Variations in Employment Transportation Outcomes: Role of Site-Level Factors

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Abstract. The paper examines two labor market outcomes experienced by users of federally-funded transportation services for low-wage workers in the United States, using primary data from 23 locations. The propensity of users to be unemployed prior to using the service is found to be related to the type of service (fixed-route/ demand-response) and location type (urban/rural) but not to aggregate local unemployment, variability in local unemployment rates or local welfare policies. The propensity to earn higher wages is related to the type of employment transportation service and location, and local unemployment levels. Results imply a need for locally-derived, coordinated employment transportation plans.

JEL Classification: I38, O18, J60, J68, R48

Key words: employment transportation, Job Access and Reverse Commute program, transportation and labor market outcomes, multi-level mixed model

1. Introduction

The relationship of transportation to employment has been widely examined from multiple, related perspectives. A far from complete list of perspectives include investigations of the economic impacts of transportation, including employment that is created as a result of investment in transportation, and the economic development and growth that ensues (examples include Aschauer 1989; Rietveld and Bruinsma 1998; Montolio and Solé-Ollé 2009; Jiwattanakulpaisarn et al. 2009). Authors have also examined the relationship of transportation to changes in labor markets, including, on the supply side, micro-level job search behavior, and the trade-offs that workers make between commuting and migration, and on the demand side, the ability of firms to select from a broader labor pool at lower prices and the potential for a more targeted or specialized fit between jobs and employees (Haynes 1997). Others have studied the accessibility benefits of transportation programs, and ways in which accessibility is linked to employment opportunities (including Shen 1998; Sen et al. 1999). In addition, researchers have considered the relationships between labor market outcomes such as employment status, wage rates, hours worked and benefits, and how these may be related to transportation options such as car ownership (for example, Ong 2002; Raphael and Rice 2002; Lichtenwalter et al. 2006).

But while the effects of employment and training programs, human services programs and other social services interventions on these types of labor market outcomes have been widely studied, the link between transportation services and these broader outcomes have been the subject of far less attention. While changes in travel times and associated mobility benefits are included in evaluations, other meaningful outcomes, such as those experienced in the economy, labor markets or land markets, are typically excluded from impact evaluations. One reason for such exclusion is that the addition of these benefits to mobility benefits are expected to lead to "double counting" the benefits of transportation projects (Jara-Diaz 1986; Boarnet 2007). The limited literature also reflects, in part, the lack of disaggregate empirical data and evaluation designs that control for or rule out alternative explanations of the observed or reported labor market outcomes.

This paper examines the factors that explain labor market outcomes in the case of a nationwide "employment transportation program" to facilitate access to jobs by low-wage workers in the US. The employment transportation services considered are partially funded by the Job Access and Reverse Commute (JARC) program of the Federal Transit Administration (FTA) of the US Department of Transportation, and financially matched by other sources. The program was created in 1998 in response to discussions that took place around the time that the Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA, 1996) was passed, which highlighted transportation barriers faced by individuals transitioning from public assistance to work, and for low-wage workers in general. Although originally focused primarily on public transportation, the program has changed over time to reflect the vast diversity of needs relating to accessing jobs and job-supportive services, and currently funds "capital services" (such as low-cost auto loan programs, vehicles for vanpools and the use of car-sharing programs) and "information services" (such as travel training programs, ride-sharing programs and trip and itinerary planning services), in addition to traditional "operational" services (such as Fixed-Route and Demand-Responsive public transportation). The program gives local organizations considerable flexibility in designing, targeting and administering programs that suit the local context. A distinguishing characteristic of the program is that the services fill gaps in existing transportation services. An additional characteristic is that they are designed by transportation agencies in partnership with workforce development boards, human services agencies and other public, private and non-profit organizations involved in planning, financing and operating such services, as part of a Coordinated Human Services Transportation Plan. By 2006, the JARC program had funded 649 individual services in multiple urban and rural areas with widely different spatial, economic, socio-demographic and mobility conditions.

The overall objective of the paper is to determine the associations between the characteristics of the sites where a sample of such services are operational (in terms of their spatial, economic, socio-demographic and transportation characteristics), and the labor market outcomes experienced by employment transportation users at those sites, after adjusting for individual user characteristics. The paper is motivated by a stream of literature that relates "place-based characteristics" to labor market outcomes and poverty (Blank 2005; Patridge and Rickman 2006), and by the significant site-to-site variations in individual outcomes of numerous federal programs that call for strong local planning in allocating and using federal funds (an example includes Greenberg et al. (2003) in the case of job training programs). The paper is also motivated by the need to understand how local partnerships can respond to federal employment transportation funding in terms of developing projects, given the unique economic, sociodemographic and spatial characteristics of a place. Additionally, there is a need to understand whether employment transportation funding formulae should go beyond using restrictive criteria such as the number of eligible low-income individuals and welfare recipients living in each state and as a percent of the area's population size, as they currently do, and include local economic and spatial conditions, as these factors can affect may also labor market outcomes. This paper focuses only on employment transportation Fixed-Route (FR) and Demand-Responsive (DR) transit services, since the primary data used here were collected in 2002, when close to 94 percent of program funds were expended on such services.

The paper extends previous research in the following ways: first, it considers primary data on two outcomes relating to employment, which were determined to be important by a diverse group of planning partners in public transit, human services, economic development, workforce development and other, related sectors. These are: the extent to which the services have increased the propensity of previously unemployed individuals to access jobs, and the extent to which workers reported earning higher wages once the service became available. Second, the paper reports on outcomes experienced in multiple (large urban, small urban and rural) locations with a wide spectrum of spatial, economic, socio-demographic , transportation and labor market conditions, and thereby allows us to ascertain the importance of site-level factors. Third, we examine the extent of site-to-site variations in observed labor market outcomes and the associations between outcomes and site-level factors by using a multi-level mixed modeling structure to account for correlations in outcomes experienced by users within the same location; these correlations may result not only due to similarity among individuals residing along a bus route or service area, but also due to their relationship to the economic and social opportunities offered in the area. One question in this context is the extent to which certain types of transit-based mobility may be causally related to the outcomes.

The paper is organized as follows: the research design and primary data are described in Section 2. Section 3 presents the details of the outcome measures considered and examines benefits and problems with using each one of these measures. In Section 4, we examine factors that lead to site-to-site variations in the outcome measures. In Section 5, we present a series of multi-level mixed models of the selected outcomes, the purpose of which are to examine the effects of individual-level and site-level factors on the outcomes under study. Results are discussed in Section 6, followed by summary and conclusions in Section 7.

2. Research Design and Data Collection

The primary data used in this paper were collected in 2002. Our data collection strategy was to select a sample of 23 sites across the country where employment services were funded by the JARC program, stratified by federal region, type of location (large urban, small urban and rural), type of transit service funded (FR or DR) and dollar amounts of the funds received per year. Since the vast majority of service users are FR users, for whom there is no systematic point of contact in transit agencies or social services agencies that might keep a roster of users, we followed an intercept survey approach, as is typically followed by transit agencies (Schaller 2005). Intercept surveys have many advantages including the ability to survey harder-to-reach segments of the population, the ability to survey during the immediate experience of the service and therefore to obtain better information (including accuracy, reliability and detail) from respondents.

Intercept methods however do not easily lend to surveying “non-users”, in this case, individuals similar to the riders, but who do not use the program’s services. Identifying similar non-users and surveying them (which would have yielded a “control” group) would have been difficult and cost-prohibitive, due to the uniqueness of the services in many cases (for example, virtually all the low-income workers in the case of some rural areas were already service users, leaving no one else to be used as control). Due to these difficulties in establishing a control group, the study followed a “before” and “after” design, based on the subjects’ recall of their travel and employment conditions before they started to use the service and after. A two-page survey which implemented this design was developed and pretested for this purpose.

While intercept surveys onboard transit vehicles pose survey administration challenges under any circumstances, the measurement of the characteristics and behavioral experience among members of the low-income and welfare populations pose particular difficulties with respect to reducing various sources of response error (Mathiowetz et al. 2001). We worked with Literacy Chicago, which is a provider of free, individualized adult literacy services in Illinois, to ensure that the survey instrument met the eighth grade reading standard. The survey instrument was also pre-tested in Literacy Chicago and a JARC-funded bus service run by the Chicago Transit Authority, in the City of Chicago. The reliability and validity of retrospective self-reported behaviors based on recall have been studied by several authors. For instance, it has been noted that questions on personal and factual information are much less vulnerable to recollective loss or distortion than subjective, attitudinal or less personally relevant factual information. Further, researchers have also noted that data collection by retrospective self-reports based on recall requires that data be collected within a short period of time after the intervention in order to avoid recall decay, which in our case would be soon after the starting date at which the employment transportation services that were sampled became operational. It is possible that responses to some survey questions including that asking respondents to report whether they received welfare assistance may be subject to recall bias either because as noted elsewhere (Luks 2003), respondents may be subject to the fallibility of memory and possibly to social pressures to minimize being on welfare.

The questionnaire asked about the sociodemographics of the riders and their travel and employment experiences. The questionnaire also asked respondents about several economic, travel, employment and activity-related factors, “before-using-the-service” and “after-using-the-service”. Coverage errors were minimized to the extent possible by ensuring that the surveys were administered at the appropriate times (for example, if the transit service being surveyed is a night-owl service of a 24-hour bus service, the surveys were administered during the night, after regular service ended for the day). The short length of the survey instrument attempted to minimize refusals, item non-response and potential selection biases associated with surveying only those riders traveling longer distances and with not giving sufficient time for completion by those individuals who had to leave the transit vehicle after a short ride. Measurement errors were minimized to the extent possible by ensuring that the survey instrument was understandable by the target group, by using short and “colloquially-worded” questions. The survey yielded a total of 534 usable responses. We use subsets of the total responses (on current workers) in the models; sample sizes will be indicated in the appropriate sections.

As reported in Thakuriah et al. (2006), we compared survey respondents to commuters in 23 sites where the survey was administered, using the 5 percent Public Use Microdata Sample of the decennial 2000 Census for the 23 locations, and found that the typical employment transportation service user is of lower income than automobile users in the same region, as well as users of regular transit services, particularly bus services, who tend to be of lower income than rail transportation users. Respondents were also more likely to be without a valid driver’s license and without an automobile. The median employee tenure among the survey respondents was less than 1 year. This may be contrasted to the median employee tenure of all wage and salary workers (referred to as employee tenure), which was 3.7 years in 2002, and that of workers in lower-paid occupations (in the service industries), which was 2.4 years. Based on such estimates, the employment transportation services surveyed appear to have targeted a pool of riders, who, without the service, would either be unable to commute to work or would face tremendous hardship in doing so.

3. Outcomes Considered

Previous researchers have considered a number of labor market outcomes, including current (binary) employment status (Ong 2002), employment rates, weekly hours worked, and hourly earnings (Raphael and Rice 2002) and monthly wages, including tips before taxes and the sum of the number of Positive Employment Characteristics such as the number of job characteristics that the subject desires or receives, including paid sick days, flexible work hours and so on (Lichtenwalter et al. 2006). Given that the JARC program funds a variety of employment transportation services across the country, the same measures may not be meaningful for the universe of JARC projects and may not be agreed upon by the universe of stakeholders. Over time, stakeholders have concluded that: (1) comparative JARC outcome evaluation (cross-site evaluation) should not be based on a single outcome measure, but on a variety of measures; (2) there might be value in trying to develop comprehensive benefit-cost measures of the services, taking into account the full (user, non-user and societal) costs and benefits of the services; and (3) both employment-related and mobility-related measures are important to analyze, since the services attempt to bring about not only employment-related benefits but also to improve the quality of the commuting trip, so that users are motivated to seek employment and to stay employed.

The scope of this paper is restricted to two employment-related outcomes that were frequently articulated in the context of the services: whether previously unemployed users were able to access jobs after using the service, and whether previously employed users have been able to increase their earnings after using the service (by being able to reach a job at a new location or different shift at the same job). Two binary variables indicating such employment-related outcomes are constructed from the survey data. Summary statistics on these and the exploratory factors considered in the paper are given in Table 1.

Table 1. Outcome and exploratory variables considered and sample means

Variable	Type	Explanation	Sample Mean
Outcome/Response Variables			
UNEMP_BEF	Dummy	1 if respondent was unemployed prior to using the service	0.17
WAGE_HIGHER	Dummy	1 if respondent reported earning more after using the service	0.19
Site-Level Explanatory Variables			
D_URBAN	Dummy	1 if resident of large or small urban area	0.74
D_SERVICE	Dummy	1 if Fixed-Route (FR) employment transportation service	0.57
TRAVTIME	Continuous	Mean commuting time in region	23.64
PERDRIVE	Continuous	Percent of commuters in region driving alone	72.2
PERTRANSIT	Continuous	Percent of commuters using public transit	7.11
UNEMP_PER	Continuous	Percent of civilian labor force unemployed	5.54
DIFUNEMP_PER	Continuous	Difference between maximum and minimum values of census tract-level unemployment rates along fixed route or in demand responsive service area	17.75
WELFARE_POL1	Dummy	1 if state had full family sanction in year 2002	0.13
WELFARE_POL2	Dummy	1 if state had full family or graduated sanction in 2002	0.65
Individual-Level Explanatory Variables			
D_GENDER	Dummy	1 if male	0.48
D_CAROWN	Dummy	1 if respondent owns a car	0.15
D_HIGH_SCHOOL	Dummy	1 if high school graduate and higher	0.65
AGE	Continuous	In years	33.14
D_ASSISTANCE	Dummy	1 if respondent reported earning public assistance in last 5 years	0.28
TRAVEL_TIME	Continuous	Travel time of current trip in minutes	27.18

1) **Propensity of previously unemployed workers to use the service (*UNEMP_BEF*):** The first binary variable is *UNEMP_BEF*, which takes a value of 1 for those who were unemployed prior to using the service and 0 otherwise. Table 1 shows that, overall, over 17 percent reported being new workers in the labor force after using the service. This measure is beneficial to consider because one of the primary goals of the JARC program is to connect welfare clients and unemployed individuals to jobs. This measure as an indicator of a successful service is also problematic. (A) First, the targeted service might have as its end goal not only access to jobs but also to employment supportive services such as educational facilities and job-training centers, day-care centers and destinations that allow other activities that are supportive of a work life. While such service goals are as important as accessing jobs in many cases, individuals who access such employment-supportive services might not do as well on this indicator. (B) Second, many projects do not provide new, dedicated service for welfare clients and the like, but modify existing services used by commuters, by means of extensions in service hours, and with extra stops, route extension and deviation – these additions are also

funded by JARC. Some localities have preferred this approach in order to be able to cater to the target population, but at the same time, to ensure that the basic service (without the JARC-funded additions) would continue to operate, in the event that JARC funds became unavailable. In such cases, the proportion of new workers might be low, but the service might still enable existing low-wage riders to complete their trip more efficiently and also perhaps to increase or at least retain their earnings levels. (C) Third, low-wage workers are more likely to have multiple jobs. Multiple jobholders as a percent of total employment were roughly 5.3 percent in 2002, the year when the data were collected, with considerable variation at the state level around this national average (Campbell 2003). A disproportionate share of all low-wage workers work multiple jobs (11.4 percent) compared to higher-wage workers (7.6 percent) (Office of Human Services Policy of the U.S. Department of Health and Human Services 2009). In the 23 site sample, close to 56 percent of the respondents indicated that they worked full-time, about 25 percent worked part-time and about 13 percent were unemployed and were looking for a job whereas the remainder were unemployed but not looking for jobs. There is a strong possibility that some of the workers were already employed before they started to use the employment transportation service (such that *UNEMP_BEF* is 0 for these individuals) but that with the service, they could access a second or even a third job reliably, perhaps accruing overall gains in earnings.

2) **Propensity of users to earn higher wages after using service (*WAGE_HIGHER*):** The second binary variable is *WAGE_HIGHER*, which takes a value of 1 for those workers who self-reported earning a higher hourly wage rate after using the service and 0 otherwise. Table 1 shows that over 19 percent of workers who were employed prior to using the service reported an increase in their hourly wage rate. Using the propensity of workers to earn more after using the service as an indicator is also problematic. While access to higher-paying jobs is ideal and services that rank high in the proportion of riders that increase their wage rate by using the service might be deemed successful, this measure downplays the fact that riders might be economically benefiting from the service by managing to stay on in the labor force even if by working for the same or lower wages, or simply by looking for jobs or by improving their skill levels through training programs. The measure also downplays the quality of the work experience which might be better captured by indicators such as the number of hours worked or number of days per week at the same job.

Employment transportation service users who are currently working but were unemployed at the time they first started to use the service (those with *UNEMP_BEF*=1*)*, may have simultaneously increased their propensity to be employed because of completion of job-training, due to graduation from school by younger workers, and due to a variety of other reasons. The latter reasons may also explain higher wage placement experienced after starting to use the services. These alternative explanations for the outcome measures are not considered here; hence we consider these to be “gross” outcome measures and not net impact measures of employment transportation.

4. Site-Level Characteristics

In this section, we examine the major site-level factors that may potentially contribute to variations in labor market outcomes that were experienced in the context of employment transportation services in the 23 sites. Summary information on site-level factors is given in Table 1. Table 2 gives detailed information at the level of the individual sites, including the sample size at each site, the type of service, and several site-level factors under three groupings: local economic factors, transportation factors and state-level welfare policy and practice factors. In addition, Table 2 also presents likelihood-ratio χ^2 statistics of tests of independence between the two outcome variables described in the previous section and each of the site-level exploratory factor.

4.1 Type and Scope of Employment Transportation Services

The types of transit services considered in this study were FR bus services or DR bus or van service. Column 2 of Table 1 shows that approximately 57 percent of the services studied were FR operations whereas close to 43 percent were demand-responsive; this split is close to the 60-40 percent split in funding allocation between FR and DR services by FTA between 1999 and 2002.

The sampled transit services reflect variations in operations such as time-of-day of operation, weekday/weekend day service, route deviation, route extension, extended hours of service and other operational considerations that are representative of the universe of trip-based employment transportation services as a whole. Services were planned and developed with the input of stakeholders in the sectors described earlier. One particular type of service that we surveyed in a few locations were FR bus services that have multiple stops in low-income neighborhoods, and terminates at the location of a single large employer (for example, a factory) or an area with multiple employers such as a shopping mall or an airport. Several services surveyed did not connect low-income neighborhoods with a specific, single job-rich location, but were routed through areas with varying levels of employer locations, community colleges and job-training centers, where passengers could board and exit. A key feature is that several services provide access to jobs that are located in a scattered fashion along a route or within a service area and were not restricted to connecting low-income neighborhoods to areas that are ranked high on traditional gravity-based accessibility measures of employment opportunities.

4.2 Locational Site-Level Factors

Sites differ on a variety of factors including size, regional unemployment patterns, general transportation and mobility conditions and prevailing welfare policies and practices.

4.2.1 Location Type

Column 3 of Table 2 shows that roughly 44 percent of the sites in the sample were large metro areas (where the population of the city where the service is operating greater than 100,000), 26 percent were non-urbanized (rural) areas (with population less than 50,000) while 30 percent of the sites were in small urban areas (with population between the large

Table 2: Site-Level Factors and Summary Statistics

				Local Economic Factors			Transportation Factors			State Welfare Policy & Practice Factors			
(1)	(1A)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
										State Sanctioning Policies			
Site No.	Sample Size	Type of Service	Type of Site	Regional Unemployment Rate (2002)	Rank within US Distribution of County Unemployment	Min. and Max. Census-Tract Level Unemployment Rate	Regional Mean Commuting Time (minutes)	Percent of Commuters Driving Alone to Work	Percent of Commuters Using Public Transit	Full Family Sanction	Graduated Sanction	Partial Sanction	Welfare Caseload Reduction (June 2001-June2002)
1	44	FR	Small	4.9	Medium-Low	(0, 40.6)	29.0	76.0	5.0		1996-2002		-12.6
2	75	FR	Large	4.6	Medium-Low	(0, 16)	31.1	59.9	19.7			1996-2002	10.2
3	40	FR	Rural	5.3	Medium-Low	(0, 11.8)	32.9	74.7	8.5		1996-2002		7.4
4	20	DR	Rural	5.6	Medium-High	(0.5, 5.7)	19.7	85.3	1.3		1996-2002		-1.2
5	46	FR	Rural	3.5	Low	(0, 19)	29.8	80.4	3.6	1996-2002			3.0
6	5	DR	Rural	6.7	Medium-High	(0.7, 16.1)	21.4	84.6	0.3	1996-2002			-13.4
7	23	FR	Large	7.4	High	(0, 57.9)	34.0	52.2	25.9		1996-2002		28.3
8	23	DR	Small	3.8	Low	(0, 28.7)	15.4	80.5	2.3		1996-2002		28.3
9	12	DR	Large	4.4	Low	(0, 45.1)	21.9	74.7	6.4			1996-2002	-2.0
10	11	FR	Small	4.3	Low	(0, 5.8)	15.1	73.3	1.9	1996-2000	2000-2002		-5.1
11	12	FR	Large	4.4	Low	(0, 15)	21.6	61.8	13.1			1996-2002	-2.0
12	25	FR	Large	4.9	Medium-Low	(0, 10.4)	23.8	79.8	1.6		1996-2002		5.5
13	25	FR	Small	6.5	Medium-High	(1.3, 25.2)	17.3	67.8	3.0		1996-2002		-5.5
14	42	DR	Small	4.4	Low	(0.5, 8.2)	16.3	81.9	1.1	1998-2002	1996-1998		3.4
15	5	FR	Small	4.7	Medium-Low	(1, 9.8)	19.5	73.8	0.9		1996-2002		-14.4
16	29	FR	Rural	3.4	Low	(0.9, 10)	23.4	81.8	0.1		1996-2002		-14.4
17	24	FR	Small	5.1	Medium-Low	(0.1, 10.3)	21.2	74.3	2.9			1996-2002	2.4
18	9	DR	Large	8.4	High	(0, 12.2)	25.5	77.6	3.7			1996-2002	2.4
19	12	FR	Large	6.7	Medium-High	(0.2, 10.8)	26.4	63.5	15.0			1996-2002	2.4
20	16	DR	Rural	8.1	High	(1.0, 7)	23.7	71.7	6.6		1996-2002		-8.0
21	19	DR	Large	8.1	High	(0, 22.7)	23.7	62.0	12.5		1996-2002		-8.0
22	11	DR	Large	6.1	Medium-High	(0.3, 13)	24.6	55.5	17.9			1996-2002	2.6
23	7	DR	Large	6.1	Medium-High	(0.5, 15)	26.5	67.5	10.2			1996-2002	2.6

Likelihood Ratio χ2 Test Statistics:

	D_SERVICE	*D_URBAN*	*UNEMP_PER*	*DIFUNEMP_PER*	*TRAVTIME*	*PERDRIVE*	*PERTRANSIT*	*WEL_POL1*	*WEL_POL2*
UNEMP_BEF	0.01	7.99**	24.63*	36.59**	35.15**	33.57**	36.59**	0.002	0.08
WAGE_HIGHER	0.59	1.93	0.50***	52.79***	46.18***	44.86***	52.74***	0.13	0.48

*: Significant at .1 level; ** Significant at .05 level; *** Significant at .01 level

urban and rural levels). This split is close to the split in program awards by area (47 percent of the JARC funds were awarded to Major Urban Areas, and Non-Urbanized Areas and Medium Urban Areas split the remainder almost equally). Whereas the universe of sites receiving funds were stratified into these three categories for the purposes of sampling, large urban and small urban sites were combined in the final analysis to create a single dummy variable *D_URBAN*, which takes a value of 1 if large or small urban and 0 if rural.

The size of the area can potentially affect outcomes because the spatial distribution of economic opportunities with respect to residential locations of low-income workers tends to be different in urban and rural areas; further, the availability of transit and opportunities to rideshare or form vanpools may also differ because of these locational attributes. The Likelihood Ratio (LR) χ^2 test results given at the bottom of the column “Type of Site” in Table 2 shows a statistically significant association of *D_URBAN* with *UNEMP_BEF*.

4.2.2 Local Economic Factors

The outcomes experienced by employment transportation users could potentially vary with the economic opportunities that the service is able to connect users with. Three site-level local economic factors are considered: the regional unemployment rate (average of the counties where each service operational), rank of the average county-level unemployment at each site within the U.S. distribution of county-level unemployment in 2002, and small area variability in unemployment rates in areas within a walking distance within the FR bus route, or are within the service area of the DR service.

Regional unemployment rate: Table 1 shows that the mean county-level unemployment rate in the sample sites is 5.54 percent, while column 4 of Table 2 shows that the minimum value among the 23 sites was 3.4 and the maximum, 8.4. Overall, the longest postwar expansion in the U.S. was noted to have ended in 2001, as the economy entered a recession in March 2001, after an unprecedented growth over 10 years (Langdon et al. 2002). The unemployment rate rose to 5.6 percent in the fourth quarter of 2001, an increase of 1.6 percentage points from the 30-year low of 4 percent, which occurred in the fourth quarter of 2000. At about the same time, there were structural changes in the public welfare system, to which low-wage workers could turn to for financial help when they were unemployed, but did not qualify for unemployment insurance.

Site ranking in U.S. distribution of unemployment rate: The ranks of the counties where the services operate indicate the quartile of the U.S. distribution of unemployment in 2002 that the site falls in. For example, the rank of the counties where the service in Site 1 is operational is labeled “Medium-Low” in column 5 of Table 2, indicating that the average unemployment in those counties fall in the third highest quartile of the U.S. distribution of county-level unemployment. Similarly, sites labeled “Highest” are in the highest quartile of unemployment within the U.S. county-level distribution of unemployment, “Medium-High” sites are in the second highest quartile and “Low” sites are in the lowest quartile of unemployment levels. The sampled sites fall roughly equally among the cut-offs given by quartiles of the U.S. distribution of unemployment by county and is hence, at the county-level, representative of the U.S. distribution of unemployment patterns.

Small-area variability in unemployment along route or in service area: The county-level unemployment rate masks the large variability in small-area unemployment patterns. The small-area unemployment rates, at the level of census tracts, were obtained from the 2000 census and therefore may potentially under-represent the conditions in 2002, because of changes in the overall economic conditions described above. Column 6 of Table 2 shows, for example, that FR bus route in Site 1, which is a small urban area with a 4.9 percent county-level unemployment rate, is within walking distance from census tracts that had a minimum unemployment rate of 0%; however, the route also provides opportunities for individuals residing in extremely disadvantaged neighborhoods with unemployment rates of 40.6%. The maximum unemployment rate in a census tract served by a sampled employment transportation service tended to increase with the regional mean and, in general, there was greater variability in large and small urban areas, compared to the rural sites.

Table 2 shows that both outcome variables have a significant association with *UNEMP_PER* (percent of the civilian labor force unemployed, with a mean of 5.54%) and *DIFUNEMP_PER* (the difference between the maximum and minimum unemployment rates along the route or in the service area, with a mean of 17.75%).

4.2.3 Local Transportation Factors

Table 2 gives information on three factors describing the transportation conditions in the sites, including the regional mean commuting time, the percentage of commuters driving alone to work (excluding carpooling), and the percent of commuters using public transportation. The average commuting time denotes an expectation of what residents in an area may perceive to be typical separations of jobs and residential locations, with a greater degree of separation between home and work for areas with higher mean commuting times. The percent using public transportation may be an indicator of the extent to which transit culture and opportunities for alternative methods of commuting that exist in the region, and the extent to which local organizations dealing with public transportation are present to organize planning and financial partnerships needed to operate employment transportation.

Large urban areas in the sample have the highest mean commuting time, indicating the greatest separation of residential locations and job locations, followed by rural areas and small urban areas. Approximately 65 percent of commuters in the large urban areas drove, compared to 80 percent of small urban commuters and 75 percent of rural commuters. Small urban area commuters in the sampled sites were also least likely to take transit – whereas the average over the entire sampled sites is 7.1 percent, transit in the small urban sites accounted for only 2.4 percent of total commuting trips.

4.2.4 Welfare Policies and Practices

The sites were located in states with varying policies and practices regarding public assistance between 1996 and 2002. Only 31 percent of the users self-reported receiving public assistance in the 5 years prior to our survey year, but this information may have possible underreporting. One of the stipulations of the PRWORA was to end the entitlement status of Aid to Families with Dependent Children (AFDC) and to replace it with a time-limited assistance and work requirement program called Temporary Assistance to Needy Families (TANF). Further, PROWRA gave states more leeway to structure their welfare administration, and different states accordingly adopted different sanctioning policies: (1) Full family sanctioning: some states sanction the entire TANF check at the first instance of nonperformance of required work or other activities; this is the strongest sanction a state can apply. (2) Graduated sanctioning: states that do not sanction the entire TANF check at the first instance of nonperformance but will sanction the full TANF check after multiple infractions. (3) Partial sanctioning: some states sanction only the adult portion of the TANF check, even after repeated infractions, which enable recipients to retain the bulk of their TANF benefits even if they fail to perform workfare or other required activities. Some states changed the type of sanctioning policy over time. The last three columns of Table 2 show the types of sanctioning policies that were operational at the state level in the sampled sites.

According to TANF caseload data from the U.S. Health and Human Services, there was about a 58 percent decline in state welfare caseload from 1996 through 2001. Nationally, in the year before the data was collected for this study, caseloads declined by 8.81 percent. The state-level percent reduction during this period at the selected sites is shown in the last column of Table 2. The largest caseload reduction among the sites during this period was 28.3 percent and the largest increase in caseload was 14.38. Interestingly, in both these cases, the state-level sanctioning policy followed was that of a graduated approach.

5. Multilevel Mixed Models of Selected User Outcomes

In order to assess the extent to which site level factors are related to user outcomes, we use multi-level mixed modeling (Guo and Zhao 2000; Weiss 2005) as a function of the attributes of the individual and sites that are given in Table 1. There are several reasons why multilevel mixed models are appropriate for these types of data: First, multilevel models provide a convenient framework for studying multi-level data. The primary question addressed in this paper - what is the strength of the association between site-level factors and individual outcomes, adjusting for individual characteristics of users - is a natural fit for the multi-level approach, with individuals at Level 1 and site-level factors at Level 2 and cross-level interaction effects. Second, multilevel modeling corrects for the biases in parameter estimates and standard errors resulting from clustering of outcomes experienced by users at the same site (we will demonstrate that within-site outcomes are, in fact, correlated). Third, multi-level modeling involves explicit modeling and partitioning of the covariance structure of outcomes between and within sites – partitioning the variance in outcome allows the calculation of the proportion of the variance in the outcome due to site-to-site variation against that due to variance among individuals within a site.

The main questions addressed are as follows:

1) How much do sites vary in users' labor market outcomes?
2) What is the relationship between the characteristics of the sites (in terms of their spatial, economic, socio-demographic and transportation characteristics) to labor market outcomes, after adjusting for individual user characteristics? This research question involves two sub-questions:
    a) Is there a causal relationship between labor market outcomes and the use of a particular type of transit service (i.e., FR or DR) due to differences in the degree to which commuting trips are personalized by DR versus FR, and due to differences in user cost?

b) Is the strength of the association between individual factors and outcomes mediated by site-level factors (for example, is an employment transportation user with a certain level of education more likely to do better in certain types of sites than in others) and if so, which "cross-level" interactions (i.e., interactions between site-level factors and individual factors) are important?

Let $p_{ij} = \Pr(y_{ij} = 1)$ where the values taken by y_{ij} lead to two different multi-level, mixed models for:

Model 1: y_{ij} = $UNEMP\_BEF_{ij}$ =1 if the i^{th} respondent in the j^{th} site reported being unemployed prior to starting to use the service and 0 otherwise;

Model 2: y_{ij} = $WAGE\_HIGHER_{ij}$ =1 if the i^{th} respondent in the j^{th} site reported higher wages after using the service and 0 otherwise;

In general, we use a mixed multi-level logit specification of the form:

$$\eta_{ij} = \log(p_{ij}/(1-p_{ij})) = X_j\gamma + Z_j u_j \qquad (1)$$

where $\boldsymbol{X}_j$ is the design matrix for fixed effects γ, $\boldsymbol{Z}_j$ is the design matrix for the random effects $\boldsymbol{u}_j$ and j denotes sites j=1,2,…,J.

The model for *UNEMP_BEF* was estimated on all users who reported they were currently working (N=438), whereas the model for *WAGE_HIGHER* was estimated for those current workers who previously worked (N=243). To achieve model parsimony, an incremental model-building approach was followed to determine which variables are to be kept in the final models.

Model A: One-Way Random Mixed Effects ANOVA: Preliminary unconditional means analyses or one-way random mixed effects Analysis of Variance (ANOVA) of the form

$$\eta_{ij} = \log(p_{ij}/(1-p_{ij})) = \beta_{0j} \qquad (2)$$
$$\beta_{0j} = \gamma_{00} + u_{0j} \text{ where } u_{0j} \sim N(0, \tau_{00})$$

established that there are substantial site-to-site variations in the outcomes, necessitating the use of multi-level models. The results are summarized in the lower panel of Table 3.The intercept fixed effect is significant at the .05 level indicating that there is substantial site-to-site variation in *UNEMP_BEF*. The intercept random effect variance is also significantly different from 0 indicating that for this data, using a single-level binary logit model would be problematic. The intraclass correlation for *UNEMP_BEF* is estimated to be 0.16 indicating that 16% of the variance in the dichotomous *UNEMP_BEF* outcomes can be attributed to the differences between sites, while the intraclass correlation for *WAGE_HIGHER* indicates that 10% of the variability in *WAGE_HIGHER* is estimated to be due to differences between sites (also significant at the .05 level). Although the intra-class coefficients in the above analysis are not very large, they offer statistical evidence that variations in outcomes exist partly due to factors that are associated with, or are unique to the sites.

There are several causal relationships that are worth examining in the data, but as indicated earlier, one hypothesis to pursue is that some forms of transit-based mobility, particularly those given by DR services, which, unlike traditional fixed route transit services, offer point-to-point connections between home locations and job locations, may also be causally related to positive employment outcomes, leading to greater potential for being successfully employed by unemployed individuals and to a higher possibility of being placed in a better-paying job. DR services are also considerably more expensive to operate and use, compared to FR services, making affordability a concern. However, transitioning from unemployment to work and from a lower to a higher-paying job may lead to a greater propensity to use DR services, compared to using FR services, leading the relationship to run the other way around.

The issue of determining and addressing endogeneity in multi-level models has recently received attention in the literature (for example, Grilli and Rampichini 2006); however, these authors have considered linear cases, in contrast to the requirements of the current paper, where the models consider binary outcomes. Hence, in order to test the possibility of simultaneity bias, we apply Hausman tests on linear probability models of *UNEMP_BEF* and *WAGE_HIGHER*, using two variables that are related to *D_SERVICE* but not to the outcomes and several exogenous variables. More complex formulations of endogeneity in this multi-level situation are left for future research. The instruments used here are *TOTAL_COST*, or the annual cost of using the service and *REF*, which is a binary variable that takes a value of 1 if the user obtained information about the service from a social network that includes friends/relatives or a social service and 0 otherwise. Regressing *D_SERVICE* on the instruments and the exogenous variables and using the residuals ($\hat{e}$) on OLS regressions of *UNEMP_BEF* and *WAGE_HIGHER*, we found no statistical evidence of simultaneity at any reasonable level of significance (the t-statistic of $\hat{e}$ for *UNEMP_BEF* is -1.13 whereas it is 1.8 for *WAGE_HIGHER*). Finally, to determine if there should be concerns over weak instruments, we used results from Stock et al. 2002. Specifically, we used the finding that two IVs would be weak if the F-statistic is <11.59 for testing if the coefficients of the IV's in the regression of *D_SERVICE* on the exogenous variables and the instruments are 0 (given in Table 1 of Stock et al. 2002). The F statistic for the first stage regression (of *D_SERVICE* on the exogenous variables and the instruments *TOTAL_COST* and *REF*) for the *UNEMP_BEF* and *WAGE_HIGHER* models are 95.81 and 77.86 respectively, both much larger than threshold of 11.59.

Given the discussion above, it is fruitful to examine why there is no evidence of simultaneity between *D_SERVICE* and outcomes. Most DR services surveyed (which tend to be vans or larger personal vehicles) were established by means of planning and financial partnerships between transit operators and local human services or workforce development agencies. As such, the users tend to be recipients of social services such as public assistance, be less educated, and earn lower incomes. Although fares are typically much higher for DR services, the out-of-pocket cost for the group considered here is very low and comparable to FR services, or they effectively do not pay for their trip at all, since they receive passes, fare vouchers or tokens as assistance towards transportation. An estimated $584 million or 2.3 percent of all TANF expenditures in FY 2002 were made towards transportation (allowances, bus tokens, car payments, auto insurance reimbursement, and van services) (Administration for Children and Families, 2002).

Model B: Mixed Random Intercept Models with Level 2 (site-level) Covariates: To find out site-level factors that might be contributing to variability in individual outcomes, we estimate mixed random intercept models with Level 2 (site-level) covariates. For the sake of brevity, these results are not discussed in detail, but the inclusion of certain combinations of site-level factors improves model fit, based on AIC and χ^2/df, compared to Models A. The results indicate that *D_URBAN*, *UNEMP_PER* and *D_SERVICE* were significantly related to both outcomes considered. Surprisingly, both models at this stage performed similarly whether *UNEMP_PER* or *DIFUNEMP_PER* was used as proxies for the local economy. The site-level transportation factors were not important, as was the case with the welfare indicators, *WELFARE_POL and WELFARE_POL1*, which did not have a significant effect on either outcome examined. Hence, we decided to drop these variables from further analysis.

Model C: Mixed, Multi-Level Models With Fixed and Cross-Level Interactions: The site-level factors found to be significant at the previous stage were included as fixed and cross-level interaction effects in the full models on the four outcomes. The fullest form of the models estimated, in multiple equation form, was:

$$\begin{aligned}\eta_{ij} = \log(p_{ij}/(1-p_{ij}) = \beta_{oj} + \beta_{1j}D\_Gender + \beta_{2j}D\_Carown + \beta_{3j}D\_High\_School \\ + \beta_{4j}Age + \beta_{5j}D\_Assistance + \beta_{6j}Travel\_Time \qquad (3)\end{aligned}$$

$$\begin{aligned}\beta_{0j} &= \gamma_{00} + \gamma_{01}D\_Urban + \gamma_{02}PerDrive + \gamma_{03}Unemploy\_per \\ &\quad + \gamma_{04}D\_Service + u_{0j} \qquad \text{where } u_{0j} \sim N(0,\tau_{00}) \\ \beta_{2j} &= \gamma_{20} + \gamma_{21}D\_Urban + \gamma_{22}D\_Service + \gamma_{23}Unemploy\_per + u_{2j} \quad \text{where } u_{2j} \sim N(0,\tau_{20}) \\ \beta_{3j} &= \gamma_{30} + \gamma_{31}D\_Urban + \gamma_{32}D\_Service + \gamma_{33}Unemploy\_per + u_{3j} \quad \text{where } u_{3j} \sim N(0,\tau_{30}) \\ \beta_{1j} &= \gamma_{10},\ \beta_{4j} = \gamma_{40},\ \beta_{5j} = \gamma_{50},\ \beta_{6j} = \gamma_{60}\end{aligned}$$

In the above system of equations, the random effects are (u_{0j}, u_{2j}, u_{3j}), γ_{00} is the intercept, γ_{10}, γ_{20}, γ_{30}, γ_{40} and γ_{50} and γ_{60} are the fixed effects coefficients for the individual-level covariates, while the fixed effects γ_{21}, γ_{22}, γ_{23}, γ_{31}, γ_{32} and γ_{33} are cross-level interactions between individual level covariates *D_CAROWN* and *D_HIGH_SCHOOL* with site-level factors *D_URBAN*, *D_SERVICE* and *UNEMPLOY_PER.* Not all effects were included in the models for all response variables; the choice of variables to retain depends on overall fit and individual *p* values. Table 3 shows the coefficient estimates, significance levels and odds ratios of the fixed effects of the final models for the two outcomes, along with the measures of fit.

Table 3. Multi-level mixed models of labour market outcomes (Model C)

		Model I (*UNEMP_BEF* =1)		**Model II (*WAGE_HIGHER* =1)**	
Variable	**Parameter**	**Estimate**	**Odds**	**Estimate**	**Odds**
Intercept	γ_{00}	**-0.4112**	0.6629	-0.35	0.7047
Site-Level Factors					
D_URBAN	γ_{01}	**-0.1492**	0.8614	**0.31**	1.3634
PERDRIVE	γ_{02}	-	-	-	-
UNEMP_PER	γ_{03}	-0.07633	0.9265	**0.14**	1.1503
D_SERVICE	γ_{04}	***-0.35674***	0.7000	**-1.85**	0.1572
Individual Factors					
D_GENDER	γ_{10}	-0.1321	0.8763	0.11	1.1163
D_CAROWN	γ_{20}	***-0.3481***	0.7060	-1.19	0.3042
D_HIGH_SCHOOL	γ_{30}	***1.1475***	3.1503	-0.79	0.4538
AGE	γ_{40}	***-0.0244***	0.9759	0.001	1.0010
D_ASSISTANCE	γ_{50}	-0.4875	0.6142	**0.74**	2.0959
TRAVEL_TIME	γ_{60}	0.0002	1.0002	-0.015	0.9851
Cross-Level Interactions					
D_HIGH_SCHOOL X D_URBAN	γ_{31}	***-0.618***	0.5390	-0.22	0.8025
D_HIGH_SCHOOL X D_SERVICE	γ_{32}	***-0.7675***	0.4642	**1.83**	6.2339
D_HIGH_SCHOOL X UNEMP_PER	γ_{33}	***-1.2533***	0.2856	-0.58	0.5599
Covariance Estimates	**Parameter**	**Estimate**	**Std. Error**	**Estimate**	**Std. Error**
Intercept	u_{0j}	0.14	0.1700	0.28	0.13
D_HIGH_SCHOOL	u_{3j}	0.72	0.2300	0.21	0.24
Sample Size		438		243	
Generalized χ2/DF		0.97		0.99	
AIC		1852.94		1867.27	
Model A (One-Way Random Effects Model)					
Intraclass correlation ρ		0.16		0.1	
Generalized X^2 /DF		0.94		0.87	
AIC		2599.03		2534.71	

Bold and italicized items are significant at p<0.01. Bold items are significant at p<0.05.

6. Discussion of Model Results

Overall, the models show improvements in fit over the preliminary one-way effects model and the Level 2 covariate model, based on the AIC and χ^2/df measures. Table 3 shows that *D_URBAN* is significantly related to both *UNEMP_BEF* and *WAGE_HIGHER*. Rural location increases the propensity of riders to report being unemployed prior to using the service - the model predicts that urban service users are significantly less likely to be unemployed previously compared to rural residents perhaps reflecting the greater barriers that rural users face in being employed without transportation assistance. The significance of the cross-level interactions between *D_HIGH_SCHOOL* and *D_URBAN* indicates that education levels mediate the locational propensity to be unemployed prior to using the service. In general, high school graduates are more likely to report being unemployed prior to using the service – rural high school graduates are significantly more likely to be unemployed prior to using the service compared to urban high school graduates.

Urban workers are significantly more likely to report higher wage placements by using the service. The effect of location on *WAGE_HIGHER* is also mediated by education levels – urban users both with and without high school level education are more likely to report employment in higher wage jobs after using the service, compared to rural users with and without such educational levels, respectively.

UNEMP_PER is not significant in the *UNEMP_BEF* model, and has only a small, positive effect on *UNEMP_BEF*. An alternative model, with *DIFUNEMP_PER* instead of *UNEMP_PER* and with the related cross-level interactions including *DIFFUNEMP_PER* instead of *UNEMP_PER*, had very similar measures of fit and was not significant at any reasonable level either. This implies that employment transportation services may have the potential to connect unemployed individuals, controlling for ability and skills, to employment across a wide spectrum of local economies, from those with high unemployment (or higher levels of variations in unemployment levels) to those with low employment (or limited variations in unemployment levels along the route or service area). This is in contrast to earlier findings regarding the positive role played by tight labor markets (areas with low rates of unemployment where employers are actively seeking employees) to improve employment and earnings prospects of low-income and low-skilled individuals in general (Freeman 1991) and welfare leavers in particular (Holzer 1999).

There are alternative possible explanations regarding the non-significance of *UNEMP_PER* (and *DIFFUNEMP_PER*). First, aggregate unemployment rates (or differences in small-area unemployment rates) may not be reflective of labor market opportunities for the target population. Unemployment rates among low-skilled labor may be a more useful measure in this context. Second, the differences in small-area unemployment rates, which was constructed using 2000 Census data, may have changed by the time the transit services were surveyed (in mid-2002), when the economy entered a recession in 2001, with a reportedly much greater dip in unemployment among "short-tenured", typically low-skilled workers, compared to "long-tenured" workers (Redfield 2005).

Education levels affect the relationship of unemployment rates to *UNEMP_BEF*. Riders with high-school and higher levels of education (*D_HIGH_SCHOOL*=1) as a whole are significantly more likely to report being new workers after using the service. One implication of this finding is that of all unemployed workers, employment transportation services have greater potential to connect those with appropriate skills. However, the significance of the negative *D_HIGH_SCHOOL X UNEMP_PER* cross-level interaction term shows that those with high school level education in higher unemployment areas are less likely to report being previously unemployed, compared to those without high school level education.

Areas with higher levels of unemployment have a small but significant effect on *WAGE_HIGHER*; every unit increase in unemployment rate increases the odds of earning higher at the job by 1.15. These findings beg the question of what types of jobs employment transit service users are being placed, in slack labor markets, where unemployment is high. This question is explored in further detail in Thakuriah et al. (2008) where employment transportation users are shown to incur positive benefits from service use, but where the societal benefits including impacts on local labor markets, when analyzed using a job chains model (Persky and Felsenstein 2006) show potential wage deflation, job loss and other impacts on existing workers, as employment transportation services open up a new supply of labor at specific job locations, at lower wages compared to existing workers. While *D_ASSISTANCE* was not significant in the *UNEMP_BEF* model, reporting receipt of public assistance at least once in the five years prior to using the service increases the odds of earning higher wages by a factor of close to 2.

Practitioners and program managers are also interested in differences in outcomes of FR versus DR services. From a cost-efficiency standpoint, FR operations might be deemed to be more desirable (our analysis shows that the mean cost per ride of the sampled FR and DR services were $8.25 and $16.36, respectively). The Model I results show that, holding other factors constant, FR service users are less likely to be unemployed prior to using the service compared to DR service users. DR users with high-school and higher level of education are more likely to be previously unemployed compared with FR users with similar education levels. The *WAGE_HIGHER* model estimates that overall, controlling for other factors, DR services are more likely to lead to placements in higher-paying jobs; DR users who are high-school graduates exhibit a greater propensity to report earning higher wages, compared to similarly educated FR users.

Gender and being on public assistance are not significantly related to the propensity to be previously unemployed or to earning higher wages; the propensity of prior unemployment significantly decreases with increase in age.

7. Summary and Conclusions

The paper uses primary data on outcomes relating to employment transportation services operating in 23 large, medium and rural locations across the U.S. We examined the role of several site-level factors relating to the type of employment transportation program, overall employment conditions, commuting patterns and state-level welfare policies. We found that there are significant site-to-site variations in labor market outcomes experienced by users; that different site-level factors affect outcomes differently and that the strength of the association between individual attributes and different labor market outcomes are mediated by the site-level factors in different ways.

Previous researchers have considered a number of labor market outcomes, including current employment status, employment rates, weekly hours worked, hourly earnings, and monthly wages, including tips before taxes. Since the labor market outcomes considered here are different from those considered by previous researchers, the results presented here are not directly comparable. Besides, previous researchers considered private cars and our analysis is on public transportation and our findings highlight the relationship of public transportation availability and labor market outcomes. Specifically, we found evidence that the type of location (urban or rural) differentially affects the propensity of previously unemployed users to report being employed after using the service, and those working prior to using the service to report earning more. Services in rural areas are more likely to be transporting individuals to work who self-reported being unemployed prior to using the service, while urban workers are significantly more likely to report higher wage placements by using the service. Additionally, rural workers who are high school graduates are significantly more likely to be unemployed prior to using the service compared to urban high school graduates. We did not find evidence that aggregate local unemployment levels or variability in local unemployment rates affect the propensity of users to be previously unemployed but found statistically weak evidence that for the sample of services considered, local unemployment levels explain higher wage job placements. Local welfare policies do not seem to have an effect but the type of service plays a role in both the employment outcomes considered.

The study implies that the presence of unique site-level factors calls for local employment transportation planning partnerships that leverage the unique socioeconomic and spatial characteristics of a location. Demand-Response transit remains a strong alternative to car loan programs that is also being funded by the Federal Transit Administration and building strong partnerships that financially match DR services (especially with employment centers, individual employers and the like) should continue to be a goal for federal, state and local transportation policy. While this is already being done under the scope of the Coordinated Human Services Transportation Plan requirements, a greater emphasis should be laid to encourage the involvement of private companies and labor/employment-related agencies.

Additionally, the results show that the significant site-to-site variability that exists in the outcomes may make generalizations of program outcomes across sites difficult; hence employment transportation funding formulae should go beyond using criteria such as the number of eligible low-income and welfare recipients living in each state and population size, as they currently do, and include local economic conditions and the type of area, as these factors can affect labor market outcomes. Overall, no single measure is adequate to assess the effectiveness of all projects and hence projects should be evaluated for outcomes on a variety of measures relating to mobility, service reliability, perceptual measures relating to barriers to accessibility, safety and cost, in addition to labor market outcomes, such as job placement and wage levels.

The paper has several limitations that should be addressed in future research. First, as noted, the analysis is based on a recall-after design, which, despite precautions to address internal and external validity, may be subject to memory decay and recall bias. It may be useful to survey immediately after a service becomes operational, although we have noted that ridership takes time to build up and sample sizes may be a problem. Second, we note that the sample of sites is not a random sample of employment transportation services that were funded and therefore the results are not generalizable to the universe of ET services. Generating and maintaining a sampling frame of services that is current would be important for future research. Third, to preserve model parsimony given the modest sample size, we included only a selected number of site-level factors in the multi-level model. One class of site-level factors may be particularly important in connecting low-wage workers to jobs through employment transportation – the type of local partnership between transportation organizations and local workforce development, labor and economic development organizations. Future research should test the effects of such variables. Finally, more research is needed in identifying and addressing endogeneity issues in a multi-level modeling situation such as this, which is called for by the correlations that exist among observations at a site.

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