the transit system in each area shows that approximately 100% of the transit share belongs to the Boston metropolitan area.

Description of explanatory variables along with some statistical information regarding metropolitan areas are outlined in Table 3.2.

Table 2: Description of explanatory variables used in the analysis

Variable	*Definition*	*Average*	*St. Dev.*	*Min*	*Max*
E	The expenses associated with the operation of the transit agency (Thousand $US)	361746.0	906907.0	10020.32	6000137
E_{Bus}	E only for bus services	225499.1	418645.6	10020.32	2670582
E_{Train}	E only for train services	140813.1	499213.3	0.0	3329554
R	The kilometers that vehicles are scheduled to or actually travel while in revenue service.	54562.6	118125.8	2718.34	774854.7
R_{Bus}	R only for bus services	30583.8	38814.5	2718.34	223096.1
R_{Train}	R only for train services	24159.0	83055.4	0.0	551758.6
L_{Bus}	The kilometers in each direction over which bus vehicles travel while in revenue service.	3283.5	3030.4	329.30	13093.30
L_{Train}	The kilometers in each direction over which train vehicles travel while in revenue service.	317.24	538.05	0.0	2330.540
Q	$= R \div (L_{Bus} + L_{Train})$	51.32	56.55	3.58	253.79
Q_{Bus}	= $R_{Bus} \div L_{Bus}$	9.02	3.66	1.06	17.78
Q_{Train}	= $R_{Train} \div L_{Train}$	42.30	55.24	0.0	236.75
V	Number of vehicles operated in annual maximum service	1354.0	2595.5	68.0	16547.0
Y	Employment rate in each metropolitan area	0.603	0.035	0.52	0.68
L	Number of individuals who are compensated by the transit agency	5220.3	11952.9	35.0	78184.80
A_{30}	Net transit accessibility to jobs in 30 minutes threshold	12063.1	24733.6	849.96	162854.0

4 Methods

This study follows two main objectives: exploring financial effects of transit service operators by measuring accessibility returns to scale, and comparing the efficiency of individual metropolitan areas against the envelope of output for the largest US metropolitan areas. Two modeling formulations are employed: a set of linear regression models along with a quadratic functional form to analyze the accessibility returns to scale, and a data envelopment analysis (DEA). The regression methods are straight-forward. Returns to scale are discussed in the next subsection. The DEA method is discussed in the following subsection.

4.1 Accessibility returns to scale

This part of the study is dedicated to introduce the notion of accessibility returns to scale in transit systems. Accessibility returns to scale describes the interrelation between the amount of accessibility to jobs that is provided by a transit service and inputs of the system. The accessibility returns to scale function is represented by Equation 5. In this quadratic formula function, A_s stands for accessibility to jobs by service s, and I_s is a vector of inputs for that service. In accordance with economies returns to scale concept, the accessibility returns to scale may be constant, increasing, or decreasing. The U-shaped or up-side-down shape of quadratic function allows measuring both increasing and decreasing returns to scale subject to inputs of the system.

$$A_s = a{I_s}^2 + bI_s + c \tag{5}$$

Increasing return to scale:

$$I_s > \frac{-b}{2a} \; \forall a \neq 0 \; and \; a > 0, \;\; or \; I_s < \frac{-b}{2a} \; \forall \, a \neq 0 \; and \; a < 0 \tag{6a}$$

Decreasing return to scale:

$$I_s < \frac{-b}{2a} \; \forall a \neq 0 \; and \; a > 0, \;\; or \; I_s > \frac{-b}{2a} \; \forall \, a \neq 0 \; and \; a < 0 \tag{6b}$$

Constant return to scale:

$$I_s = \frac{-b}{2a} \tag{6c}$$

4.2 Data envelopment analysis

To indicate the operating efficiency of a group of decision making units (DMU), numerous methods have evolved in recent years. From production theory, methods might be divided into two major categories, namely, parametric and non-parametric techniques, each of which has its pros and cons (Hollingsworth, 2003). The main goal of these, however, is to determine whether a DMU is operating near the frontier of its production possibility set (Read, 1998). Production is a procedure that converts a number of inputs into a set of outputs. For instance, a public transit firm uses the inputs of operating expenses and vehicle revenue km.

In the late 1970s two broad operating efficiency models were presented that include data envelopment analysis (DEA) and stochastic frontiers (Read, 1998). The former is a theoretical non-parametric model, whereas the latter is fully parameterized model. DEA models are widely used in the fields of engineering, economics, and management for ease of estimation. To investigate the production efficiency of public transit in metropolitan areas, DEA is employed to avoid the danger of imposing an incorrect functional form. Using linear programming in the DEA technique eases the way to describe the structure of the production frontier comprehensively (Cooper et al., 2007).

Following the Pareto efficient concept, the DEA technique explores either an input-orientated model or an output-oriented model (Nunamaker, 1985). The former determines which decision making unit achieves the lowest input for a given level of output. The later, on the other hand, seeks a decision making unit which gains the highest output for a given level of input (Cooper et al., 2007). DEA also encompasses some models with different assumptions such as constant, increasing, and decreasing return to scale. Banker et al. (1984) derived a DEA formulation as the following linear programming problem. This technique aims to maximize the level of output for decision making units subject to a set of constraints. In each iteration, the model is solved for every decision making units. In this vein, Constraint 7a maximizes the optimal output level and Constraint 7b identifies that the output level is as good as the decision making unit which is under evaluation in the program. Constraint 7c limits the input of the evaluating decision making unit to less than the observed amount of input. Finally, the non-negativity restriction for weight of decision making units is imposed by Constraint 7d.

Maximize θ:

Subject to:

$$y_{ro} \leq \sum_{j=1}^{J} y_{rj}\gamma_j, \quad r = 1,\ 2,\ \ldots,\ R \tag{7a}$$

$$x_{io} \geq \sum_{j=1}^{J} x_{ij}\gamma_j, \quad i = 1,\ 2,\ \ldots,\ I \tag{7b}$$

$$1 = \sum_{j=1}^{J} \gamma_j \tag{7c}$$

$$0 \leq \gamma_j, \qquad j = 1,\ 2,\ \ldots,\ J \tag{7d}$$

Where, j stands for decision making unit, r and i are output and inputs of the system, respectively. Moreover, y_{rj} and x_{ij} are output and inputs for each decision making units, respectively. The results of the efficiency scores depends on returns to scale.

5 Results and Discussion

This part of the study represents the analysis of results in three sections. First, the results of the regression models and impact of financial and operating expenses on accessibility to jobs are discussed in detail. The notion of accessibility returns to scale, then, is analyzed. This is followed by performance measurement of transit agencies at the metropolitan area level.

5.1 Regression analysis results

The financial characteristics of transit systems are highly correlated and thereby developing a model using all significant variables requires caution. Neglecting to mention pivotal variables, on the other hand, spawns misspecification in policy analysis. From the modeling viewpoint, the variable selection process is built on a wide spectrum of theories and hypothesis, while the availability of data is considered in the analysis.

For instance, net transit accessibility should be larger for metropolitan areas which have a more active fleet. Hence, there should be a positive correlation between accessibility to jobs and number of vehicles operated in annual maximum service.

Frequency of service varies, and number of jobs that can be reached at a given time varies with the headway of services. Our measure of accessibility is averaged over time, not just the peak service available. This study, therefore, attempts to test the hypothesis that more frequent transit service provides more accessibility to jobs. In this vein, the vehicle revenue kilometers is divided by directional route kilometers to obtain an indicator of transit frequency at the metropolitan area level.

This study also struggles to disentangle the noisy confusion in transit debates over the benefits of bus and rail services. It has long been a mantra among transport economists that bus transit is more cost effective per rider (considering capital and operating costs) than rail. By detaching the annual vehicle revenue kilometers and operating expenses of bus from rail transit, the efficiency of both systems are evaluated in terms of providing accessibility to jobs.

To test the above-mentioned hypotheses, two different types of linear regression models are developed. First, bivariate linear regression models are applied to analyze the impact of explanatory variables, independently. Table 3 shows the final results of the individual models.

Further, a parsimonious multivariate regression analysis is developed to scrutinize the interaction of pivotal variables in a linear equation. The results of this model are outlined in Table 4.

To understand the quantitative impact of variables, elasticity of explanatory variables are calculated through sample enumeration. An elasticity value shows the percentage of change in the dependent variable as a result of a 1% increase in the independent variable at the margins. As per Table 3, operating expenses, vehicle revenue kilometers, number of active fleets in services, frequency of the system, and number of employees have a positive correlation with accessibility to jobs. Among which, operating expenses and frequency of the system have the highest and lowest fit as per adjusted R^2 criteria, respectively.

Table 3: Bivariate Models: Dependent variable: Net transit in 30 minutes threshold

	Variable	*Coefficient*	*t-test*	*Elasticity*	*Adj. R^2*
1	E	0.026	33.57	0.713	0.961
	Constant	2384.57	3.09	-	
2	E_{Bus}	0.057	25.91	1.216	0.937
	Constant	-843.054	-0.81	-	
3	E_{Train}	0.047	25.43	0.320	0.934
	Constant	5312.45	5.49	-	
4	R	0.205	32.01	1.005	0.957
	Constant	876.221	1.06	-	
5	R_{Bus}	0.571	13.43	2.210	0.799
	Constant	-5410.81	-2.59	-	
6	R_{Train}	0.289	27.80	0.340	0.944
	Constant	5065.11	5.68	-	
7	Q	284.802	5.69	2.253	0.41
	Constant	-2555.35	-0.67	-	
8	V	9.092	21.14	1.267	0.908
	Constant	-247.709	-0.20	-	
9	L	1.989	23.26	0.914	0.923
	Constant	1675.32	1.52	-	

The results show that 1% increase in operating expenses, increases transit accessibility by 0.713%. This ratio, however, varies considerably from bus to rail transit systems. The elasticity results indicate that accessibility rises 1.216% when the operating expenses of bus system increase 1%, while this gain is only 0.320% for the rail transit system. In other words, using the same operating expenses for both bus and rail transit systems, the bus transit provides roughly 4 times net transit accessibility than rail transit. In terms of vehicle revenue kilometers, further, the bus transit operates 7 times better than rail transit in providing net transit accessibility with the same input. Such findings can give policy-makers and planners considering investments information about the possible returns.

As expected, one of the highest influence on accessibility to jobs is attributed to frequency of the system. The results of the elasticity analyses show that 2.25% increase in accessibility to jobs by transit is followed by a 1% increase in frequency of transit system. Finally, a 1% increase in number of vehicles operated in annual maximum service and number of laborers, raises the accessibility to jobs by 1.26 and 0.91%, respectively.

A parsimonious multivariate model is also developed to host the most significant variables, while controlling for multicollinearity issue. Analyzing the influential parameters in a multivariate regression model gives more realistic results for policy recommendations. The model contains vehicle revenue kilometers and directional route kilometers for both bus and rail transit systems separately. To control the demographic side of the accessibility to jobs, the number of workers in each metropolitan area is considered in the model.

The elasticity results imply that the accessibility rises 0.464 and 0.298% as a result of a

Table 4: Multivariate Model: Dependent variable: Net transit in 30 minutes threshold

Variable	*Coefficient*	*t-value*	*Elasticity*
R_{Bus}	0.12015	1.83	0.464
R_{Train}	0.25413	12.25	0.298
L_{Bus}	1.02646	1.32	0.561
L_{Train}	-7.77113	-2.46	-0.300
W	48332.0	2.51	7.624
Constant	-27826.8	-2.37	-
Sample Size	46		
Adjusted R^2	0.966		

1% increases in the vehicle revenue kilometers for bus and rail transit, respectively. Likewise the bivariate model results, the bus services provide more accessibility with respect to the same vehicle revenue kilometers. The results also show that a 1% increase in the length of the bus services results in 0.561% increase in access to jobs. The length of the rail system has a negative correlation with accessibility. In other words, a 1% increase in the route length of rail service diminishes the net transit by 0.300% while controlling for the route length of bus services and revenue km of service. This is likely an indicator of suburban and exurban commuter rail services draining resources from more intensive use of urban metro systems with more R per L. As expected, the more workers in metropolitan areas the more accessibility to jobs. It is rooted in the interrelationship between number of jobs and number of workers in each metropolitan areas. It is found that 7.624% increase in accessibility is followed by 1% increase in the number of workers in metropolitan areas.

Figure 2 represents the observed net transit amount against the predicted amount based in the logarithmic form for the parsimonious linear regression model. Cities on the upper left of the line have more accessibility than predicted, while those on the lower right are underperforming.

5.2 Accessibility returns to scale

The hypothesis behind the accessibility returns to scale analysis is that the size of transit service providers will affect their ability to produce accessibility to jobs efficiently. Hence, simply assuming constant returns to scale is inappropriate and begets return to scale misspecification. The proposed model considers accessibility as the output of the system. The length of routes, vehicle revenue kilometers, and frequency of the services are considered separately for both bus and rail services as inputs of the system at the metropolitan area level. To explore the accessibility returns to scale, different quadratic models are developed for several reasons. First, the input variables are highly correlated and developing a model which encompasses all variables faces multicollinearity. Further, investigating accessibility returns to scale for both individual inputs function and when controlling with other variables sheds light on the exact effect of variables.

The results of the models are outlined in Table 5.2. The revenue kilometers for bus service (R_{Bus}) has a increasing return to scale to the turning point of the quadratic function (92857 km). After this point, the bus system faces decreasing return to scale. While, the rail

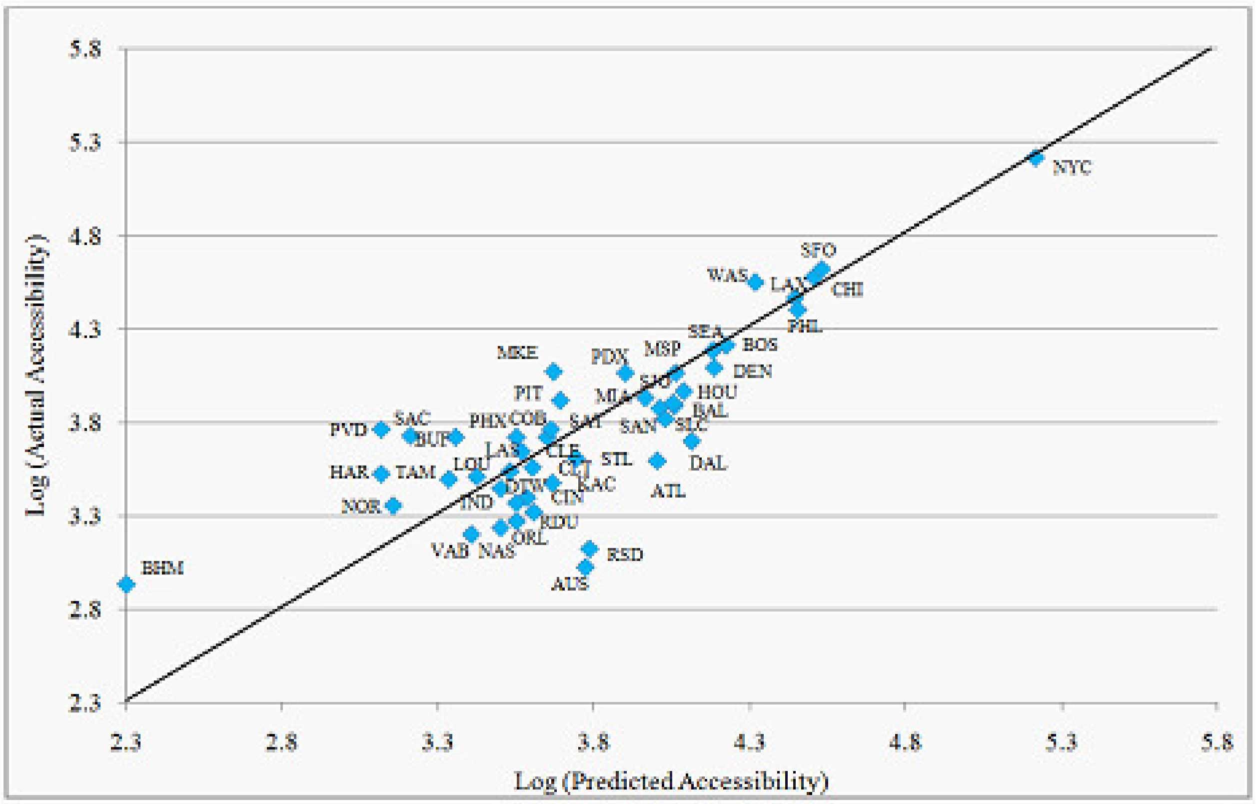

Figure 2: Residual plot of the parsimonious regression model

Table 5: The results of the quadratic regression models

Dependent variable: *Net transit in 30 minutes threshold*						
	Model 1		*Model 2*		*Model 3*	
Variable	*Coefficient*	*t-value*	*Coefficient*	*t-value*	*Coefficient*	*t-value*
R_{Bus}	0.338	2.22	-	-	-	-
$(R_{Bus})^2$	-0.182×10^{-5}	-1.27	-	-	-	-
R_{Train}	0.236	3.39	-	-	-	-
$(R_{Train})^2$	0.212×10^{-6}	1.04	-	-	-	-
L_{Bus}	-2.298	-1.08	7.985	3.14	-	-
$(L_{Bus})^2$	0.028×10^{-2}	1.35	-0.56×10^{-3}	-2.70	-	-
L_{Train}	9.043	1.21	-19.037	-1.90	-	-
$(L_{Train})^2$	-0.010	-2.44	0.014	2.57	-	-
P	-	-	-0.004	-2.99	-	-
$(P)^2$	-	-	0.000	6.86	-	-
Q_{Bus}	-	-	-	-	-2090.83	-1.84
$(Q_{Bus})^2$	-	-	-	-	163.221	1.25
Q_{Train}	-	-	-	-	-157.627	-1.18
$(Q_{Train})^2$	-	-	-	-	2.194	3.27
Constant	2102.62	1.07	229.473	0.06	11679.3	1.06
Sample Size: 46	0.966		0.884		0.567	
Adjusted R^2:	0.966		0.884		0.567	

revenue km has increasing accessibility returns to scale over the whole range. It should be noted that the quadratic term is statistically insignificant in both of these cases.

The results of the length of routes variable show that the length of bus routes is statistically insignificant. In contrast, any increase in the length of rail routes (L_{Train}) above 425 km is negative (consistent with the previous findings), while the linear term is statistically insignificant.

5.3 Transit performance measurement

One of the main goal of the study is to assess the performance of transit systems using an output that matters like accessibility. Comparing individual metropolitan areas against the envelope of output for the largest US cities gives guidance for implementing effective policies to allocate funding resources properly in the public transport arena. To appraise the performance of transit agencies in terms of providing accessibility to jobs by transit, a number of parameters are independently considered as the input of the model, along with a multi-inputs model. This approach simplifies comparative effectiveness of transit agencies while controlling for various inputs. Furthermore, including too many inputs inflate the efficiency scores, particularly in small samples. Consequently, the smallest number of inputs which captures all essential aspects of the transit services is the ideal selection.

The final results of the DEA analysis are outlined in Table 6 in which operational expenses, travel vehicle revenue kilometers, and size of fleet are considered as an individual input of the system. While, a multi-inputs analysis is employed when the independent variables of the parsimonious model are considered as the inputs of the system.

Given the DEA definition, a transportation agency is delineated as 100% efficient if and only if accessibility to jobs by transit is increased by rising one or more of inputs. As shown in Table 6 the performance of the transit agencies varies from one input to another input, but the overall pattern is consistent. Although it makes the overall performance assessment complicated, it gives policymakers an in-depth insight into the performance of transit agencies while considering a variety of inputs. In terms of the operational expenses, New York, Washington, Milwaukee, and San Francisco metropolitan areas perform 100% efficient; while, Riverside, Austin, and Detroit metropolitan areas have the lowest efficiency, respectively. The average efficiency score of DEA analysis with share of workers, vehicle revenue kilometers, and length of routes for both bus and rail services as the inputs of the system is 0.54. It means a metropolitan area on average could provides the same level of accessibility to jobs by transit with 54% of the current inputs.

6 Conclusion

Boosting accessibility to jobs by transit is an opportunity to improve public transit ridership. However, while upgrading transit accessibility requires long-term policies and investments and is not achieved overnight, there are a number of strategies that agencies can use that will better deploy existing resources in a manner to improve accessibility. This study examined not only the influence of financial and physical characteristics of transit systems, but the performance of operating agencies in 46 of the 50 largest metropolitan areas in the United States. To the best of the authors' knowledge, this is the first endeavor to shed light on the relationship between transit system characteristics and transit accessibility at the metropolitan area level. Two general methods were employed to reach the conclusion: a set of linear regression models to investigate influential economic variables on accessibility, and a data envelopment analysis to assess the performance of transit agencies. Moreover, a quadratic functional form is represented to scrutinize the accessibility returns to scale of the transit systems.

On the influential parameters side, vehicle revenue kilometers and operational expenses play a pivotal role in enhancing the accessibility to jobs by transit. Relying on the bivariate linear regression model, 1% increase in the operational expenses and vehicle revenue kilometers augments the number of jobs which can be reached by transit by 0.9 and 1.0%, respectively. On the performance side, the highest performance is found in the New York, Washington, and Milwaukee metropolitan areas; while, Riverside, Detroit, and Austin perform with the lowest efficiency. The results of the quadratic functional form, also, show the transit services has both increasing and decreasing accessibility return to scale and the results are sensitive to the model.

While the results of this research offer pivotal insights into the role of the long term policies to boost accessibility to jobs by transit, there are some limitations that further studies can proceed them more.

Table 6: Data envelopment analysis result when net transit considered as the output

Operational Expenses		**Travel Vehicle Kilometers**		**Total Vehicles in Service**		**Parsimonious Model**	
Mean: 0.49 St. Dev.:0.22		*Mean: 0.43 St. Dev.:0.22*		*Mean: 0.37 St. Dev.:0.24*		*Mean: 0.54 St. Dev.:0.26*	
Rank	*Metropolitan*	*Rank*	*Metropolitan*	*Rank*	*Metropolitan*	*Rank*	*Metropolitan*
1	New York	1	New York	1	New York	1	New York
1	Washington	1	Washington	1	Washington	1	Washington
1	San Francisco	1	Milwaukee	1	Milwaukee	1	Milwaukee
1	Milwaukee	4	San Francisco	4	San Francisco	1	San Francisco
5	Columbus	5	Buffalo	5	Chicago	1	Los Angeles
6	Indianapolis	6	Columbus	6	New Orleans	1	Chicago
7	Chicago	7	Chicago	7	Portland	7	Seattle
8	Raleigh	8	Louisville	8	Indianapolis	8	Indianapolis
9	Louisville	9	Pittsburgh	9	Los Angeles	9	Minneapolis
10	Birmingham	10	New Orleans	10	Columbus	10	Buffalo
11	Denver	11	Minneapolis	11	Denver	11	Providence
12	Buffalo	12	Portland	12	Louisville	12	Houston
13	Salt Lake City	13	Los Angeles	13	Buffalo	13	Denver
14	Sacramento	14	Providence	14	Pittsburgh	14	Portland
15	Los Angeles	15	Indianapolis	15	Raleigh	15	Columbus
16	New Orleans	16	Sacramento	16	San Antonio	16	New Orleans
17	Kansas City	17	Seattle	17	Salt Lake City	17	Pittsburgh
18	Minneapolis	18	Denver	18	Sacramento	18	Raleigh
19	Portland	19	Raleigh	19	Minneapolis	19	Sacramento
20	San Antonio	20	Phoenix	20	Seattle	20	Louisville
21	Houston	21	Philadelphia	21	Boston	21	Miami
22	Pittsburgh	22	Salt Lake City	22	Phoenix	22	Hartford
23	Providence	23	Kansas City	23	Houston	23	Salt Lake City
24	Charlotte	24	Birmingham	24	Charlotte	24	Philadelphia
25	Phoenix	25	Boston	25	Miami	25	San Antonio
26	Nashville	26	San Antonio	26	Kansas City	26	Phoenix
27	Philadelphia	27	Charlotte	27	Birmingham	27	Boston
28	Boston	28	Nashville	28	Philadelphia	28	Baltimore
29	Tampa	29	Houston	29	Cleveland	29	Charlotte
30	Seattle	30	Cleveland	30	St. Louis	30	Kansas City
31	Cleveland	31	Baltimore	31	Baltimore	31	Birmingham
32	Cincinnati	32	Las Vegas	32	Las Vegas	32	Cleveland
33	Las Vegas	33	Miami	33	Tampa	33	Nashville
34	Baltimore	34	Hartford	34	Nashville	34	San Jose
35	St. Louis	35	San Jose	35	Dallas	35	Las Vegas
36	Miami	36	Cincinnati	36	San Jose	36	Tampa
37	Hartford	37	Tampa	37	Orlando	37	St. Louis
38	Virginia Beach	38	St. Louis	38	San Diego	38	Cincinnati
39	San Diego	39	San Diego	39	Cincinnati	39	San Diego
40	Orlando	40	Dallas	40	Atlanta	40	Dallas
41	San Jose	41	Virginia Beach	41	Virginia Beach	41	Detroit
42	Dallas	42	Orlando	42	Detroit	42	Atlanta
43	Atlanta	43	Detroit	43	Providence	43	Virginia Beach
44	Detroit	44	Atlanta	44	Hartford	44	Orlando
45	Austin	45	Austin	45	Austin	45	Austin
46	Riverside	46	Riverside	46	Riverside	46	Riverside

- The performance of the system in terms of providing accessibility to jobs by transit is measured at the metropolitan area level in this study; while, having the enough information at the disaggregated level helps to disentangle the role and performance of the transit agencies.

- Transit networks include various characteristics, including connectivity, circuity, and speed. Exploring the geometric characteristics of transit networks along with their performance will aid in providing network design guidance.

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