The Impact of Ride-hailing on Employment: Results from an RCT

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Abstract

The standard model of labor supply predicts that a reduction in commute cost increases labor force participation. We test this prediction using an RCT in which we evaluate the impact of subsidized ride-hailing trips on employment for a population with tenuous labor force attachment: economically disadvantaged women who have dependent children and do not have reliable access to a car. Study participants are assigned to receive $200 in monthly ride-hailing credits for either one month (the control group) or six months (the treatment group). We estimate the effect on employment using quarterly unemployment insurance wage records for a three-month period during which the treatment group, but not control group, received the monthly transportation credits. The average treatment effect estimate is 0.054 (SE 0.027), on a base of 0.597. The corresponding estimated LATE is 0.098 (SE 0.049).

Keywords: Labor Supply; Transportation and Employment; Commuting Costs; Randomized controlled trial

JEL: J22, R48

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1 Introduction

For people who work at a location away from their home, the labor market participation decision depends in part on the monetary and time costs of commuting to the job site. The idea that high commute costs deter labor force participation is a basic prediction of the standard model of labor supply. However, a lack of credible natural experiments makes it difficult to test this prediction and, more generally, difficult to estimate the magnitude of the labor force participation response to a given change in commute costs. Furthermore, there appears to be no relevant experimental evidence on this topic.

We contribute new evidence from a randomized experiment in which treatment reduces the commute costs faced by a population for whom even moderate costs may deter labor force participation: low-income women who have dependent children and do not have regular access to a car. We randomly assign participants to receive $200 in monthly ride-hailing credits for either one month (our control group) or six months (our treatment group). We then evaluate the impact on employment using quarterly unemployment insurance (UI) records for a three-month period during which the treatment group, but not control group, received the monthly transportation credits. A $200 monthly ride-hailing subsidy provides a potentially meaningful reduction in commute costs. A typical employed woman in our study sample works about 13 days per month, and the provided level of ride-hailing credits is sufficient to cover the costs of the daily round-trip commute for about six of these days. Our treatment potentially saves the cost of a bus fare and, more importantly, saves recipients about 90 minutes in commute time on each day when ride-hailing is used for the commute.

We find that, as predicted, the commute cost-reducing treatment increases employment. The estimated effect on employment is 5.4 percentage points (SE 0.027) on a base employment rate of 59.7% among the control group. The estimated local average treatment effect (LATE) is 9.8 percentage points (SE 0.049). Both estimates are statistically significant at the 0.025 level, using a one-tailed test. Our results provide a cleanly-identified test of the prediction that a reduction in commute costs increases employment.[1] Our results also offer a useful input for potential public policy interventions that focus on low-income women with children. Our work builds upon the large literature that studies the importance of transportation-related barriers to employment among economically vulnerable populations (e.g. Kain (1968) and Oi (1976)).

The paper proceeds as follows: In Section 2 we set the stage by analyzing a simple

[1]Heckman (1979) famously argues that participation in the labor market (the extensive margin of labor supply) is far more important than the number of hours worked by those who are employed (the intensive margin). The predicted effects of the commute time on the intensive margin are not as clear-cut, but we also evaluate the effect of our treatment on earnings, which are affected by both margins.

version of the standard model of labor supply. This model clarifies interpretation of our experiment and links our analysis to the extant literature. In Section 3 we describe the design and implementation of our RCT, and present the results. Section 4 provides concluding remarks.

2 Background

We begin by setting out a simple version of the standard model of labor supply. The model shows why it is difficult to assess the impact of commute costs on employment using observational data. We also use the model to help interpret the results of our experiment and link those results to existing literature.

2.1 A Simple Theoretical Structure

Consider an individual who is endowed with L_0 hours of time and R dollars of non-labor income per day, and who has human capital h, which allows her to earn an hourly wage $w(h)$ if she chooses to take a job in the labor market. She derives utility from y, dollars available for consumption, and $L \leq L_0$, hours devoted to activities other than commuting and working. In the textbook model L is denoted "leisure", but it includes such important and non-leisurely activities as childcare. For the sake of clarity, we assume utility takes a quasi-linear form:[2]

$$U(y, L) = y + \theta u(L) - \varepsilon_c \tag{1}$$

where $\theta > 0$, $u'(L) > 0$ and $u''(L) < 0$, and ε_c is a money-metric utility cost component (positive or negative) associated with commuting.[3] Let H be the number of hours worked if the individual is employed. Then (1) is maximized subject to the constraints:

$$\begin{array}{ll} y = w(h)H + R - p_c \text{ and } L = L_0 - t_c - H & \text{if employed} \\ y = R \text{ and } L = L_0 & \text{if not employed} \end{array} \tag{2}$$

where p_c is the monetary cost of commuting and t_c is the corresponding time cost.

[2]This makes it easy to illustrate how the labor supply decision is driven by the preference for leisure (relatively high-θ individuals have a stronger preference for leisure), and also simplifies analysis, because we can ignore income effects. Fortunately, this simplification, relative to a more general utility function, does not change predictions about the labor force participation decision, which is the focus of our study.

[3]In the textbook model, $\varepsilon_c = 0$, which implicitly assumes the only costs to commuting are the monetary cost and the opportunity costs of time (priced at the market wage). Here we generalize by allowing additional variation in individual preferences for commuting (e.g., some may enjoy driving to work while others find it highly stressful).

Before analyzing this maximization problem, we consider the choice of commute transportation mode. This helps to interpret the treatment provided in our study, in which we subsidize a commute mode (transport by car through a ride-hailing service) which is not the commute mode typically used by workers in our population (transport by bus). Let transportation Mode M have time cost t_c^{M}, monetary cost p_c^{M}, and utility component $\varepsilon_c^{\mathrm{M}}$. As an example, suppose the best available options are commute by bus (B) or car (C), where commute by car is more costly in monetary terms but less time-consuming. Commute mode choice boils down to a comparison of $[w(h)t_c^{\mathrm{C}} + p_c^{\mathrm{C}} + \varepsilon_c^{\mathrm{C}}]$ to $[w(h)t_c^{\mathrm{B}} + p_c^{\mathrm{B}} + \varepsilon_c^{\mathrm{B}}]$. With this in mind, we can conceptualize our individual's labor force participation decision as follows. She first deduces which commute mode will be optimal if she were to participate in the labor market. She next solves for the maximum indirect utility achievable if she works in the labor market:

$$V^{\mathrm{W}} = w(h)H^* + R - P_c + \theta u(L_0 - t_c - H^*), \tag{3}$$

where $H^*(h, \theta, t_c)$ is the optimal number of work hours and $P_c \equiv p_c + \varepsilon_c$ is the full money-metric utility cost of commuting when using the optimal commute mode.[4] Finally, she compares this utility level to the utility achieved by not working:

$$V^{\mathrm{NW}} = R + \theta u(L_0), \tag{4}$$

and makes the appropriate labor force participation choice.

Figure 1 depicts the maximization problem for two individuals who have the same preferences and face the same commute costs, but differ in terms of human capital h. The individual in Panel A has a low level of h relative to her counterpart in Panel B, and thus flatter budget constraints (which have slope $-w(h)$). The high-h individual (Panel B) commutes by car, and the utility she achieves by participating in the labor market far exceeds her utility from non-participation. The low-h individual (Panel A) commutes by bus, and in this example is just indifferent between labor force participation and non-participation. It follows that the value of employment is relatively higher, all else equal, for high-h individuals, and the high-h individual chooses the transportation mode that has a lower time cost (i.e. commutes by car) because her time has a relatively higher opportunity cost.

The individual depicted in Panel A, who is indifferent between employment and non-employment, is said to be earning reservation wage $\hat{w}$. Of course, individuals for whom $w(h) > \hat{w}$ will choose to work. An individual's reservation wage generally depends on her preferences and on commute costs. Those with a stronger preference for leisure will have a

[4] $H^*(h, \theta, t_c)$ is chosen so as to equate the wage and the marginal rate of substitution between income and leisure: $w(h) = \theta u'(L_0 - t_c - H^*)$.

higher reservation wage.[5] As for commute costs, the relevant comparative statics in elasticity form are:[6]

$$\frac{d\hat{w}}{dP_c}\frac{P_c}{\hat{w}} = \frac{P_c}{\hat{w}H^*(\cdot)} > 0, \quad \text{and} \quad \frac{d\hat{w}}{dt_c}\frac{t_c}{\hat{w}} = \frac{w(h)t_c}{\hat{w}H^*(\cdot)} > 0. \tag{5}$$

A simple numerical example makes clear how an increase in commute cost affects labor force participation: Suppose we have a population of workers who commute by bus, paying a daily fare of $P_c = \$8$. Each individuals works 8 hours per day and has a reservation wage $\hat{w} = \$10$ (and therefore earns $w(h) \geq \$10$). Now, the elasticity of $\hat{w}$ with respect to P_c is the ratio of the daily commute cost to the daily income earned at the reservation wage, so this elasticity is 0.10. Thus, if P_c were to increase by 20%, the reservation wage increases by 2%, inducing low-h workers—those with $\$10 \leq w(h) < \$10.20$—to exit the labor market.

In sum, an increase in commute cost generally reduces employment, and the proportional impact on the employment rate depends on the fraction of the population whose market wages are sufficiently close to their reservation wage. These effects are analogous for the time cost of commuting.

2.2 Extant Evidence On Commute Costs and Employment

The above theoretical predictions line up well with the general features of real-world labor markets. Individuals with high human capital tend to have higher labor-force participation than those with low human capital. High-human capital workers also disproportionately commute by car, and individuals living in places with longer average commute times have relatively lower labor force participation. These patterns, however, do not constitute a test of the proposition that higher commute costs reduce labor force participation.[7]

Many existing papers have studied transportation costs and employment. Bastiaanssen et al. (2020) systematically review 93 such studies, including 42 studies looking at car access in particular. They characterize the body of results as generally "mixed" and "not conclusive or consistent." The mixed findings in this literature are likely due to a lack of natural

[5] To see this, first note that $\hat{w}$ equates (3) and (4), and then use the implicit function theorem: $\frac{d\hat{w}}{d\theta} = \frac{u(L_0)-u(L^*(\cdot))}{H^*(\cdot)} > 0$. Individuals with a stronger preference for leisure (higher θ) require a higher wage to enter the labor market. θ is plausibly a persistent trait, but it may change over time for an individual (For instance, it could increase for a parent in a household that has just added an infant).

[6] We again use the implicit function theorem as in footnote 5.

[7] The problem, of course, is causal direction. For example, the finding that labor force participation is lower in places with longer commutes comes from Black et al. (2014), who study labor force participation among married women. The authors acknowledge that causality likely goes two ways: long commute times likely deters labor force participation *and* families that plan to have one parent stay out of the labor force (often the mother) likely sort into neighborhoods with longer commute times, which typically have lower-priced housing.

experiments suitable for identifying causal effects.

The positive correlations between car access and employment found in many observational studies do not establish a causal effect of transportation cost on employment. After all, as shown in the labor supply model above, a positive correlation between "car access" and "employment" is expected simply because individuals with relatively high human capital disproportionately choose to work, and tend to use more time-efficient modes of transportation, which in most locations means commuting by car. Stronger evidence comes from research that examines how variation in the local labor force participation is affected by corresponding variation in the "use cost" of a car for the purpose of commuting. In pioneering work, Raphael and Rice (2002) estimate employment as a function of car access, using local car insurance rates and gas taxes as instruments for car access. They find an economically meaningful and statistically significant effect of car ownership for women, but not men.[8]

The evidence provided in Raphael and Rice (2002) and similar studies relies on indirect causal links: places with higher gas taxes have higher gas prices, which increases the cost of commuting by car, which in turn reduces employment. Our work contributes by providing more direct evidence from an innovative RCT.[9]

3 Our Experiment

3.1 Study Design and Sample Characteristics

We conducted our RCT in Allegheny County, Pennsylvania, which contains Pittsburgh and surrounding suburbs. Study participants were recruited primarily by text messages sent to recipients of social services from the Allegheny County Department of Human Services (ACDHS). We recruited the study sample this way in order to target economically disadvantaged mothers. We focus on this population because of its policy relevance (many public programs target low-income families with children) and because the extant literature suggests that labor force participation among this group is particularly sensitive to transportation costs.

Enrollment took place on a rolling basis between September 2019 and June 2022. Prospective participants were directed to a study website, and those who were interested signed a consent form and answered a short set of questions to establish eligibility. Ap-

[8] A strand of literature building on this instrumental variable approach includes Bansak et al. (2010), Ong (2002), Baum (2009), and Bee (2009), all of which find that car access increases employment.

[9] We know of no comparable RCT's to date. Brough et al. (2023) and Chizeck and Mbonu (2025) provide experimental evidence showing that public transportation fare discounts increase transit ridership among low-income adults and may lead to increased employment among certain groups.

plicants were screened out if they were not female, did not have at least one dependent minor-aged child, or if they self-reported having reliable access to a car. When possible, participant eligibility was checked using ACDHS administrative records.

Eligible applicants were randomly assigned to treatment or control immediately upon submitting their application, and were notified of their randomization outcome. Participants then completed a second consent form that contained the standard terms of service for using the ride-hailing app. Finally, the participants completed an optional baseline survey with questions about demographics, employment status, and transportation use.

Participants also received instructions to download a smartphone app that contained a GPS tracking function to collect data on their spatial mobility, a platform for administering optional follow-up study surveys, and a list of resources for job-seekers (e.g. contact information for local employment and training programs). All participants received $200 in ride-hailing credits for use over the course of a month. Those assigned to the treatment arm received $200 per month in credits for five additional months. The monthly allotments could not be carried over to a subsequent month.

We enrolled 1,022 study participants. Among those individuals, we were able to link 902 to Pennsylvania UI wage records.[10] Participants who could not be matched to UI records are excluded from the analyses in this paper. Table 1 describes the baseline characteristics of our 902 UI-linked study participants. Participants are quite young and have relatively low levels of education. About 90% receive Medicaid and 80% receive SNAP benefits. These high rates of public assistance are as expected, given our channel for recruiting participants. The treatment and control groups are well-balanced on key characteristics, including on the pre-treatment measures of our focal labor market outcomes.

Fewer than 60% of study participants have any paid employment in the calendar quarter prior to enrolling in the study. Those who were employed in this quarter have relatively low earnings, averaging $4,558 ($1,519 per month). As shown in Panel C, among the survey respondents who reported commuting to work, most spend more than 30 minutes per day commuting and many spend more than an hour. The most commonly reported transportation mode is public transit (67.4%), which would typically be the bus. Over half (58.4%) of participants reported using ride-hailing apps at least occasionally.

3.2 Results

Table 2 shows participants' use of the offered ride-hailing credits. Take-up of the ride-hailing opportunity was well below 100%—about 68% for the treatment group and 59% for

[10]The linkage to UI records is based on social security number, and the 120 failed matches were primarily due to the individual not having a social security number on file with ACDHS.

the control group. Not surprisingly, those in the treatment group (who received six months' worth of ride-hailing credits) took about six times as many rides and spent about six times as many ride-hailing credits as those in the control group (who received only one month of ride-hailing credits). Due to an administrative error, 11.7% of control group members were allowed to take more than $200 worth of trips, with 2.6% taking more than $300 worth of trips.

The first row of Panel A in Table 3 presents our estimates of the effect of treatment on employment during the first full calendar quarter after the quarter in which the woman enrolled in the study.[11] The estimate in column (1) is from a regression in which the dependent variable is an indicator variable for employment status (1 if UI records show any employment in the quarter, 0 otherwise), and independent variables are an indicator for treatment status (1 if treated, 0 if in control) and quarter-of-enrollment indicator variables, which capture time-varying labor market conditions over the duration of the study. In regression (2), our preferred specification, we additionally control for the individual's employment status in the quarter prior to enrollment, which should increase the precision of our estimates. The longer-duration ride-hailing subsidies increase the likelihood of employment by 5.4 percentage points, a meaningful increase relative to a control-group employment rate of 59.7%.

The increase in employment aligns with our predictions. The modal working woman in our study commutes by bus, meaning that her budget constraints are as depicted in Panel A of Figure 1. Access to free car rides shifts the "budget constraint if commute by car" up and to the right. For some women (but not all), this budget constraint now shifts above the previously binding "budget constraint if commute by bus,"[12] and a subset of these latter women—those with wage $w(h)$ particularly close to their reservation wage $\hat{w}$—now find that they can achieve higher utility by working than by full-time leisure.

We expect earnings to increase, but as shown in the second row of Panel A in Table

[11] Recall that the employment outcomes are measured at the quarterly level, and the treatment group received $200 worth of ride-hailing credits per month for six months. Thus, if a woman assigned to treatment enrolled in January and received her first monthly allocation of credits in February, her final month of treatment would be July. The first complete calendar quarter after enrollment for this woman is April through June. A comparable woman in the control group would have no credits available during that quarter. There are a few control participants, however, who received limited credits during the quarter in which we measure employment status. For example, an control individual who enrolled in March might receive some credits during April. Also, as noted above, there were a small number of individuals in the control group who erroneously received credits for more than one month. Such cases create a slight downward bias in our estimates of the treatment effect.

[12] We know that the "budget constraint if commute by car" is not above the previously binding constraint for some women by virtue of the fact that they do not take up the offered ride-hailing credits. For these non-takers, hassle costs or other utility costs may lead them to prefer their pre-existing commute mode if they decide to work.

3, our estimates are not precise enough to draw a definitive conclusion in this regard. In Panels B and C we report a *post hoc* analysis in which we estimate treatment effects for two subsets of our sample: participants who were employed in the quarter prior to joining the study and those who were not employed in this quarter. The effects of the treatment appear to be concentrated among those with stronger prior labor force attachment.

How might our results compare with those from prior studies that used quasi-experiments with instrumental variables? In such studies, employment status is regressed on a measure of car access. A suitable instrument affects an individual's likelihood of having car access but otherwise has no impact on their employment decision. An example might be the state-level price of automobile insurance, which for simplicity we take to be "high" or "low." Then, conceptually, individuals fall into three groups: 1) "always takers", who secure car access regardless of the insurance price 2)"never takers", who lack car access regardless of the insurance price, and 3) "compliers", who secure car access only when the insurance price is low. The instrumental variables design enables estimation of the local average treatment effect (LATE), the average effect of car access on employment status among the compliers.

Our experiment similarly varies the cost of car access in the form of ride-hailing credits that can be used for commuting and other transportation needs. A study participant who takes full advantage of the ride-hailing subsidy for commuting could substantially reduce the time and monetary costs of getting to work.[13] Treated participants had the opportunity to secure this car access over a six-month period at a very low cost—mainly the costs of setting up and maintaining the smartphone app plus any disutility from ride-hailing service utilization itself. Nonetheless, many participants made little or no use of ride-hailing credits. Table 2 shows that fewer than 60% of treatment group women used $300 or more of their ride-hailing credits (i.e. $50 or more per month), while the remaining 40% did not take up the offered benefit at all or made minimal use of the benefit. Our experiment therefore generates a similar LATE setup, where the never-takers do not use the ride-hailing credits even when offered, the compliers use the credits only if they are randomized into treatment, and (thanks to administrative error) there are a very small number of always-takers who use $300+ in ride-hailing credits regardless of treatment status.

With this in mind, we estimate an OLS regression in which the dependent variable is

[13]Ride-hailing trips taken by study participants cost an average of $2.76 per mile, and employed participants had a mean daily round-trip commuting distance of about 11.5 miles. This distance is estimated based on smartphone GPS data that was collected from 323 of the 1,022 study participants for whom we were able to identify home and work locations. A $200 monthly ride-hailing subsidy therefore covers the average participant's commute for about 6.3 days per month. An average working participant would have worked about 13 days per month. Commute by alternative travel modes is also time-consuming, on the order of 1.5 hours per day.

employment status and the key independent variable is a "car access" variable equal to 1 if an individual uses $300+ in ride-hailing Credit and 0 otherwise. We have two variants of this regression, which are reported in columns (1) and (2) in the first row of Panel A in Table 4. These regressions do not have a causal interpretation; they simply describe the correlation between a woman's usage of the ride-hailing subsidy and her employment outcomes. We present these regressions only for reference, as similarly problematic models are common in the extant literature.

Columns (3) and (4) in Table 4 present IV estimates in which the woman's assigned treatment status instruments for car access. Treatment status is a strong predictor of car access due to the randomization (note the very high first-stage F statistics). Our LATE estimates indicate that, among compliers, car access increases employment by roughly 10 percentage points.[14] As with the intent-to-treat effects, the positive LATE impacts on employment are concentrated among participants who were employed in the quarter prior to joining the study (Panels B and C of Table 4). The LATE is 13.2 percentage points for this subgroup.

By way of comparison, the estimated LATE of car ownership on women's employment probability in Raphael and Rice (2002) is 16.6 percentage points (SE 0.086). The measures of car access in our two studies are very different—their measure is car ownership and ours is ride-hailing access. Also, we study somewhat differing populations, inasmuch as we focus on disadvantaged mothers while they study women more generally. Nonetheless, it turns out that our preferred LATE estimates of the effect of car access do not differ substantially from the estimates in prior credible quasi-experimental studies.

Finally, we note that labor market disruptions due to the COVID pandemic may have affected the impact of car access on employment. While only 91 of the 902 study participants received their ride-hailing subsidies during the peak period of economic disruption in March through December of 2020, we still cannot rule out the possibility that the effects of subsidized ride-hailing trips would have differed had we conducted our experiment under more typical economic conditions. More generally, further experimental research is required to gauge the generalizability of our results to other populations and locations.

[14]The $300+ threshold for defining treatment take-up is arbitrary. We tried several alternative definitions of take-up, including taking at least six rides in the first quarter after enrollment, taking at least 12 rides during the study, and taking at least $150 worth of rides during the first full calendar quarter after enrollment. Our LATE estimates are robust to these various definitions.

4 Concluding Remarks

Our work provides one of the first experimental tests of the link between commute costs and employment. We find, as predicted, that a reduction in commute costs in the form of ride-hailing subsidies causes an economically meaningful and statistically significant increase in employment among the low-income mothers who choose to take advantage of the subsidies. This is true even though the offered amount of ride credits covers less than half of the average participant's total commute costs, leaving her to use alternative forms of transportation as her primary mode of commuting. Our findings suggest the potential for innovative transportation assistance programs to provide ride-hailing trips as a supplementary mode of commuting for economically vulnerable individuals.

References

Bansak, C., Mattson, H., & Rice, L. (2010). Cars, Employment, and Single Mothers: The Effect of Welfare Asset Restrictions: Cars, Employment, and Single Mothers. *Industrial Relations: A Journal of Economy and Society*, *49*(3), 321–345 (Cited on page 5).

Bastiaanssen, J., Johnson, D., & Lucas, K. (2020). Does transport help people to gain employment? A systematic review and meta-analysis of the empirical evidence. *Transport reviews*, *40*(5), 607–628 (Cited on page 4).

Baum, C. (2009). The effects of vehicle ownership on employment. *Journal of Urban Economics*, *66*(3), 151–163 (Cited on page 5).

Bee, C. A. (2009). The effect of car ownership on employment: Evidence from state insurance rate regulation (Cited on page 5).

Black, D. A., Kolesnikova, N., & Taylor, L. J. (2014). Why do so few women work in New York (and so many in Minneapolis)? Labor supply of married women across US cities. *Journal of Urban Economics*, *79*, 59–71 (Cited on page 4).

Brough, R., Freedman, M., & Phillips, D. C. (2023). Eliminating fares to expand opportunities: Experimental evidence on the impacts of free public transportation on economic and social disparities. *American Economic Journal: Economic Policy* (Cited on page 5).

Chizeck, S., & Mbonu, O. (2025). *The role of the 'fare' in welfare: Public transportation subsidies and their effects on low-income households* (Working paper). (Cited on page 5).

Heckman, J. J. (1979). Sample selection bias as a specification error. *Econometrica*, 153–161 (Cited on page 1).

Kain, J. F. (1968). Housing segregation, negro employment, and metropolitan decentralization. *Quarterly Journal of Economics*, *82*(2), 175–197 (Cited on page 1).

Oi, W. (1976). Residential Location and Labor Supply. *Journal of Political Economy*, *84*(4, Part 2) (Cited on page 1).

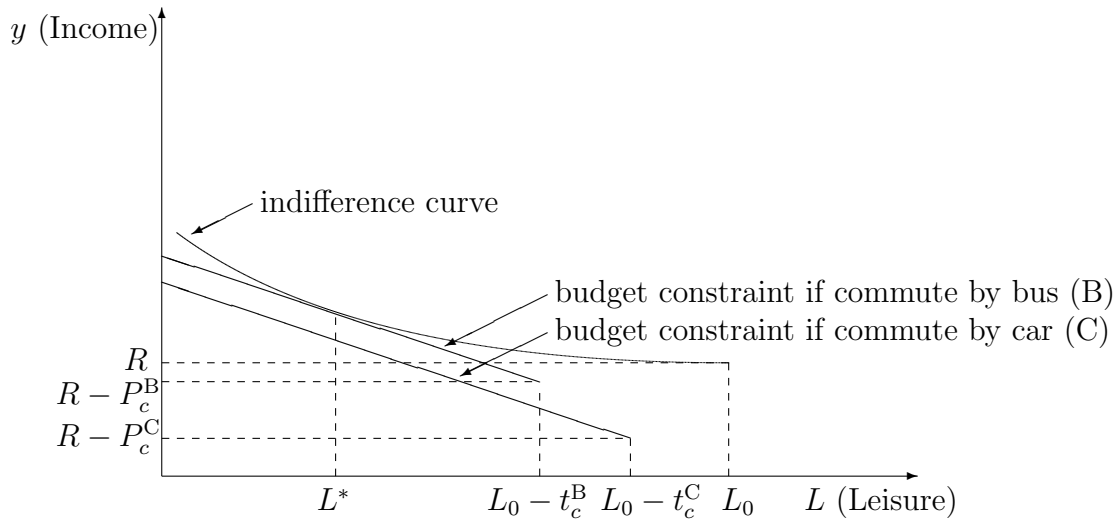
Ong, P. M. (2002). Car ownership and welfare-to-work. *Journal of Policy Analysis and Management*, *21*(2) (Cited on page 5).

Raphael, S., & Rice, L. (2002). Car ownership, employment, and earnings. *Journal of Urban Economics*, *52*(1) (Cited on pages 5, 9).

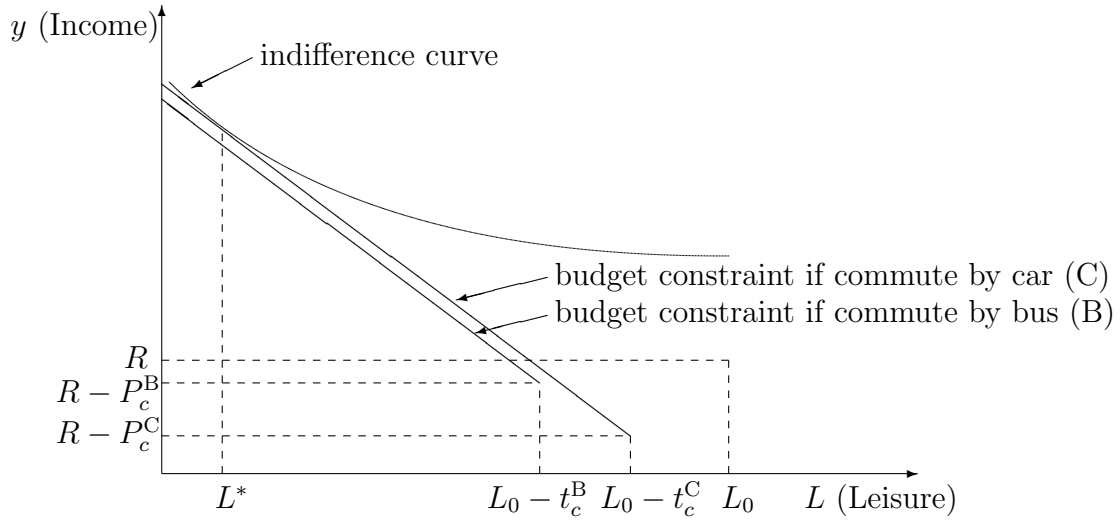
Figures

Figure 1: Commute Costs, Commute Mode, and Labor Force Participation

(a) Individual with Low Human Capital h



(b) Individual with High Human Capital h



Notes: Individuals depicted face the same dollar cost P_c^{M} and time cost t_c^{M} for commute mode M, and have the same preferences. The lower-human capital individual (Panel A) commutes by bus, and is indifferent between employment and non-employment. The higher-human capital individual (Panel B) commutes by car and strictly prefers employment

Tables

Table 1: Sample characteristics

	Means		
	Treatment	Control	Difference (SE)
A. Demographics and public benefit receipt (n_T = 406, n_C = 496)			
Age (years)	30.10	29.16	0.935 (0.527)
Black	0.704	0.742	-0.038 (0.030)
Highest education			
Less than high school	0.033	0.086	-0.053 (0.023)
High school	0.412	0.444	-0.033 (0.042)
More than high school	0.250	0.250	<0.001 (0.037)
Public benefits received in quarter before enrollment			
Medicaid	0.916	0.917	-0.001 (0.019)
Supplemental Nutrition Assistance Program (SNAP)	0.808	0.793	0.014 (0.027)
Temporary Assistance for Needy Families (TANF)	0.152	0.118	0.034 (0.023)
Supplemental Security Income (SSI)	0.051	0.058	-0.007 (0.015)
B. Employment in quarter prior to enrollment (n_T = 406, n_C = 496)			
Any paid employment	0.552	0.565	-0.013 (0.033)
Earnings among those employed ($)	4,586	4,536	49.06 (413)
Received UI benefits	0.067	0.048	0.018 (0.016)
C. Commuting, reported in baseline survey (n_T = 154, n_C = 168)			
Total daily commute time last week, for those who commute			
Less than 30 min	0.307	0.247	0.060 (0.052)
30 to 60 min	0.386	0.457	-0.071 (0.057)
1 to 2 hours	0.243	0.179	0.064 (0.047)
More than 2 hours	0.064	0.117	-0.053 (0.033)
Mode of commuting in past 4 weeks, for those who commute			
Drive self	0.032	0.030	0.003 (0.019)
Public transit	0.675	0.661	0.015 (0.053)
Carpool	0.052	0.065	-0.014 (0.026)
Bicycle	0.006	0.006	0.001 (0.009)
Walk	0.234	0.190	0.043 (0.046)
Ride-hailing apps	0.643	0.530	0.113 (0.055)

Notes: Table presents mean baseline characteristics of the study sample. The demographic characteristics in Panel A come from a combination of Allegheny County Department of Human Services (ACDHS) administrative records and baseline survey responses. The information on public benefit receipt comes from ACDHS records. The characteristics in Panel B come from Pennsylvania unemployment insurance (UI) administrative records. The characteristics in Panel C come from the baseline survey. Sample sizes vary across characteristics due to differing baseline survey item response rates and differing rates of administrative data availability. The table excludes the 102 study participants who could not be matched to UI administrative records. Robust standard errors are in parentheses.

Table 2: Use of subsidized ride-hailing during the entire study period

	Means		
(n_T = 406, n_C = 496)	Treatment	Control	Difference (SE)
Took at least one ride-hailing trip	0.682	0.591	0.092 (0.032)
Number of trips (N)	35.84	6.04	29.79 (1.65)
Dollar value of trips ($)	627.5	101.8	525.8 (27.42)
Used $150 or more in trips	0.633	0.419	0.214 (0.033)
Used $300 or more in trips	0.591	0.026	0.565 (0.025)
Used $450 or more in trips	0.571	0.006	0.565 (0.025)
Used $600 or more in trips	0.542	0.002	0.540 (0.025)
Used $750 or more in trips	0.510	0.002	0.508 (0.025)
Used $900 or more in trips	0.441	0.002	0.439 (0.025)

Notes: Table presents various measures of the sample's use of subsidized ride-hailing rides over the entire study period. Data comes from ride-hailing platform administrative records. Robust standard errors are in parentheses.

Table 3: RCT results: Intent-to-treat effects on outcomes in first full calendar quarter after enrollment

		Estimates	
	Control mean	(1)	(2)
A. Full sample (n_T = 406, n_C = 496)			
Any paid employment	0.597	0.058 (0.032)	0.054 (0.027)
Earnings ($)	3,353	220.9 (321.3)	106.5 (211.0)
B. Those employed in quarter before enrollment (n_T = 224, n_C = 280)			
Any paid employment	0.832	0.073 (0.030)	-
Earnings ($)	5,183	629.2 (482.7)	410.5 (336.4)
C. Those not employed in quarter before enrollment (n_T = 182, n_C = 216)			
Any paid employment	0.292	0.031 (0.048)	-
Earnings ($)	979.9	-268.4 (209.9)	-
Includes quarter-of-enrollment indicators		X	X
Includes outcome in quarter before enrollment			X

Notes: Table presents estimates of the effect of being assigned to the treatment group on employment outcomes in the first full calendar quarter after the person enrolled in the study. The effects are disaggregated by whether the person had paid employment in the quarter prior to the quarter in which they enrolled in the study. Data comes from Pennsylvania unemployment insurance (UI) administrative records. Estimates are from a regression of the outcome on an indicator for treatment status. Column (1) adjusts for the calendar quarter in which the person enrolled in the study. Column (2) additionally adjusts for the outcome measured in the quarter prior to the quarter of enrollment. Robust standard errors are in parentheses.

Table 4: Effect of ride-hailing usage ($300+ over the entire study period) on outcomes in first full calendar quarter after enrollment

		OLS estimates		IV estimates	
	Control mean	(1)	(2)	(3)	(4)
A. Full sample (n_T = 406, n_C = 496)					
Any paid employment	0.597	0.078	0.071	0.105	0.098
		(0.036)	(0.029)	(0.058)	(0.049)
Earnings ($)	3,353	320.4	38.17	400.2	193.1
		(374.9)	(218.0)	(582.0)	(382.6)
First-stage F stat		-	-	538.3	537.4
B. Those employed in quarter before enrollment (n_T = 224, n_C = 280)					
Any paid employment	0.832	0.080	-	0.132	-
		(0.035)		(0.056)	
Earnings ($)	5,183	648.1	173.8	1,132	740.0
		(531.6)	(379.6)	(851.3)	(609.1)
First-stage F stat		-	-	316.0	314.7
C. Those not employed in quarter before enrollment (n_T = 182, n_C = 216)					
Any paid employment	0.292	0.067	-	0.056	-
		(0.052)		(0.086)	
Earnings ($)	979.9	-68.46	-68.46	-490.9	-490.9
		(230.3)	(230.3)	(384.6)	(384.6)
First-stage F stat		-	-	219.4	219.4
Includes quarter-of-enrollment indicators		X	X	X	X
Includes outcome in quarter before enrollment			X		X

Notes: Table presents estimates of the effect of making substantial use of the subsidized ride-hailing trips on employment outcomes. We define a person to have made substantial use of the subsidized rides if they took at least $300 worth of rides over the entire study period. The benefit receipt outcomes are measured in the first full calendar quarter after the person enrolled in the study. The effects are disaggregated by whether the person had paid employment in the quarter prior to the quarter in which they enrolled in the study. Data comes from Pennsylvania UI records and ride-hailing platform administrative records. The OLS estimates in columns (1) and (2) are from a regression of the outcome on an indicator for taking at least $300 worth of rides. The IV estimates in columns (3) and (4) are from a two-stage least squares regression that uses the person's randomly-assigned treatment status as an instrument for taking at least $300 worth of rides. Robust standard errors are in parentheses.