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The effects of car access on employment outcomes for welfare recipients ☆

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Abstract

We use four waves of a longitudinal survey of current and former welfare recipients in Tennessee to examine the effects of car access on employment, weekly hours of work, and hourly wages. Contributions include a focus on car access instead of ownership, treatment of urban and rural differences, and controls for the simultaneity of car access and employment outcomes. Results indicate that car access generally increases the probability of being employed and leaving welfare. Car access also leads to more hours of work for welfare recipients with a work requirement and enables participants to find better-paying jobs.

1. Introduction

The imposition of work requirements in 1996 as part of the shift from Aid to Families with Dependent Children (AFDC) to Temporary Assistance for Needy Families (TANF) marked a major change in US welfare policy and prompted states to take a broader approach to welfare assistance. Requiring participants to work meant not only providing cash assistance but also identifying and removing barriers to employment. This broader

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approach was evidenced by both a change in policy and a shift toward more spending on support services and less emphasis on cash benefits. The primary goal of support services is to remove barriers to work by providing such things as transportation, childcare, dental, and optical assistance.

Among barriers to work, participants consistently identify transportation as a significant problem. Consequently, many states provide some form of reimbursement, shuttle, or public transportation to work-related activities. States also permit asset exemptions (for the purposes of calculating eligibility and benefit level) either for one entire vehicle or for a set value amount. Researchers have argued that car ownership allows for job search in a broader area, increased reliability on the job, and shorter commute times that translate into higher employment rates. The recent literature has provided evidence that car ownership does indeed increase the probability of being employed.

However, previous studies suffer from a few key limitations that are potentially important to policy makers. First, they do not always adequately account for the simultaneity of car ownership and employment (i.e., the idea that correlation between car ownership and employment might not indicate causation) or selection bias in the estimation of hours and wages. They also have not fully considered the important differences across urban and rural populations. Finally, they have focused almost exclusively on car ownership rather than access. We address each of these, while also improving upon estimation methods and making use of more diverse panel data, in order to provide a more accurate account of the effects of car access on employment outcomes and welfare participation. We have a rich set of policy related control variables including participation in education and training programs. Our intent is to inform the policy debate over the relative merits of personal vehicle support programs as components of a broad welfare program.

We rely on a unique panel of individual survey data from the state of Tennessee in our analysis. Tennessee's low-income cash assistance program, *Families First* (FF), operates under a waiver from US federal guidelines. Significant features include stricter, more immediate work requirements (40 hours upon entry into the program), shorter interim time limits (18 months at a time followed by three months of ineligibility), and a generous array of non-cash support services (including an allowance of up to 20 hours of the weekly work requirement for education and training activities).[1]

An examination of Tennessee data is useful for a number of reasons. First, Tennessee has recognized the importance of automobile access for welfare recipients. In addition to a standard vehicle asset exemption amount, their unique benefit program, *First Wheels*, provides zero-interest loans for the purchase of a used automobile for program participants and for leavers up to 12 months after cash assistance payments end. Second, Tennessee's gen-

[1] For more details on program rule differences, see Center for Business and Economic Research [8]. Despite the apparent difference in policies, Tennessee's welfare caseload is very similar to the national caseload. A comparison of the 2003 Families First Case Characteristics Study (Center for Business and Economic Research [9]) and the 6th Annual Report to Congress (US Department of Health and Human Services [45]) revealed only a few potentially important differences. Specifically, Tennessee's caseload has more Black and White recipients and fewer Hispanic recipients and recipients of other races. Average monthly TANF benefits are also lower in Tennessee ($170 versus $355 for the US). On the whole, we view the results in this study as broadly applicable to other states.

eral welfare policies closely resemble those currently being proposed for implementation at the national level. Third, Tennessee data enable a more complete treatment of urban-rural differences. While most *Families First* recipients live in urban areas, a significant minority are spread across the many rural counties in the state.

2. Why car access, and how is it promoted?

Proponents argue that the lack of transportation places welfare recipients and the working poor at a disadvantage for several reasons. They note the "spatial mismatch" between rural and inner-city residents and suburban employment opportunities.[2] Personal vehicles might therefore allow for a broader job search, generally more reliable transportation, shorter commute times, and the ability to work during hours not supported by the mass transit system. A broader search area and the ability to work non-traditional hours might allow individuals to find higher paying jobs. Further, more convenient and reliable transportation is likely to increase job retention. Additional trips to day care providers and retailers are also less complicated with a personal automobile. Supporters also note that inner-city car ownership can lead to entrepreneurship as those with cars shuttle neighbors on the way to jobs.[3] Car ownership might also provide secondary benefits in the form of stronger credit ratings.[4]

Those opposed to promoting car ownership also raise compelling arguments. First, given the low asset limits for eligibility, the cars available to welfare recipients and the working poor might be older or have higher mileage. This problem is exacerbated by policies that provide an asset exemption for a set value amount. Older vehicles are costlier to maintain and emit more air pollutants than their newer counterparts.[5] Further, personal vehicle promotion strategies can also lead to increased congestion, especially in urban areas.

Despite these arguments, several states have adopted measures to facilitate car access or ownership among current and former welfare recipients. Table 1 presents a comparison of Tennessee's transportation-related benefits with its eight neighboring states. All of these states permit an asset exemption, ranging from a low of $1500 in Mississippi to a high of the value of one vehicle in several states. Recent evidence suggests that these asset limitations effect car ownership. Bansak et al. [3] find that car ownership is higher for female headed households with children in states with higher asset exemptions and in states

[2] For more discussion, see Ihlanfeldt and Sjoquist [23], Preston and McLafferty [37], or Blumenberg and Waller [7].

[3] See Davis and Johnson [13] and Cervero [10].

[4] Research in this area is sparse and focuses on loan or lease default rates. A study of five programs places the default rate between 2 and 7 percent and as high as 17 percent when additional criteria are considered, such as maintaining employment for the duration of the payment period (Port JOBS [36]).

[5] Older vehicles are subject to less stringent emission standards, and emission control systems deteriorate over time. For more discussion, see Barbour [4].

Table 1
Transportation benefits in Tennessee and neighboring states

State	Vehicle asset limit	Reimbursement	Bus passes	Repair allowance	Other
Alabama	Value of one vehicle	$32 per month	X		County specific solutions in rural areas
Arkansas	Value of one vehicle		X	X	County specific solutions
Georgia	$4650	State: $3 per day County: $25 per month	X	X	
Kentucky	Value of one vehicle			X Up to $300 per year	Regional providers and districts provide payment and coordinate transportation
Mississippi	$1500	$.20 per mile up to $8 per day	X		
Missouri	Value of one vehicle	$5 per day			
North Carolina	$5000	Allowances determined at local level			
Tennessee[a]	$4600	$6 per day[b]	X	X Up to $800 per year	
Virginia	$7500	No specific limit or cap.			Benefits paid from overall work program allocation

Source (except Tennessee): Maiers, P., June, 1999 Transportation in Welfare Reform. Office of Family Assistance.
[a] Source (Tennessee): Tennessee Department of Human Services. Families First Handbook, 2000.
[b] Reimbursement rate reduced to $4 per day as of July 1, 2003.

that exempt the value of multiple vehicles. Further, they find suggestive evidence that labor market outcomes are affected by asset limitations through their effect on car ownership.[6]

In addition to asset exemptions and the other programs listed in Table 1, a number of other unique transportation benefit programs can be found in the US. As noted above, Tennessee's *First Wheels* program provides zero-interest loans for the purchase of a pre-owned automobile. Wisconsin and Michigan also offer low interest loans while Texas, Maryland, Vermont, and Colorado operate in conjunction with car donation programs.[7] Virginia and Ohio allow the purchase and resale of government vehicles. New York provides participants with mechanical training and then allows them to purchase cars they have re-conditioned.

[6] Hurst and Ziliak [22] find no evidence that the increase in vehicle asset limits corresponds with an increase in savings for these households. This suggests that the increase in car ownership comes at the expense of other investment in other (liquid) assets.

[7] Lucas and Nicholson [28] find a positive effect of Vermont's Good News Garage (GNG) on earned income and the probability of being employed. See their paper for more program details.

Given that promoting car ownership has already become an important policy goal for many states, understanding the impacts of these programs on employment outcomes is vital to recognizing whether the stated objectives—namely increased employment rates—are likely to be met. Following a review of the prior literature in Section 3, we turn to a discussion of our data and methods in Section 4. Section 5 presents results, and Section 6 concludes.

3. Prior research

The primary objective of TANF is to encourage self-sufficiency among recipients. Employment has been identified as a means to this end, which makes identifying and removing barriers to employment a key concern. Program participants and administrators consistently identify transportation as an important barrier to employment.[8] Reasons for the transportation difficulties are well documented. Welfare recipients often live within inner-city areas which are frequently isolated from suburban jobs, and they are often poorly qualified for jobs in the central business district.[9] Transportation also affects the job-search area, as many entry-level positions require applying in person for face-to-face interviews.[10]

Transportation difficulties among current and former Tennessee welfare recipients are consistent with the literature. A 2002 study of welfare leavers found that 6.5 percent of unemployed leavers identified lack of adequate transportation as prohibiting employment (Perkins and Homer [35]). Consistent with "spatial mismatch," leavers in urban counties reported transportation difficulties more often than those in rural counties. Lack of a reliable car and limited public transportation were the concerns most often reported by welfare recipients; again the transportation problems were more common for urban residents (Fletcher et al. [16]; Social Work Office of Research and Public Service [43]).

A number of studies have examined the effects of labor market conditions on welfare dynamics. Blumenberg and Ong [5] examine access to low-wage jobs and find that those who live in areas of greater job concentration are less likely to be on welfare.[11] However, even among those living in job-rich areas, most work outside of their immediate living area. This study, along with others discussed below, makes use of data from urban California. Consequently, its applicability for policy makers in other areas may be somewhat limited.

Given the above, one would expect that improved transportation might increase employment levels. Cervero et al. [11] find that among forms of transportation, private and public, private mobility is most effective in moving participants from welfare to work. Data limitations in their work, including a rather small sample size, the use of pre-TANF data, and a focus on urban California residents, indicate that findings may not apply in other areas

[8] See Blumenberg and Ong [6], Cox, et al. [12], Ebener and Klerman [14], Fein, et al. [15], Iowa Department of Human Services [24], Julnes and Halter [25], Owen, et al. [34], and Social Research Institute [42] for empirical evidence.

[9] For more discussion, see Bania et al. [2], Holzer [20], Rich [40], Kain [26], Kasarda [27], Holzer et al. [21], and Stoll [44].

[10] See Henly [19], and Ong and McConville [33].

[11] Also see Ong and Blumenberg [32].

and more recent time periods.[12] However, the general association of car ownership and improved employment levels has been consistently established elsewhere in the literature.[13]

Several studies have proceeded beyond association to causality. These studies control for the simultaneity of the car ownership/employment decision either by using the instrumental variable approach or panel data. Again, the evidence is largely consistent with car ownership accounting for higher levels of employment (Raphael and Stoll [39]; Raphael and Rice [38]; Ong [31]; Cervero et al. [11]). Differences in car ownership rates have been shown to account for a portion of inter-racial employment gaps, including 43 percent of the black-white differential (Raphael and Stoll [39]). Evidence also suggests that car ownership increases hours worked (Ong [30]; Raphael and Rice [38]). Raphael and Rice [38] find a negative relationship between hourly wage rates and car ownership. However, failure to control for urban and rural differences may be driving this result as those in rural areas might be more likely to own cars and work for lower wages.

We extend the literature in a variety of ways. First, we use a transition analysis similar to that of Cervero et al. [11] along with panel data to account for the possibility that being employed leads to car ownership or access. This approach overcomes the difficulties of finding appropriate instrumental variables.[14] In addition, instead of measuring car ownership, our data provide a proxy for car access (study participants were asked whether anyone in their household owned a vehicle). This distinction is potentially important as household members are likely to share use of a vehicle, making access at least as relevant as ownership when considering employment benefits. In other words, it is not clear that ownership would yield greater employment benefits than (the less restrictive) access.

Further, earlier work either did not control for urban and rural differences or relied on a primarily urban sample. Ong [31] and Cervero et al. [11] use data from urban areas of Los Angeles and Alameda Counties in California, respectively. Raphael and Rice [38] and Raphael and Stoll [39] use national Survey of Income and Program Participation (SIPP) data, however, the former study does not control for urban and rural differences, and the latter focuses exclusively on 242 metropolitan areas. Our data include both urban and rural residents from across the state of Tennessee. This distinction is important to state policy makers as differences in transportation needs and employment opportunities affect the potential benefits of a wide-scale personal vehicle promotion program.

While there is strong and consistent evidence that car ownership improves the probability of being employed, the effects of car ownership on hours and wages are sparsely documented. Our analysis explores each of these employment outcomes. Finally, our rich survey data permit a comparison of different samples: all survey respondents (including

[12] Cervero et al. [11] use a multinomial logit to estimate AFDC and employment transitions. Their Alameda County, California sample consists of two points in time and 466 individuals of which only 66, or about 7 percent, transition into employment.

[13] See Ong [30], Fletcher et al. [16], Blumenberg and Waller [7], and the references therein. Ong's sample included four counties and consisted of 1112 observations from 1993–1994 AFDC-FC recipients. Owning a car increased employment by 12 percentage points, monthly hours by 23, and monthly earnings by $152. Fletcher et al. [16] used cross-sectional survey data from a 5-county area in Iowa and find positive effects of transportation resources on the probability of employment and on hourly wages.

[14] Raphael and Stoll [39], Raphael and Rice [38], and Ong [31] use an instrumental variable approach to address the simultaneity problem.

those who had recently left the welfare rolls), those who were program participants at the time of the survey, and the subset of program participants for whom a work requirement was in effect.[15]

4. Data and estimation procedure

Data for this analysis are taken from the first four waves of the *Family Assistance Longitudinal Study* (FALS).[16] The respondents include a large random sample of individuals who were on Tennessee's welfare program, *Families First*, as of January 2001. Maximum sample sizes are 1935, 1474, 1810, and 1919 for each of the four Waves.[17] In each Wave, participants are asked whether anyone in their household owns a car or other vehicle. Those answering yes are assumed to have car access.

We exploit the panel nature of the FALS data in order to control for the simultaneity of car access and employment. Specifically, we estimate the effects of car access in one wave of the survey on employment (and program participation) in a subsequent wave. Due to the larger sample sizes in Waves 1 and 4 of the survey and the length of time (18 to 24 months) between these two Waves, these two endpoints are selected for the analysis. While this approach does not completely control for simultaneity, experimentation with alternative estimation techniques led us to prefer it over less reliable instrumental variables approaches.[18]

Multinomial logits are used to estimate the effects of Wave 1 explanatory variables (including demographics) on the probabilities of making transitions from being on *Families First* (FF) in Wave 1 to being in one of four employment and FF participation categories as of the Wave 4 survey.[19] These categories are unemployed/on FF, unemployed/off FF, employed/on FF, and employed/off FF. Separate multinomial logits are estimated for those

[15] There is evidence that evaluating low-income households separately is appropriate for policy questions as it has been shown that poor households respond differently to factors influencing automobile ownership (Gardenhire and Sermons [17]).

[16] The FALS is an ongoing collaborative effort of the Tennessee Department of Human Services, the Bureau of Business and Economic Research/Center for Manpower Studies at the University of Memphis, and the Social Work Office of Research and Public Service, the Center for Literacy Studies, and the Center for Business and Economic Research, all at the University of Tennessee in Knoxville. As of this writing, the first four waves of data were available for analysis and the sixth Wave was in the field.

[17] Observations from two over-sampled groups (those referred to or participating in Adult Basic Education or Family Services Counseling) are omitted from our analysis. While a direct analysis of First Wheels participants would be useful, sample sizes of First Wheels participants in the FALS data are unfortunately too small. Note that efforts were made to contact earlier-wave non-respondents in later waves. As such, the Wave 4 sample is not a strict subset of the Wave 1 sample.

[18] We experimented with county-level instruments using such things as automobile insurance costs and local vehicle taxes, but all of our chosen instruments turned out to be quite weak due especially to lack of variability within the state. In the absence of suitable instrumental variables, we use the panel properties of the data to address the potential simultaneity of car access and employment outcomes. Regressing employment outcomes on *prior* car access status minimizes the possibility that significant results could be attributed to reverse causality or some common unobserved factor.

[19] See Green [18, pp. 720–723] for more information on multinomial logit models.

who were unemployed in Wave 1 and those who were employed in Wave 1. This approach allows us to assess the impact of car access on transitions off welfare and into employment.[20] In addition to the multinomial logit transition analysis, Heckman selection regressions are estimated to evaluate the effects of car access and other factors on hours worked per week and average hourly wages.

Following Cervero et al. [11], we include three variables to measure car access. The first indicates whether the participant had access to a car in Wave 1. The remaining two variables account for the effects of gaining or losing access to a car between Waves 1 and 3.

We include a variety of control variables in all multivariate models. The age of the survey respondent is entered in quadratic form. Education variables consist of dummies for less than or more than high school, with high school graduate (and nothing more) as the reference category. We also include three dummies for participation in GED courses, vocational training, and Fresh Start (a program that provides basic job market survival skills). In models that are not restricted to participants with work requirements, we control for work requirement status with an additional dummy variable. Marital status enters in the form of dummies for divorced (including married but separated) and committed (including married, engaged, or living together), with single being the reference category. We control for race using a series of three indicators for White, Hispanic, and other race, with Black serving as the reference category. We also include the number of non-caretaker adults in the household, the dollar amount of spouse's earnings, and a dummy for whether childcare was being provided by one of the child's parents as control variables.[21] Region-level controls consist of county population density, a dummy for residence in one of the four major urban counties, and the county's unemployment rate at the time of the survey.[22]

Summary statistics for all variables used in the analysis can be found in the Appendix Table. To highlight a few of the key variables, we first note that 36 percent of all respondents were employed as of Wave 1. This rate increases to 42 percent as of Wave 4. The Wave 1 employment rate among FF participants was slightly lower at 29 percent, while about one-third of those FF participants with work requirements were employed. Employment rates as of Wave 4 rose to 40 and 45 percent for these two sub-samples, respectively. Nearly three quarters of the Wave 1 respondents were participating in FF at the time of the Wave 1 survey, a participation rate that falls to 55 percent in Wave 4. Average weekly hours of work in Wave 4 ranged from 33 to 35 for the three groups, while hourly wages were on the order of $7.75 to $8.00. Nearly half of the respondents reported having access to a car in Wave 1 (43 percent of FF participants and 44 percent of FF participants with work

[20] Another advantage of estimating separate multinomial logits by Wave 1 employment status involves the issue of unobserved heterogeneity. To the extent that important factors associated both with Wave 1 car access and Wave 4 employment have been omitted from our specification, results could be biased. However, if those factors are correlated with Wave 1 employment then running separate models reduces the impact of the unobserved heterogeneity.

[21] Due to data inavailability in earlier Waves, spouse's earnings are taken from the Wave 3 data.

[22] Unemployment for June of 2002 was collected from the Bureau of Labor Statistics. Population and land area data are from the US Census Bureau, 2000 Census (http://factfinder.census.gov/servlet/BasicFactsServlet). The four urban counties (and the cities they contain) are Shelby (Memphis), Davidson (Nashville), Hamilton (Chattanooga), and Knox (Knoxville). These counties account for nearly two-thirds of Tennessee's welfare caseload.

requirements). Roughly 30 percent either lost or gained access to a car between Waves 1 and 3.

5. Results and discussion

5.1. Preliminary transition matrix analysis

Before undertaking multivariate analysis, it is instructive to examine the relationships between employment, program participation, and car access in isolation. Table 2 presents two transition matrices, one for program participants and another for program participants with work requirements. Casual observation indicates that the data support earlier findings: car access does seem to improve subsequent employment rates.

Table 2
Program and employment transitions between Wave 1 and Wave 4

Wave 1 status			*Wave 4 status*					
			Unemployed			Employed		
			Total	On program	Off program	Total	On program	Off program
All program participants	All	Unemployed ($N = 777$)	69.78	53.53	16.25	30.22	11.96	18.26
		Employed ($N = 299$)	33.99	26.73	7.26	66.00	23.76	42.24
	No car	Unemployed ($N = 447$)	72.85	57.76	15.09	27.15	10.99	16.16
		Employed ($N = 136$)	39.59	34.03	5.56	60.42	25.00	35.42
	Car	Unemployed ($N = 329$)	65.24	47.56	17.68	34.75	13.41	21.34
		Employed ($N = 163$)	28.94	20.13	8.81	71.07	22.64	48.43
Program participants with work requirements	All	Unemployed ($N = 154$)	65.00	51.11	13.89	35.00	13.89	21.11
		Employed ($N = 144$)	34.14	26.95	7.19	65.87	25.75	40.12
	No car	Unemployed ($N = 94$)	68.72	53.55	15.17	31.28	11.85	19.43
		Employed ($N = 73$)	38.55	32.53	6.02	61.45	31.33	30.12
	Car	Unemployed ($N = 60$)	59.46	47.30	12.16	40.54	16.89	23.65
		Employed ($N = 71$)	29.76	21.43	8.33	70.24	20.24	50.00

Entries are row percentages except in the "Total" columns, where entries are row sums of "On program" and "Off program" entries.
Source: Authors' calculations using the Family Assistance Longitudinal Study (random sample only).

Entries in the sixth column indicate that 16 percent of unemployed Wave 1 participants without car access gained employment and left *Families First* as of Wave 4. The number was significantly higher for those with car access, 21 percent. The difference was also appreciable between employed Wave 1 program participants. Thirty-five percent of employed participants without car access became employed and exited the program while 48 percent of those with car access achieved the same outcome. In general, Wave 1 program participants were more likely to be employed in Wave 4 if they had access to a car in Wave 1 (regardless of program participation status in Wave 4). Car access in Wave 1 also generally reduced the likelihood of remaining on FF in Wave 4. These findings are also observed among Wave 1 program participants with work requirements.

5.2. Multivariate analysis of employment and program participation

Table 3 presents results of the multinomial logit analysis for those on the program and unemployed in Wave 1. The first four columns of numbers represent marginal effects on the probability of being in each of the four categories given a one-unit change in each explanatory variable, holding all other variables constant at their mean values.[23] The last three columns present results for a sub-sample of the first group—unemployed program participants with a work requirement in Wave 1.[24]

To interpret the results in this table, consider the marginal effects associated with the car access variables in the model. Among these unemployed program participants, having car access in Wave 1 decreases the probability of remaining unemployed and on *Families First* by 9.78 percentage points (or about 16 percent, given that the overall probability of this outcome is 62.64 percent). The increase in the probability of becoming employed and leaving the program is quite substantial, 7.96 percentage points or about 59 percent. Car access, including gaining or losing a car between Waves 1 and 3, has no statistically significant effects on the other two transitions among the group of all program participants. Note that this result pertains to all FF participants, including those who are exempt from work requirements (many of whom are not able to work).

Perhaps a more relevant exercise would be to focus on those participants with work requirements. After all, vehicle supports are typically intended to help participants—namely those required to work—achieve self-sufficiency more quickly. Columns 5 through 7 of Table 3 restrict the analysis to the group of unemployed program participants with work requirements.

There are two statistically significant effects of car access among this sub-sample. Access to a car in Wave 1 dramatically reduces the probability of remaining unemployed but

[23] For dummy variables, the marginal effect represents the change in the particular probability given a change in the dummy variable from 0 to 1. Note the marginal effect of age-squared has not been adjusted as recommended in Ai and Norton [1] and Norton et al. [29].

[24] The data were adequate for estimating the multinomial logit model but were not sufficient for calculating marginal effects for the transition from unemployed and on the program to employed and on the program for Wave 1 participants with a work requirement (the estimated probability of making this transition was just slightly greater than zero).

Table 3
Multinomial logit results—Wave 1 to Wave 4 transitions for unemployed Wave 1 program participants

Variables	All program participants ($N = 611$)				Program participants with a work requirement ($N = 283$)[a]		
	Unemployed		Employed		Unemployed		Employed
	On program	Off program	On program	Off program	On program	Off program	Off program
Car in Wave 1	−9.78*	−1.40	3.22	7.96*	0.68	−10.91*	10.23
	(5.88)	(4.20)	(2.99)	(4.12)	(8.95)	(6.47)	(7.28)
Lost car access	4.73	−6.74	1.63	0.38	−4.82	−1.48	6.30
	(6.84)	(4.86)	(3.48)	(4.27)	(12.13)	(10.17)	(10.08)
Gained car access	−5.88	−1.17	0.15	6.90	−16.18	−4.39	20.56*
	(6.43)	(4.71)	(3.12)	(4.95)	(11.49)	(5.96)	(10.75)
Age	−20.01	−8.93	23.41**	5.53	14.06	−2.28	−11.79
	(18.88)	(10.96)	(10.69)	(17.01)	(28.74)	(20.71)	(24.78)
Age^2	4.09	1.88	−4.40***	−1.57	−1.71	0.95	0.76
	(2.91)	(1.57)	(1.67)	(2.78)	(4.41)	(3.12)	(3.90)
Density	0.22	0.15	−0.73	0.36	−0.57	1.83	−1.27
	(1.29)	(1.08)	(0.54)	(0.79)	(2.46)	(2.29)	(1.56)
Urban	−2.02	−3.81	9.62**	−3.79	21.50	−31.14	9.64
	(13.67)	(11.65)	(4.39)	(8.91)	(30.72)	(33.44)	(13.87)
Divorced	−2.24	5.47	−0.27	−2.97	−3.71	−3.13	6.84
	(6.16)	(5.27)	(2.81)	(3.35)	(9.56)	(6.74)	(7.54)
Committed	1.34	1.95	−1.72	−1.57	18.33*	−11.23*	−7.09
	(8.50)	(6.33)	(3.71)	(4.99)	(10.06)	(6.16)	(8.34)
Other adults in household	−2.93	3.53**	−1.11	0.52	−3.90	2.48	1.42
	(2.39)	(1.43)	(1.65)	(1.70)	(4.58)	(3.08)	(3.69)
Less than high school	13.53***	−3.76	−0.31	−9.46***	11.29	1.32	−12.61**
	(4.59)	(3.39)	(2.31)	(2.84)	(7.96)	(6.49)	(5.36)
More than high school	2.35	−7.11*	1.30	3.46	−3.97	−1.03	5.00
	(5.84)	(4.09)	(2.76)	(3.69)	(8.57)	(6.68)	(6.19)
Spousal earnings	−3.74**	3.03***	−0.53	1.24	−5.10**	3.59***	1.54
	(1.90)	(0.87)	(0.90)	(0.81)	(2.24)	(1.34)	(1.31)
Parent provided childcare	10.77**	−5.56	−2.96	−2.26	−13.66	0.33	13.33
	(5.47)	(3.96)	(2.35)	(3.53)	(12.49)	(9.02)	(10.78)

(*continued on next page*)

Table 3 (*continued*)

Variables	All program participants ($N = 611$)				Program participants with a work requirement ($N = 283$)[a]		
	Unemployed		Employed		Unemployed		Employed
	On program	Off program	On program	Off program	On program	Off program	Off program
Unemployment	−0.81	0.46	0.40	−0.06	−3.34	1.08	2.26
	(1.78)	(1.19)	(0.85)	(1.05)	(2.96)	(2.25)	(1.79)
White	−13.65**	8.39	0.27	4.99	−7.19	2.93	4.25
	(6.42)	(5.21)	(3.13)	(3.99)	(8.91)	(6.83)	(6.89)
Hispanic	−0.53	28.53	−10.47***	−17.53***	−39.89	62.04**	−22.15***
	(23.58)	(23.55)	(1.76)	(1.95)	(25.42)	(25.49)	(3.38)
Other race	−28.69**	12.25	3.69	12.75	−43.86**	11.23	32.62
	(13.87)	(15.97)	(9.26)	(13.19)	(21.12)	(19.55)	(22.27)
Work requirement	−6.01	0.44	2.14	3.43	n.a.	n.a.	n.a.
	(4.48)	(3.48)	(2.01)	(2.83)	n.a.	n.a.	n.a.
GED training	1.81	3.14	−0.80	−4.16	2.77968	4.74	−7.52
	(5.02)	(4.21)	(2.21)	(2.91)	(7.53)	(6.41)	(5.49)
Vocational training	7.37	−1.29	−3.00	−3.08	2.63	−0.87	−1.75
	(6.52)	(5.55)	(2.33)	(3.28)	(8.47)	(6.72)	(5.63)
Fresh start	−1.78	−1.40	2.58	0.61	4.13	−10.94**	6.81
	(5.99)	(4.68)	(2.98)	(3.78)	(7.81)	(5.12)	(6.74)
Mean probability	62.64	15.98	7.98	13.40	66.81	15.92	17.27

Entries are marginal effects and standard errors in parentheses.

[a] The probability of transitioning from unemployed on the program (Wave 1) to employed on the program (Wave 4) was 0.0014 percent precluding the calculation of meaningful marginal effects. Results are available upon request.

* Significant at the 10% level.

** Idem., 5%.

*** Idem., 1%.

moving off the program (by 10.91 percentage points, or about 69 percent).[25] Gaining car access between Waves 1 and 3 of the survey increases the probability of becoming employed and leaving the program by 20.56 percentage points or over 100 percent. While results differ from those in Columns 1 through 4 for all unemployed program participants, it is refreshing to find that car access has positive impacts on the more policy-relevant sub-sample of those with work requirements.

The analysis in Table 3 was duplicated for those who were on the program and *employed* in Wave 1, and results are presented in the same format in Table 4. Among all employed program participants in Wave 1, having access to a car in Wave 1 reduced the probability of becoming unemployed while remaining on the program by 25.96 percentage points (88 percent) and increased the probability of remaining employed but leaving the program by 27.92 percentage points (41 percent). Restricting the analysis to employed Wave 1 program participants with work requirements, we find similar but larger effects. In a series of robustness checks, the car effects remained virtually unchanged in more parsimonious models and were robust to the omission of urban and rural controls.[26] Overall, the results are consistent and indicate large and significant benefits from car access in encouraging self-sufficiency through employment. These findings are generally in line with the only other similar study in the literature (Cervero et al. [11]).

It is interesting that most of the identified car access effects are from the Wave 1 status indicator rather than the “lost” and “gained” indicators. The interpretation of this is that having access to a car in Wave 1 outweighs the negative consequences of losing that access by Wave 3. Similarly, the negative effects of not having car access in Wave 1 are not typically offset by a positive bonus from gaining access by Wave 3.[27]

Effects of other explanatory variables exhibited a few general patterns. Education variables, when significant, affected employment and program participation in the expected manner. Respondents in committed relationships were much less likely to become or remain employed and exit welfare.[28] The effects of spousal earnings suggest that the persons most likely to become or remain employed and leave the program select partners who are also more likely to experience positive outcomes. Respondents who reported higher spousal earnings were less likely to be unemployed and on the program as of Wave 4 and

[25] In this case, Wave 1 car access might be signaling the absence of other major life changes between Waves 1 and 4. Those recipients who remained unemployed but left welfare were more likely to experience a change in marital status or a change in the number of adults in the household, and less likely to transition out of poverty between Waves 1 and 4.

[26] We also experimented with an interaction between Wave 1 car access and the urban dummy. This interaction was never statistically significant in the multinomial logits. Full results are available from the authors upon request.

[27] This is not an outgrowth of small sample sizes as about one-third of those with car access in Wave 1 lose it by Wave 3 and a similar share of those without Wave 1 access gain it by Wave 3 (see the Appendix Table for details). To be sure, the lack of a significant effect from the lost or gained variables could be due to unobserved heterogeneity (as discussed above). It is also possible that a change in car access signals other life changes such as a move or change in marital status that mitigate the expected car effects. For example, a recent study finds that changes in marital status affect employment outcomes (Richards and Bruce [41]).

[28] This echoes our earlier study on marriage impacts. Using a similar set of control variables, we found that respondents married in both Waves 1 and 3 of the survey were significantly *less* likely to be employed in Wave 4 than those who were unmarried in both of these earlier waves (Richards and Bruce [41]).

Table 4
Multinomial logit results—Wave 1 to Wave 4 transitions for employed Wave 1 program participants

Variables	All program participants ($N = 235$)				Program participants with a work requirement ($N = 125$)[a]		
	Unemployed		Employed		Unemployed	Employed	
	On program	Off program	On program	Off program	On program	On program	Off program
Car in Wave 1	−25.96***	−1.96	0.00	27.92***	−34.64**	−0.37*	35.01**
	(10.13)	(2.30)	(0.26)	(10.15)	(14.76)	(0.19)	(14.78)
Lost car access	14.01	3.62	0.02	−17.65	27.53	0.07	−27.59
	(15.90)	(5.12)	(0.33)	(14.97)	(23.17)	(0.21)	(23.10)
Gained car access	5.25	−0.64	−0.35	−4.26	14.40	−0.17*	−14.22
	(12.47)	(1.14)	(0.22)	(12.63)	(21.61)	(0.09)	(21.64)
Age	82.37**	−6.62*	−0.64	−75.11*	56.47	0.45	−56.92
	(41.44)	(3.98)	(0.90)	(41.05)	(52.43)	(0.85)	(52.57)
Age^2	−14.46**	1.04*	0.07	13.34**	−9.48	−0.07	9.55
	(6.68)	(0.60)	(0.14)	(6.59)	(8.10)	(0.14)	(8.12)
Density	−1.44	0.57	−0.11*	0.99	3.56	−0.06	−3.50
	(2.69)	(0.51)	(0.07)	(2.74)	(4.00)	(0.07)	(4.01)
Urban	11.99	−3.00	1.70**	−10.69	−47.72	0.39	47.33
	(27.52)	(7.74)	(0.82)	(28.21)	(48.52)	(0.40)	(48.53)
Divorced	9.17	−0.55	0.05	−8.67	−4.57	−0.03	4.60
	(11.10)	(1.37)	(0.28)	(11.17)	(14.98)	(0.12)	(14.99)
Committed	51.82***	13.12	−0.21	−64.72***	79.54***	−0.09	−79.46***
	(15.86)	(11.77)	(0.36)	(9.32)	(8.37)	(0.14)	(8.35)
Other adults in household	7.45	−2.61*	0.06	−4.90	4.25	−0.10	−4.14
	(4.68)	(1.52)	(0.14)	(4.80)	(7.45)	(0.10)	(7.48)
Less than high school	17.83*	−0.65	−0.21	−16.96	14.17	−0.15	−14.02
	(10.13)	(1.01)	(0.21)	(10.35)	(14.87)	(0.16)	(14.88)
More than high school	−8.93	0.21	−0.31	9.03	−3.11	−0.15	3.25
	(9.72)	(1.21)	(0.22)	(9.74)	(14.35)	(0.12)	(14.37)
Spousal earnings	−4.87*	0.10	−4.64***	9.41***	−10.12**	−1.73***	11.85**
	(2.79)	(0.11)	(0.82)	(2.91)	(4.74)	(0.52)	(4.85)
Parent provided childcare	15.32	−0.90	−0.16	−14.26	15.76	0.05	−15.81
	(13.62)	(0.80)	(0.29)	(13.60)	(22.14)	(0.20)	(22.15)

(*continued on next page*)

Table 4 (*continued*)

Variables	All program participants ($N = 235$)				Program participants with a work requirement ($N = 125$)[a]		
	Unemployed		Employed		Unemployed	Employed	
	On program	Off program	On program	Off program	On program	On program	Off program
Unemployment	−6.32*	0.17	0.19*	5.96	−13.32**	−0.02	13.33**
	(3.65)	(0.30)	(0.11)	(3.67)	(6.65)	(0.06)	(6.66)
White	−28.05***	53.22***	−0.16	−25.01	−15.42	−0.06	15.48
	(9.10)	(20.30)	(0.23)	(20.46)	(19.37)	(0.15)	(19.41)
Hispanic	−32.28***	−1.39	−0.66***	34.33***	−34.78***	−0.27***	35.05***
	(4.78)	(0.99)	(0.12)	(4.70)	(8.21)	(0.08)	(8.22)
Other race	−29.25***	−1.25	99.47***	−68.97***	−26.34***	99.85***	−73.51***
	(4.56)	(0.90)	(1.56)	(4.54)	(7.03)	(0.69)	(7.04)
Work requirement	4.19	−0.12	0.29	−4.35	n.a.	n.a.	n.a.
	(8.04)	(1.00)	(0.22)	(8.08)	n.a.	n.a.	n.a.
GED training	−0.18	0.24	0.08	−0.14	*11.95*	−0.06	−11.89
	(12.58)	(0.99)	(0.36)	(12.49)	(19.27)	(0.12)	(19.28)
Vocational training	1.21	−0.91	0.04	−0.34	−7.65	*0.02*	7.62
	(15.23)	(0.91)	(0.42)	(15.15)	(16.29)	(0.24)	(16.27)
Fresh start	−1.09	1.71	−0.21	−0.41	10.34	−0.15	−10.19
	(10.08)	(2.25)	(0.23)	(10.43)	(13.75)	(0.19)	(13.78)
Mean probability	29.53	1.28	0.61	68.58	27.35	0.22	72.43

Entries are marginal effects and standard errors in parentheses.

[a] A very small number of respondents (7) made the transition from employed on the program (Wave 1) to unemployed off the program (Wave 4), which precluded the calculation of marginal effects. A model excluding this category yielded qualitatively similar results for the other three transition choices.

* Significant at the 10% level.

** Idem., 5%.

*** Idem., 1%.

respondents employed as of Wave 1 were more likely to remain employed and exit the program as of Wave 4 the higher their reported spousal earnings.

5.3. Multivariate analysis of weekly hours worked and average hourly earnings

Table 5 presents the results from Heckman selection regressions of hours worked per week in Wave 4.[29] Explanatory variables remain the same as those in the preceding multinomial logit analyses, and results for all study respondents, program participants, and program participants with a work requirement are presented separately. For the most part, car access does not seem to be an important determinant of work hours. However, among Wave 1 program participants with work requirements, gaining access to a car between Waves 1 and 3 increases work hours in Wave 4 by nearly 9 hours per week.[30] As with our analysis of employment, effects of the car variables remained consistent in more parsimonious models and were robust to exclusion of urban control variables.

The lack of a strong effect of car access overall may be indicative of a general inability among the samples in question to alter their hours of work. Having access to a car might increase one's ability to find and keep a job, but the jobs are likely to be characterized by standard labor hours contracts (e.g., with a 40-hour work week). Survey evidence adds credence to this contention that employers generally offered a limited set of available hours.[31]

Regression results for hourly wages are reported in Table 6. We find that Wave 1 car access increases Wave 4 average hourly wages for all three of our samples. In fact, the increases are quite large, ranging from \$0.70 per hour for all respondents to \$2.06 for Wave 1 program participants. Losing car access between Waves 1 and 3 reduces the Wave 4 wage by slightly more than one dollar per hour among all respondents. Even though car access has little to no effect on hours of work, it does seem to enable respondents to find better-paying jobs.

Interestingly, the effects of car access on hourly wages are sensitive to the inclusion of urban control variables, at least for the more inclusive samples.[32] Coefficients for the

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[29] We employ a two-stage selection model to account for the fact that hours and wages are only observed for working respondents. The identification variables for the first-stage employment probit are the household's unearned income (as of Wave 3) and the number of children under age 18 in the household (as of Wave 1). Results from first-stage probits are available upon request.

[30] This magnitude may seem large, but it echoes similar findings by Ong [30] and Raphael and Rice [38].

[31] Participants were asked how many hours per week they usually worked. The most frequent response in Wave 4 was 40 hours per week (34 percent). Other common responses were 20 hours (7 percent), 30 hours (9 percent), 35 hours (9 percent), and 50 hours (3 percent). The average number of hours worked was 34 and the majority of respondents reported that they usually worked less than 40 hours per week (54 percent) suggesting that full-time employment opportunities might have been limited. Fifteen percent worked 20 or fewer hours per week and 39 percent worked between 20 and 39 hours per week. Twelve percent of the respondents reported working more than 40 hours per week.

[32] Urban control variables include a dummy variable for residence in an urban county (Davidson, Hamilton, Knox, and Shelby) and a variable for population density. To be sure, we have not addressed potential simultaneity between car access and urban residence. Since both enter our models as Wave 1 values, we have minimized problems of simultaneity with employment outcomes. Relationships between car access and urban residence variables will only have the usual multicollinearity consequences of inflating standard errors.

Table 5
Determinants of Wave 4 work hours

Variables	All respondents ($N = 1273$)	Wave 1 program participants ($N = 939$)	Wave 1 program participants with a work requirement ($N = 460$)
Car in wave 1	0.18	−1.65	4.44
	(2.36)	(2.45)	(2.96)
Lost car access	−2.30	−1.32	−1.96
	(1.63)	(2.11)	(2.74)
Gained car access	1.30	2.07	8.65***
	(1.69)	(1.99)	(2.96)
Age	9.56	3.18	8.40
	(6.82)	(6.54)	(12.30)
Age^2	−1.30	−0.38	−1.92
	(1.14)	(1.08)	(1.97)
Density	0.45	0.66*	0.26
	(0.30)	(0.39)	(0.56)
Urban	−4.23	−7.34*	−3.29
	(3.15)	(4.01)	(6.13)
Divorced	−0.44	1.20	6.02**
	(1.66)	(2.10)	(3.01)
Committed	−0.80	2.37***	2.81
	(2.26)	(2.95)	(3.35)
Other adults in household	0.01	0.78	−0.35
	(0.74)	(0.97)	(1.92)
Less than high school	−2.40	−1.38	−2.69
	(2.22)	(2.32)	(2.60)
More than high school	−2.38	−3.74**	−3.28
	(1.49)	(1.64)	(2.58)
Spousal earnings	−0.20	−0.44	−0.16
	(0.20)	(0.33)	(0.38)
Parent provided childcare	0.92	3.19	4.52
	(1.85)	(2.08)	(2.92)
Unemployment	−0.63	−0.87	−0.81
	(0.47)	(0.53)	(0.71)
White	0.80	−0.47	−2.72
	(1.78)	(2.15)	(2.81)
Hispanic	−1.97	−10.93**	−8.41
	(8.79)	(5.58)	(6.91)
Other race	−5.97	−5.32	−6.11
	(4.77)	(5.26)	(6.22)
Work requirement	−0.22	1.13	−4.19
	(1.06)	(1.40)	2.49
GED training	0.55	0.26	1.81*
	(1.65)	(2.01)	(3.05)
Vocational training	0.74	2.19	−0.15
	(2.36)	(2.54)	(2.22)
Fresh start	−1.39	−1.61	20.31
	(1.48)	(1.93)	(18.98)
Selection parameter	−6.98	2.56***	8.33*
	(4.99)	(0.16)	(5.06)
Constant	27.41*	40.36***	22.07
	(16.16)	(13.43)	(18.33)

Note: Entries are coefficients from the second stage of a two-stage Heckman selection model, with standard errors in parentheses.

* Significant at the 10% level. ** Idem., 5%. *** Idem., 1%.

Table 6
Determinants of Wave 4 hourly wages

Variables	All respondents ($N = 1273$)	Wave 1 program participants ($N = 939$)	Wave 1 program participants with a work requirement ($N = 463$)
Car in Wave 1	0.70*	2.06***	1.70**
	(0.42)	(0.54)	(0.76)
Lost car access	−1.06***	−0.82	−0.61
	(0.37)	(0.59)	(0.84)
Gained car access	0.39	0.69	1.13
	(0.48)	(0.69)	(1.12)
Age	1.79*	2.09	2.12
	(1.04)	(1.90)	(4.14)
Age^2	−0.24	−0.43	−0.43
	(0.15)	(0.29)	(0.61)
Density	0.14	0.12	−0.20
	(0.09)	(0.12)	(0.18)
Urban	−1.15	−0.69	3.10*
	(0.84)	(1.26)	(1.86)
Divorced	−0.38	−0.09	0.89
	(0.37)	(0.56)	(0.80)
Committed	0.04	−1.20	−0.97
	(0.50)	(0.88)	(1.28)
Other adults in household	0.05	−0.39	−0.69
	(0.22)	(0.31)	(0.63)
Less than high school	−0.50	−1.43***	−1.81**
	(0.41)	(0.45)	(0.80)
More than high school	1.33***	1.47***	1.09
	(0.34)	(0.52)	(0.70)
Spousal earnings	−0.03	−0.11	−0.08
	(0.05)	(0.08)	(0.09)
Parent provided childcare	−0.83***	−1.02*	−0.22
	(0.30)	(0.61)	(0.93)
Unemployment	0.08	0.23	0.55**
	(0.11)	(0.16)	(0.27)
White	−0.46	−0.47	−0.27
	(0.51)	(0.66)	(1.03)
Hispanic	0.15	−0.70	0.32
	(0.90)	(2.47)	(3.01)
Other race	0.30	0.90	2.00
	(0.72)	(1.14)	(1.56)
Work requirement	0.18	0.40	n.a.
	(0.26)	(0.40)	n.a.
GED training	−0.06	−0.49	n.a.
	(0.44)	(0.57)	n.a.
Vocational training	0.00	−0.82	n.a.
	(0.58)	(0.66)	n.a.
Fresh start	0.19	0.71	1.23*
	(0.37)	(0.52)	(0.75)
Selection parameter	−0.25	4.68***	5.15***
	(0.45)	(0.64)	(0.89)
Constant	4.05**	−1.28	−3.69
	(1.88)	(3.32)	(8.14)

Note: Entries are coefficients from the second stage of a two-stage Heckman selection model, with standard errors in parentheses.

* Significant at the 10% level. ** Idem., 5%. *** Idem., 1%.

Table 7
Robustness checks—hourly wages without urban controls

Variables	All respondents ($N = 1273$)		Wave 1 program participants ($N = 939$)		Wave 1 program participants with a work requirement ($N = 463$)	
	Baseline model	Without urban controls	Baseline model	Without urban controls	Baseline model	Without urban controls
Car in Wave 1	0.70*	0.63	2.06***	0.49	1.70**	1.59**
	(0.42)	(0.40)	(0.54)	(0.61)	(0.76)	(0.71)
Lost car access	−1.06***	−1.04***	−0.82	−0.82*	−0.61	−0.41
	(0.37)	(0.47)	(0.59)	(0.44)	(0.84)	(0.83)
Gained car access	0.39	0.33	0.69	0.53	1.13	0.87
	(0.48)	(0.47)	(0.69)	(0.61)	(1.12)	(1.63)

Note: Entries are coefficients from the second stage of a two-stage Heckman selection model, with standard errors in parentheses. Models without urban controls exclude the dummy for urban county and the population density variable. All other variables presented in Table 6 are included in the model but omitted from the table for brevity. Full results available upon request.

* Significant at the 10% level.
** Idem., 5%.
*** Idem., 1%.

car access variables for the baseline model and the baseline model less urban controls are presented in Table 7. For all respondents and program participants, the positive effect of Wave 1 car access on wages becomes insignificant when urban controls are removed from the model. This sensitivity suggests that the omission of urban controls might partially explain the negative effects of car ownership on wages found by Raphael and Rice [38].[33] It also might reveal the importance of controlling for sample selection in the wage regression.

6. Conclusions

Early research into the effects of car ownership on employment has established a positive correlation between the two. Subsequent literature has moved toward causality by accounting for the simultaneity of employment and car ownership decisions using both instrumental variable and panel data approaches. We improve on the previous literature in several ways. First, we broaden the perspective to account for car access and not just car ownership. Second, we consider urban and rural differences rather than focusing only on urban welfare recipients. Finally, the rich survey data in the FALS allow for a more detailed analysis. Weekly hours worked and hourly wages are considered as outcomes in addition to employment levels.

[33] As with our multinomial logit analysis, we experimented with an interaction between Wave 1 car access and urban residence in our hours and wage equations. Again, this interaction was never statistically significant. Full results are available from the authors upon request.

Our results are broadly consistent with those of earlier work. Our analysis of *unemployed* Wave 1 program participants reveals that those who had car access in the first wave of the survey are much more likely to become employed and leave the program as of Wave 4 (18–24 months later). Among the subset of unemployed Wave 1 program participants who had work requirements, those who had access to a car in Wave 1 are dramatically less likely to remain unemployed and leave the program as of Wave 4. Results are similar in spirit for *employed* Wave 1 program participants, regardless of work requirement status. For this group, having access to a car in Wave 1 reduces the probability of becoming unemployed while remaining on the program and increases the likelihood of remaining employed but leaving the program. Magnitudes were generally larger for employed Wave 1 participants, suggesting that car access helps workers *keep* jobs as well as find better (higher paying) jobs as discussed below.

While car access does not seem to be an important determinant of weekly work hours for broader samples, we do find that gaining access to a car between Waves 1 and 3 increases Wave 4 work hours by nearly nine hours per week among Wave 1 program participants with work requirements. Car access also seems to enable respondents to find better-paying jobs. Wave 4 wages were $0.72 to $2.12 higher for those who had car access in Wave 1. Results for hourly wages were sensitive to the inclusion of urban controls providing a possible explanation for the negative effects of car ownership on wages found in the earlier literature. Overall, these results suggest that car access is important to the labor market success of low-income households generally and welfare recipients more specifically.

Our results suggest that promoting car access is a viable policy option for improving employment and hourly wage outcomes for welfare recipients and recent leavers. Car access improves the likelihood that participants transition into employment and off public assistance and allows welfare recipients and recent leavers to find jobs with higher wages. The results for hours worked are not as straightforward. Car access leads to more weekly hours of work among program participants with a work requirement but does not have a significant effect in more general samples. The ability to find jobs with higher wages might be contributing to this result as respondents can maintain a given level of income with fewer work hours.

In order to further guide policy decisions, important areas of future work include analyzing the effectiveness of current car promotion programs. Topics might include the determinants of participation in such programs, insurance and maintenance costs, the effects on vehicle fleet age, and the subsequent environmental effects. Further analysis of longer panels of data is needed to assess the long-term effects of car access on employment outcomes.

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Appendix Table
Summary statistics

Variable	All respondents		Wave 1 program participants		Wave 1 program participants with a work requirement	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Employment	0.36	0.48	0.29	0.45	0.33	0.47
Program participation	0.71	0.45	1.00	0.00	1.00	0.00
Employment (Wave 4)	0.42	0.49	0.40	0.49	0.45	0.50
Program participation (Wave 4)	0.55	0.50	0.61	0.49	0.61	0.49
Hours worked per week (Wave 4)	34.48	11.17	33.33	11.25	33.49	12.26
Hourly wage (Wave 4)	7.98	3.37	7.75	3.23	7.81	3.59
Car access	0.47	0.50	0.43	0.50	0.44	0.50
Lost car access (Wave 1 to Wave 3)	0.15	0.35	0.14	0.35	0.15	0.35
Gained car access (Wave 1 to Wave 3)	0.16	0.36	0.15	0.36	0.13	0.34
Age (divided by 10)	2.93	0.79	2.94	0.81	2.93	0.72
Age^2 (divided by 100)	9.22	5.33	9.29	5.47	9.09	4.70
Density (hundreds per square mile)	7.64	4.79	7.70	4.77	8.01	4.67
Urban	0.66	0.47	0.67	0.47	0.70	0.46
Divorced	0.28	0.45	0.27	0.45	0.30	0.46
Committed	0.10	0.30	0.10	0.30	0.08	0.27
Other adults in household	0.47	0.82	0.47	0.83	0.36	0.66
Less than high school	0.34	0.47	0.37	0.48	0.35	0.48
More than high school	0.23	0.42	0.23	0.42	0.31	0.46
Spousal earnings (Wave 3, $100/month)	0.53	2.68	0.39	2.24	0.49	2.46
Parent provided childcare	0.15	0.35	0.14	0.35	0.11	0.32
Unemployment rate (%)	5.24	1.31	5.25	1.33	5.23	1.32
White	0.35	0.48	0.33	0.47	0.30	0.46
Hispanic	0.01	0.08	0.01	0.09	0.01	0.09
Other race	0.01	0.12	0.01	0.11	0.01	0.12
Work requirement	0.47	0.50	0.48	0.50	1.00	0.00
GED training	0.20	0.40	0.21	0.41	0.25	0.43
Vocational training	0.10	0.30	0.11	0.32	0.16	0.37
Fresh start	0.14	0.35	0.16	0.37	0.23	0.42
Unearned income (Wave 3, $100/month)	3.03	5.12	3.06	3.44	2.89	3.13
Number of kids under age 18 in HH	2.28	1.33	2.35	1.39	2.53	1.49
Maximum sample size	1935		1370		663	

Notes: Sample sizes differ by variable and are available upon request. Statistics are calculated using Wave 1 data unless otherwise noted.

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