Faring Well in the Labor Market: The Employment Effects of Public Transportation Fare Subsidies*

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Abstract

Can reducing public transit fares improve employment outcomes for low-income individuals? We conduct a randomized experiment with a sample of 9,544 low-income adults ages 18 to 64 in one large U.S. county. Participants are randomly assigned to receive no discount, a 50% discount, or a 100% discount on all public transit trips for 16 to 19 months. For the full sample, fare discounts do not significantly affect employment or total earnings. However, among participants who were unemployed at baseline, free fares increase cumulative earnings by $1,730 (CI: $265 to $3,195, a 28% increase), and increase the likelihood of being employed by 4.1 pp (CI: -0.2 to 8.4, a 7.8% increase) during the first year of the subsidy. These positive effects persist for at least three quarters after the end of the subsidy, and the program likely pays for itself through increased income tax revenue. Fare-free transit shows promise as a cost-effective means of helping disadvantaged job seekers regain employment.

JEL Classification: H4, H7, I3, R4, R5
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1 Introduction

Does access to free public transit improve labor market outcomes for low income adults? Travel costs have been theorized to impede job search and the ability to access job opportunities among lower-wage workers (Kain, 1968; Holzer et al., 1994). Others have argued, however, that physical access is not the primary barrier to employment for disadvantaged workers (Ellwood, 1986; Card et al., 2024).

This paper uses a randomized controlled trial to study the effects of free and reduced-price public transportation fares on the employment outcomes of low-income, working-age adults. We study a sample of 9,544 adults ages 18 to 64 who receive Supplemental Nutrition Assistance (SNAP) benefits in Allegheny County, Pennsylvania, a county of 1.2 million residents that contains the city of Pittsburgh. Individuals had to apply to participate in the program; only one adult could enroll per household, which reduces the risk of treatment spillovers. The sample size makes our study the largest fare pricing experiment to date. Participants were randomly assigned to one of three conditions, each with equal probability. The first treatment group received farecards that provided a 50% discount on all public transportation trips. The second treatment group received farecards that provided a 100% discount (i.e. free fares) on all trips. The control group received farecards that contained $10 but no further discount. The discounts for the two treated groups lasted for 16 to 19 months, depending on enrollment date.

At baseline, more than 80% of our sample reported not having access to a car, and 88% of the employed participants reported using public transit to get to work. Participants in the control group spent an average of $24.50 per month on transit during the study, corresponding to about nine monthly boardings. For those in the free fare group, the value of the subsidy averaged $34.65 per month, or $624 in total over an average subsidy duration of 18 months. The reliance of the sample on public transportation, together with Pittsburgh's extensive network of bus routes that serve the area's major job centers, suggests that fare subsidies could plausibly affect labor market outcomes.

Using Pennsylvania unemployment insurance (UI) wage records, we find no detectable effect of either fare discount (half fares or free fares) on the average sample member's likelihood of being employed or their total earnings during the first four complete calendar quarters after joining the study (Q1-Q4). This is the longest time period for which the subsidies were in effect for all participants. However, this average effect is dampened by the fact that one-fourth of the sample reported being out of the labor force at baseline.[1] Among

[1] 3.8% of participants were students, 6.8% were caretakers, 27.5% were unable to work due to illness or injury, and 3.5% were retired

those who reported a status of "unemployed" at baseline, free fares caused a 4.1 percentage point (SE = 0.022) increase in the cumulative likelihood of having any paid employment in Q1-Q4 and a $1,730 (SE = 747.3) increase in cumulative earnings over this time period. These impacts represent a 7.8% employment gain and 28.4% earnings gain relative to the control group mean. These effects persist for at least three quarters after the subsidy ends, according to the most recent data available. In contrast, the half fare treatment had no detectable effect on employment (ruling out full-sample effects outside of -2% to +3% of the control mean) or earnings (ruling out -3% to +6% of the control mean), even for the baseline-unemployed subgroup, suggesting that free fares may be necessary to meaningfully reduce labor market barriers for low-income job seekers.

To formally test for heterogeneous treatment effects, we implement the machine learning framework of Chernozhukov et al. (2023). This approach provides an agnostic, data-driven way to detect and characterize variation in impacts across participants, without requiring pre-specified subgroups. Using causal forests as the predictive model, we find strong evidence of treatment effect heterogeneity. The accompanying classification analysis highlights baseline employment status as a key characteristic associated with larger treatment effects, corroborating the results of our subgroup analysis.

Using three waves of follow-up surveys, we find evidence that the increase in earnings among the baseline-unemployed is driven by increased labor supply along the extensive margin and by less frequent churning in and out of work. According to the 15-month survey, free fares had no detectable impact on this group's intensive margin of labor supply in terms of the number of hours they spent working per week (ruling out effects outside of -20% to +30% of the control mean) or the number of days per week that they went to work. Free fares also did not cause these participants to hold multiple jobs at a time when they became re-employed. Nor did it cause them to move into higher-paying occupations as measured by the occupation's education-adjusted earnings rank in the Current Population Survey. We rule out economically modest impacts on hourly wages (95% CI: -$1.18 to $1.38) and on the intensity or spatial breadth of job search activities. The baseline-unemployed free fares recipients do not appear to have regained employment more quickly after joining the study than their control group counterparts. Instead, UI records show that free fares led to more *stable* employment, as the free fares group had employment in 0.134 (8.9%) more quarters than the control group in Q1-Q4.

Smartphone GPS data confirm that free fares changed actual travel behavior, especially among participants who were unemployed at baseline. This group traveled longer distances, visited more unique locations each day, and dramatically increased their transit use, adding about 3.5 transit trips per week. These mobility gains, whether a cause or a consequence of improved employment, demonstrate that the intervention meaningfully altered participants' travel patterns.

This paper builds upon previous randomized experiments that have tested the effect of subsidized transportation on the labor market outcomes of disadvantaged urban residents. In a seminal study, Phillips (2014) documents positive impacts of transportation subsidies on job search behavior among unemployed adults in Washington DC, though estimates of downstream impacts on employment and wages are statistically imprecise.[2] In the largest prior experiment that provides public transportation subsidies to low-income individuals, Brough et al. (2025) randomize fare reductions for approximately 1,600 participants in King County, Washington (Seattle) for up to six months. In their setting, participants were already receiving half-price fares through an existing city subsidy program, so the experimental treatment reduced fares from half-price to free. They find no statistically significant effect on employment outcomes from this fare reduction, for either the full sample or the subgroup that was not employed at baseline.

Our finding of positive earnings effects does not contradict the results of Brough et al. (2025) and is instead attributable to the ways in which we extend their work. Consistent with Brough et al. (2025), we find that reducing fares from half-price to free has a negligible effect on formal-sector earnings for the full sample: our Q1 estimate (effect = \$18.46, SE = 65.77) falls well within their 95% confidence interval of -\$311 to \$327 while offering greater precision due to a six-times larger sample. We additionally contribute a finer-grained heterogeneity analysis by labor market status. Our estimated impacts on Q1 earnings fall within the intervals from Brough et al. (2025) when disaggregating the sample into employed versus not employed at baseline. Our positive earnings effects materialize most strongly when focusing on specific *subgroups* of the non-employed that are close to the margin of work, which are not explored in Brough et al. (2025), and when measuring earnings over a longer subsidy duration (12 months instead of six).Overall, our design enables us to uncover previously-undetected heterogeneity by baseline labor market status, with economically meaningful earnings gains among workers who were unemployed when they first received the subsidy.

Our results suggest that temporary free-fare programs are most cost-effective when targeted to the unemployed subset of low-income adults. An 18-month free transit pass increases this group's earnings by \$9.15 per dollar spent after two years, which exceeds the return on investment of other more expensive labor market interventions that serve similar populations, such as sectoral-focused training and subsidized job placements. Free fares for

[2] In developing countries, transportation subsidies have been shown to increase both job search intensity and (in some studies) formal employment among unemployed youth (Franklin, 2018; Abebe et al., 2021; Banerjee & Sequeira, 2023). These effects may reflect distinct labor market dynamics (e.g., the need to search for jobs in person) and have yet to be replicated in developed country contexts.

the unemployed also have a marginal value of public funds (MVPF) of infinity, meaning that the policy pays for itself, when accounting only for the policy's fiscal cost and its effects on earnings and social insurance income over the first two years. The targeted, temporary provision of free public transportation to unemployed low-income adults offers a promising way to improve employment prospects at relatively low cost.

2 Motivation

To motivate our experiment, we review several channels through which reduced public transportation fares could theoretically improve low-income individuals' employment outcomes.

Channel 1: Increased labor supply. Fare discounts can influence labor supply decisions by altering the time and monetary costs of commuting to work (Oi, 1976; Cogan, 1981). Consider an unemployed worker who would only ever take the bus to work regardless of fare prices. A fare subsidy reduces their potential commute costs but does not change their potential commute time. In this case, a standard labor supply model unambiguously predicts an increase in employment (Appendix Figure A1 panel A). The same holds true for a reduction in commute *time* (panel B), as would occur if the person responds to the subsidy by switching from walking to taking the bus as their main mode of commuting. It is also possible that the subsidy simultaneously *reduces* the commute costs and *increases* the commute time that a person would face if they chose to work. This may occur, for example, if the person would only ever take a car to work under regular fares, but then they switch to favoring the bus under the subsidy. In this scenario, the net effect on employment is ambiguous and depends on 1) the person's potential hourly wage 2) the speed of the bus relative to a car, and 3) the shape of the person's preferences over consumption and leisure (panels C and D).[3]

Regarding the *intensive* margin of labor supply, the predicted effects of changes in commuting costs are less clear-cut for several reasons. First, the interior effects of any shifts in a worker's time budget or money budget will depend on the shape of their preferences over consumption and leisure. Second, if a worker's commute time and commute costs both shift simultaneously, the net effect will depend on the worker's hourly wage and the magnitude of the time change relative to the monetary change.

[3]Our survey results suggest that this scenario is not uncommon: more than one-fourth of the baseline-unemployed control group members reported using some form of car-based travel as their primary mode of commuting in the post-endline survey (Appendix Table A5).

We estimate treatment effects on the binary work/no work decision for the participants who were unemployed at baseline. We also estimate effects on self-reported measures of intensive-margin labor supply from our follow-up surveys.

Channel 2: Increased job search effort. Fare discounts can relax a financial constraint on job search, allowing an individual to access more job opportunities by expanding their spatial search. Standard job search models predict that lowering travel costs will cause job seekers to search more intensively (Pissarides, 2000). Our fare subsidies reduce travel costs per mile and thus increase the optimal spatial search radius, raising both the likelihood of receiving a desirable job offer and the expected value of wage offers (Holzer et al., 1994; Rogers, 1997; Simpson, 1992). While the use of online job search platforms may reduce the importance of in-person search, many employment opportunities, particularly for lower-wage workers, still require travel for applications or interviews. Our experiment tests this prediction by estimating treatment effects on various measures of job search intensity, the spatial breadth of job search, time to re-employment, and earnings outcomes among active job seekers.

Channel 3: Effect on wages conditional on working. Research has highlighted several mechanisms through which a reduction in transportation costs can lead to changes in wages. In quantitative spatial models, commute costs are capitalized into the wages offered by firms, and wages follow a gradient in which firms pay relatively higher wages when they are less spatially accessible to workers (Moses, 1962; Timothy & Wheaton, 2001). Studies have accordingly found evidence of commute-related compensating wage differentials (Mulalic et al., 2014). On the other hand, reduced transit costs may increase a worker's productivity in a manner that leads to higher wages. This could occur, for example, through reductions in tardiness and absenteeism (Van Ommeren & Gutiérrez-i-Puigarnau, 2011) or by reducing fatigue through an easier commute (Koslowsky et al., 2013).

Finally, by expanding the set of feasible commuting destinations, free fares could also improve the quality of worker–firm matches, increasing the likelihood of securing higher-wage jobs.

The combined effect of these factors on wages is uncertain in sign and magnitude. We shed light on this question by estimating impacts on self-reported hourly wages among survey respondents who are employed.

3 Experimental design

Our study was designed and implemented in collaboration with two government partners: the Allegheny County Department of Human Services (ACDHS) and Pittsburgh Regional Transit (PRT). ACDHS funded the fare discounts and managed the operational logistics of the study, while PRT supplied the farecards (called “ConnectCards”) that were issued to study participants.

3.1 Study setting

The experiment took place in Allegheny County, Pennsylvania. With a population of over 1.2 million, Allegheny County is the second most populous county in the state. The county contains the city of Pittsburgh and its suburbs. Allegheny County is served by an extensive public transportation network that includes buses, light rail, two funicular railways, and approximately 19 miles of grade-separated busways that are closed off to vehicular traffic. The county's public transportation network is operated by Pittsburgh Regional Transit (PRT). Figure 1 panel A shows the PRT network on a map of Allegheny County. PRT was the 26th largest public transportation agency in the U.S. in 2023 by ridership, with 39,207,577 unlinked passenger trips taken that year.[4] In 2022, 5.1% of workers in Allegheny County used public transportation to get to work, compared with a national average of 3.1%. Among Allegheny County workers that use public transportation to get to work, 20.1% had incomes below 150% of the federal poverty line, compared with 16.3% nationwide.[5]

Allegheny County has significant income disparities across neighborhoods, as illustrated by the census tract-level poverty rates in Figure 1 panel B. The map in Figure 1 panel C presents the percentage of all jobs in Allegheny County that are accessible from each census tract within a 60-minute travel time by public transportation, with no more than 20 minutes of walking. Some low-income areas of Allegheny County, such as the outlying city of McKeesport, do not have access to the region's primary job centers within a reasonable commuting time. On the other hand, several disadvantaged neighborhoods in Pittsburgh stand out as having convenient access to a relatively large number of jobs via public transit. For residents in these neighborhoods, the affordability of fares may pose a barrier to accessing work.

Our sample of SNAP households did not face work requirements as a condition of SNAP benefit receipt. For the entirety of the study period, Allegheny County was geographically

[4] Calculations based on data from Federal Transit Administration National Transit Database.

[5] Calculations based on data from American Community Survey Table S0802 2022 5-year estimates.

exempt from the federal SNAP work requirement for non-disabled working-age adults without dependent children.

3.2 Eligibility and recruitment

Eligibility criteria. Study enrollment began on November 17, 2022. Individuals were required to apply in order to participate. The study was open to all residents of Allegheny County who were between 18 and 64 years old, received SNAP benefits at some point in September 2022, and were not already receiving a PRT fare discount through their school or employer. To reduce the risk of treatment spillovers, only one adult per SNAP household was allowed to participate.[6] The study was limited to adults under age 65 because those age 65 and over already receive free fares on all PRT trips. The study was limited to SNAP recipients because they represent a substantial share of low-income residents in Allegheny County. This population was also readily accessible to ACDHS and lent itself to a simple eligibility verification process using administrative SNAP records. On January 26, 2023, ACDHS expanded the SNAP eligibility criterion to include people who received SNAP benefits at some point between September 1, 2022 and November 30, 2022. No other changes to the eligibility criteria were made during the study enrollment period. The enrollment period ended on February 15, 2023.

Recruitment methods. ACDHS recruited participants by sending text messages to local residents who met the eligibility criteria according to administrative records. The messages contained a link to an online application portal. The text message recipients who did not apply after the first outreach received a second text message two months later that again encouraged them to apply. ACDHS also sent text messages to newly-eligible residents after the SNAP eligibility criterion was expanded on January 26th, 2023. Applicants who were previously deemed ineligible when they initially applied but became eligible with the expanded SNAP criterion were informed of the change via text message and encouraged to reapply. Advertisements for the study were also displayed inside PRT buses, within the Transit smartphone app, and on fliers that were disseminated in the community.

[6] A SNAP household is defined as people who live together and purchase or prepare food together. Multiple SNAP households can live in the same dwelling. Applicants with the same home address were allowed to participate in the study as long as they belonged to different SNAP households.

3.3 Enrollment and random assignment

Study enrollment was done on a rolling basis through an online portal. Applicants completed a short screening application followed by a mandatory baseline survey. The screening application asked for demographic information, as well as the person's Social Security Number or SNAP benefit card number. These details were used to verify eligibility in real time and to screen out applicants from households where another member had already applied. Before starting the baseline survey, applicants were shown a message emphasizing that their answers to the survey will not affect their random assignment outcome. The web-based survey collected information on individuals' demographics, primary language, level of education, employment status, access to a car, and travel behavior.

After completing the baseline survey, applicants who were deemed eligible were immediately randomly assigned to one of three study arms:

1. Free fares on all PRT trips (100% discount)
2. A 50% fare discount on all PRT trips
3. No discount (control group)

The randomization was done at the individual applicant level using simple random assignment based on a pre-generated sequence of numbers. Assignment probabilities were equal across the three arms. Participants were immediately informed about their eligibility for the study and their assigned fare discount level.

Participants indicated in their application whether they wished to receive their ConnectCard by mail or pick it up in person. For those who chose mail delivery, ACDHS mailed the card within approximately one week of enrollment. These participants received their card in the mail approximately two weeks after their date of enrollment. Participants who chose to pick up their card in person received a text message when their card was ready for pickup. Cards were ready to be picked up approximately one week after the person's enrollment date.

PRT offers an existing half fare discount for riders with disabilities. The study application asked applicants if they already receive this disability discount. Those who said yes were still allowed to participate and were treated the same as all other participants in the random assignment process. However, they were not provided with ConnectCards if they were assigned to the control group or the half fare group; they were instead told to continue using their existing disability farecard. 357 participants did not receive study-issued fare cards for this reason.

3.4 Provision of fare discounts

Each participant received a ConnectCard that was programmed with the appropriate fare discount level. ConnectCards for participants in the control group and half fare group contained $10 of preloaded fare value to encourage use of the card. Once this initial $10 balance ran out, participants in these groups had to load their own fare products onto the card in order to continue using it. The half fare group's ConnectCards automatically applied a discount to any stored cash or timed pass that was loaded onto the card, with the exception of an annual pass. The half fare group paid $1.35 for a single PRT ride, which normally costs $2.75, and paid $48.75 for a 31-day unlimited ride pass, which normally costs $97.50.[7] The ConnectCards for the free fares group were programmed to allow unlimited free trips on all PRT vehicles. Participants with these cards did not need to load any fare value onto the card. Participants in all three groups were able to obtain an unlimited number of replacement ConnectCards throughout the study if their previous card was lost, stolen, or damaged. ACDHS deactivated a person's previous card when issuing a replacement card, so that each participant had only one active assigned card at a time.

ACDHS staff made very few errors when allocating ConnectCards to participants. Among the 9,173 adult participants who were issued a ConnectCard, 0.5% erroneously received a card with a programmed discount level that did not match their assigned treatment status.

3.5 Study timeline

Participants in the half fare and free fare groups were told upon enrollment that their ConnectCard would expire 365 days after it was first assigned to them in the study database.[8] These groups were then notified on October 17, 2023 that their ConnectCards would no longer expire after 365 days as originally planned, and would instead remain active for an indefinite period of time. The active study period ended with the rollout of a new, permanent fare discount program in June 2024 that is open to all Allegheny County SNAP beneficiaries ages 6 to 64, including those who were participating in the randomized study. This new program, called "AlleghenyGo", provides a uniform 50% PRT fare discount to all participants. The study-issued ConnectCards for all free fare group members were deactivated on June 30, 2024. The study-issued ConnectCards for the half fare group and control group remained active indefinitely.

[7] PRT fares do not vary by mode or distance traveled, except for a segment of the light rail system in downtown Pittsburgh that has free fares for all riders.

[8] The ConnectCards were assigned approximately three days after the person enrolled in the study.

Table 1 summarizes the timeline of the study. The participants in the free fares group received their discount for a total of 16.5 to 19.5 months, depending on when they joined the study. The experimental contrast between the half fare discount and the control group was in effect for 18 months.

3.6 Experimental sample and baseline balance

The study enrolled a total of 9,574 individuals ages 18 to 64, each from a separate SNAP beneficiary household. Thirty individuals are excluded from the study because they are duplicates or they provided a combination of name, date of birth, and Social Security Number that made it impossible to discern their true identity. The resulting analytic sample contains 9,544 adults.

Table 2 presents the baseline characteristics of the sample. The majority of participants are female and 59% are Black. Over half reported having no more than a high school education. Not surprisingly, the average participant relies heavily on public transportation for their travel needs, taking an average of 10 PRT trips and spending $30 on transit in the past week. More than 80% of the sample reported not having access to a car.

On the labor market front, 43% of the sample reported being currently employed. Among those not employed, the largest share reported a work status of "unemployed" (47.6%), followed by being unable to work for health reasons (27.4%), being a homemaker (6.8%), being temporarily laid off and expecting to return to one's job (5.1%), being on a temporary leave of absence from work (3.9%), being a student (3.9%), retired (3.5%), and other assorted reasons for not working (1.8%). Respondents who marked their status as "unemployed" may have had a definition of unemployment in mind that differs from the technical definition used in official economic measures.[9] Among those who reported being unemployed in the baseline survey, 86.2% also reported spending non-zero hours searching for a job last week.

Those who were employed reported working around 30 hours per week at their main job and earning $13 to $14 per hour. The employed participants most commonly reported commuting to work via public transit (88.0%), followed by ridehailing apps (20.1%), walking (18.9%), personal car (9.3%), and other assorted modes of travel. The administrative UI data further demonstrates the low earning capacity of the sample. Only 64% of participants had any formal-sector employment in the four calendar quarters before enrollment. The sample had average earnings of just $9,030 during this time period, which falls well below the federal poverty line for a single individual. Despite the sample's relatively low baseline employment

[9] The Bureau of Labor Statistics classifies individuals as unemployed if they do not have a job, have actively looked for work in the prior four weeks, and are currently available for work.

rate, only 6% of participants received any UI benefits in the year before enrollment, including only 5.7% of those who reported being unemployed at baseline. This contrasts with a UI take-up rate of around 30% among all eligible U.S. workers (FRED Economic Data, 2023) and is in keeping with research that shows lower rates of UI benefit eligibility and take-up among poorer workers.[10] Overall, the sample's low education and earnings is not surprising given that participants were required to be receiving means-tested SNAP benefits in the months prior to enrollment.

Table 2 also presents some characteristics of the entire study-eligible population, which consists of all 89,024 Allegheny County residents ages 18 to 64 who received SNAP benefits in September 2022. Compared with this full population, the participants in our study were more likely to be female, Black, currently employed, and living within walking distance to high-frequency transit service. They also had greater mean earnings in the prior year, such that the study sample is positively selected on earning capacity relative to the typical working-age SNAP adult in Allegheny County. Study participants came from geographically diverse areas of Allegheny County, as shown in Figure 1 panel D. Most of the neighborhoods with the largest numbers of participants are located within the city of Pittsburgh and are proximal to high-frequency PRT bus service. However, many participants also came from suburban areas where PRT service is less frequent and accessible. In any case, all participants in our study are marginal in the sense that they actively signed up for a fare discount lottery and thus perceived some private optimization benefit to receiving lower fares.

Finally, the group mean differences in Table 2 demonstrate that the random assignment worked as intended and yielded groups that were balanced on baseline characteristics. No pairwise difference in means is larger than 0.05 standard deviations, and the small differences between the groups are not statistically significant at rates higher than what would be expected by random chance.

The baseline characteristics of our sample provide several important pieces of context for our impact analysis in light of the theoretical channels in Section 2. First, the sample's heavy baseline reliance on public transportation for commuting makes it likely that fare subsidies will reduce their monetary commute costs without affecting their time costs, which in turn is likely to increase labor force participation via theoretical channel #1. Second, over half of sample members reported actively searching for work at baseline, including 44% of people who reported being currently employed (i.e. on-the-job searching for a new job). This high

[10] See for example P. M. Anderson and Meyer (1997) and Lachowska et al. (2022). Low-income workers are less likely to qualify for UI during spells of unemployment because they often do not satisfy the minimum earnings criteria in the quarters before job loss. They are also less likely to apply for UI benefits when eligible, which studies have attributed to information frictions, hassle costs (O'Leary et al., 2022; Shaefer, 2010), and place-based economic factors (Kuka & Stuart, 2024).

rate of job-seeking raises the potential for treatment effects on search intensity via theoretical channel #2. Third, the participants have very low income and spend 17% of their annual earnings on public transportation, which suggests that many are not able to achieve optimal use of public transit under regular fare prices due to liquidity or borrowing constraints.

3.7 Outcome data

We measure participants' labor market and mobility outcomes using several administrative data sources, three waves of follow-up surveys, and two sources of mobility data (travel diaries and smartphone GPS records).

Unemployment insurance data. We link the sample to UI administrative records maintained by the Pennsylvania Department of Labor and Industry (PADLI). The data reports whether an individual had UI-eligible employment in each calendar quarter and how much pretax income the person earned from each of their respective employers in the quarter. The data also reports the amount of UI benefits that the person received in each quarter, if any. The UI data does not capture earnings from jobs that are not covered by unemployment insurance, such as independent contracting and informal work. In quarters when an individual does not have an earnings record, we consider them to have zero earnings and code them as not being employed. Outcomes from this data source should be interpreted as measuring formal-sector employment.[11]

In addition to quarterly earnings and employment, we construct several other outcome measures from the UI data, such as the number of quarters in which the person had non-zero earnings and their cumulative earnings over a relevant period of time. The UI data also reports whether the individual received UI benefits in each quarter and the dollar amount of benefits that they received.

The UI data is matched with the study sample based on Social Security Number. The data is available for at least 98.2% of participants in each quarter starting with the third quarter prior to random assignment and for at least 83% of participants in each quarter going back to 13 quarters prior to random assignment.[12] We use this data to construct an unbalanced panel of employment outcomes for up to 13 quarters prior to and eight quarters following an individual's study enrollment date. The

[11]The UI data also does not capture work outside Pennsylvania. According to American Community Survey data 2016-2020 5-year estimates, 1.1% of workers in Allegheny County reported having a primary workplace location outside of Pennsylvania. We thus expect that out of state daily commuting will have little impact on our results.

[12]UI records could not be obtained for certain SSN's in the sample due to restrictions in the data sharing agreement with PADLI.

length of this panel allows us to examine treatment effects both while treatment group members received fare discounts and for at least two full quarters after the free fares expired.

Follow-up surveys. We administered three rounds of online follow-up surveys. Participants received a midline survey six months after their study enrollment date, an endline survey 11 months after enrollment, and a post-endline survey 15 months after enrollment. Participants were notified about these surveys via text messages, emails, letters, and phone calls. They had 30 days to complete the survey after the initial notification. The surveys asked questions about dimensions of participants' paid work lives that go beyond what is captured in UI records, such the person's hourly wage, number of hours worked per week, total monthly earnings, job search activity, and satisfaction with various aspects of their work. The surveys also collected data on a broad set of socioeconomic outcomes related to mobility and travel, financial stability, health, and subjective well-being.

Each study participant was randomly assigned ex ante to receive either \$10 or \$20 for completing each survey. Respondents received payment via email immediately after completing the survey. Following the framework in Coffman et al. (2019) and Dutz et al. (2025), we leverage these randomized incentive amounts to assess the extent of selection into survey completion on the answers to the survey questions themselves. This provides a glimpse into selection on characteristics that are otherwise unobservable to the researcher. The overall response rate ranged from 40% to 43% across the three survey waves, with unbalanced non-response by treatment status (e.g. 49.8% among the free fares group versus 36.1% among the control group for the post-endline survey). We correct for selection on observable baseline characteristics using inverse propensity weights. We also place bounds on the treatment effects for the post-endline survey outcomes to address the differential response rates between study arms. However, the randomized incentives also show some evidence of selection bias in the response values to several questions in the survey, and the weighting correction does not mitigate this bias. Our survey-based results should therefore be interpreted cautiously and treated as merely exploratory. Details on survey non-response are in Appendix Section D.

Mobility Data. We collected data on respondents' mobility from two sources: self-reported travel diaries and passively collected smartphone GPS data.

The first source is a series of travel diaries collected via text message. Each diary asked respondents five short questions about their travel the previous day:

1. Did you use a car for any trips yesterday? (Y/N)
2. Did you use the bus/light rail for any trips yesterday? (Y/N)

3. Did you walk/bike for any trips yesterday? (Y/N)
4. Including all of these modes of transit (car, bus, light rail, walking, and biking), how many places did you go yesterday?
5. Here are reasons you may have left your house yesterday. Type all that apply separated by a space. (e.g., type 'a b' in one msg if you went to work & school) a) Work b) School c) Groceries d) Leisure e) Health care f) Social services g) Other h) I didn't leave

Respondents were invited to opt into the diary surveys three days after joining the study. Those who opted-in received a survey every three days for the first two months, one survey per month for the next ten months, and one survey per week for the final two months. At the start of the study, participants were randomly assigned to receive either $1 or $2 for each diary completed. 61% of study participants completed at least one travel diary.

Our second source is passive GPS mobility data collected using Google Maps. Participants were invited by text and email to share their Google Maps location history, which provides timestamped location data and inferred travel modes. Those who opted in were given instructions to enable the necessary settings in the app. Each month, a random subset of participants were prompted to export and share their Google Maps location history file with the research team. Participants received $1 for each day that their location history covered in the requested month. In total, 4.9% of the adult sample shared Google Maps data covering at least one day after study enrollment.

4 Empirical strategy

We estimate the intent-to-treat (ITT) effects of being offered a fare discount using linear regressions of the form:

$$y_i = \beta_0 + \beta_1 T_{50i} + \beta_2 T_{100i} + \beta_3 (X_i - \bar{X}) + \beta_4 T_{50i}(X_i - \bar{X}) + \beta_5 T_{100i}(X_i - \bar{X}) + \epsilon_i \qquad (1)$$

where y_i is an outcome for individual i and T_{50i} and T_{100i} are indicators for being assigned to the 50% discount and 100% discount, respectively. We include an index of baseline covariates X_i to reduce the residual variance of the outcome and improve the precision of the treatment effect estimate. We use centered covariates (i.e. demeaned using the mean across all three study arms) that are fully interacted with the treatment indicator in order to improve the asymptotic precision of the treatment effect estimates (Lin, 2013). The coefficients β_1 and β_2 are the parameters of interest and represent the causal effects of gaining access to each discount relative to status quo transit fares.

Our benchmark specification adjusts for age (years), female (yes/no), Black (yes/no), having more than a high school education (yes/no), being currently employed (yes/no), the number of PRT trips taken last week, and whether the person lives within the PRT seven-day frequent service "walkshed".[13] These covariates have non-missing data for all participants. We also adjust for the lagged outcome in the pre-treatment period when possible, such as when analyzing outcomes from UI records. We test robustness with specifications that do not include any covariates and specifications that use data-driven methods to select covariates from our high-dimensional set of baseline characteristics X_i from administrative data and the baseline survey. See Appendix B for more details.

Our UI-based employment outcomes are measured at multiple time points. We use regression (1) to estimate treatment effects at particular points in time relative to study enrollment, treating each time point as a separate cross-sectional dataset. For example, to estimate treatment effects on UI earnings in each quarter after enrollment, we run separate regressions for each quarterly earnings measurement. We also construct outcomes aggregated over the entire four-quarter interval during which the fare discounts were in effect for all 9,544 participants, including the person's cumulative earnings, cumulative likelihood of having any employment, and the number of quarters in which they had any employment.

Our pre-analysis plan listed one employment-related primary outcome: total earnings in the third calendar quarter after the quarter in which the person entered the study. The average treatment effect on this outcome is reported in Table 3 Panel A. Any statistically significant effects beyond this pre-registered outcome are exploratory and worthy of future confirmatory research due to the possibility of false positive tests. We report sharpened false discovery rate (FDR) q-values to adjust for multiple hypothesis testing (Benjamini et al., 2006; M. L. Anderson, 2008) when presenting average effects for the full sample of adults and for subgroups defined by their baseline employment status. The q-values are based on the number of hypothesis tests within each table.

All dollar-denominated values are deflated to November 2022 levels using the CPI-U (U.S. Bureau of Labor Statistics, 2025).

[13] PRT defines a walkshed as the quarter-mile area around a transit stop or the half-mile area around a transit station. The five-day walkshed includes the stops and stations that have service five days per week (i.e. the minimum level of PRT service). The six-day and seven-day walksheds include only the stops and stations that have service six days a week or seven days a week, respectively. The seven-day frequent service walkshed includes only the stops and stations where transit vehicles come, on average, every 15 minutes for 15 hours of the day and every 30 minutes for an additional five hours of the day, every day of the week.

5 Results

5.1 Treatment take-up

The majority of treated participants made use of their fare subsidy for at least one trip. Figure 2 shows the percentage of adults in each study group that ever tapped their assigned ConnectCard on a PRT vehicle.[14] In the free fares group, 92.0% of adults tapped their assigned card at least once, compared with 82.7% in the half-fares group and 81.9% in the control group. Among the 1,371 card non-users, 585 never received their card because they did not pick it up from the ACDHS office or the mailed card was returned as undeliverable. An additional 68 card non-users reported that they never received their ConnectCard for some reason.

Panel B in Figure 2 shows treatment effects on the number of study-issued ConnectCard taps per month. A tap corresponds to a single boarding of a PRT vehicle. Relative to the control group, the half fares group tapped their cards an additional six to nine times per month and the free fares group tapped their cards an additional 14 to 25 times per month. The very low rate of ConnectCard usage among the control group is not surprising because this group had no financial incentive to continue using their study-issued cards after the preloaded $10 balance ran out.

5.2 Treatment effects for full sample

For the full sample, fare discounts produced small and statistically insignificant effects on formal-sector employment and earnings measured over the first four quarters after enrollment (Q1-Q4). This time period is most relevant for examining cumulative impacts because it is the longest time period for which the fare discounts were active for all 9,544 study participants.[15] Neither fare subsidy level produced a detectable effect on the likelihood of having any paid employment, the number of quarters with employment, or cumulative earnings during this one-year time period (Table 3 panel A). For free fares, our preferred 95% confidence interval rules out employment reductions greater than -0.8 percentage points and

[14] We are not able to observe taps for the 357 adult participants who were not assigned a ConnectCard. They were not assigned a card because they were randomly assigned to the control group or 50% discount group and they noted on their application that they already receive a 50% fare discount through the PRT disability fare program. We also do not observe the ConnectCard taps for another 14 adult participants whose study-issued card number was not recorded properly in the data.

[15] The experimental contrast of discounted fares versus no discount ended on May 15, 2024 (Q2 2024) with the introduction of the countywide SNAP half fare program (Table 1). Our two treatment contrasts were therefore in effect for five complete calendar quarters for the 6,987 participants who enrolled in November and December 2022 (Q4 2022) and for only four quarters among the 2,557 participants who enrolled in January and February 2023 (Q1 2023).

gains larger than 2.7 percentage points. The upper bound of this interval is 4.3% of the control group's mean Q1-Q4 employment rate of 63.2%. We rule out cumulative Q1-Q4 earnings impacts outside the range of -$163 to $833, with a control group mean earnings of $10,878 during this period. The effect on cumulative Q1-Q4 earnings reaches thresholds of statistical significance when using machine learning-based specifications but remains relatively small in magnitude at 4% of the control mean (Table 3 panel A). There is no discernible trend over time in the quarterly effects on employment or earnings over the first eight quarters after random assignment (Appendix Figure A3).

We do find evidence of positive effects on our preregistered primary outcome. In the third quarter after enrollment (Q3), the free fare treatment increased formal-sector earnings by $178 (Table 3 panel A). This effect is statistically significant at the 0.05 level (t = 2.23) and represents a 6.4% increase from the control group mean Q3 earnings of $2,767.

5.3 Heterogeneity by baseline labor market status

The positive full-sample treatment effect on our confirmatory outcome (Q3 formal-sector earnings) appears to be driven by the participants who were not employed when they entered the study. As shown in Table 3 panel C, this group experienced a marginally significant positive impact of $321 (25.3%) on its Q3 earnings, compared with an impact of $100 (2.1%) among those who were already employed upon joining the study (panel B).

Drilling down further, the positive Q3 earnings effect among the non-employed is concentrated among those who reported being unemployed or on a temporary leave or layoff at baseline. Table 4 presents effects separately by reason for non-employment. Free fares increased Q3 earnings by an estimated $696.50 (42.5%) among participants who were unemployed and by $849.50 (37.4%) among participants who were on a temporary leave of absence or a temporary layoff from work. In contrast, free fares likely reduced Q3 earnings among those unable to work for health reasons and significantly reduced Q3 earnings by $1,139 (98%) among a combination of students, homemakers, retirees, and those with other assorted reasons for not working at baseline. Half fares yielded the same pattern of positive and negative effects for these subgroups, but the effects are much smaller in magnitude and are not statistically different from zero.

A similar pattern of results holds when measuring formal-sector outcomes cumulatively during the first year of the subsidy. The full-sample null impact on Q1-Q4 earnings reflects the combination of a negative point-estimated effect among those employed at baseline and a marginally significant positive effect of $1,030 (21.7%) among the non-employed (Table 3 panels B and C). Unemployed workers experienced a $1,730 (28.4%) increase in earnings and those on a temporary leave or layoff experienced a \$2,842 (31.6%) increase, while the earnings impacts were negative among those not working for health reasons and among the combined group of students, retirees, and homemakers (Table 4). The point-estimated effects on the cumulative likelihood of having any paid employment in Q1-Q4 are positive for all four of the non-employed subgroups in Table 4 but are largest among the unemployed and those on a temporary leave or layoff. These subgroup effects on Q1-Q4 employment and earnings vary in their degree of stability across specifications but are mostly robust for the unemployed subgroup and for those on a temporary leave or layoff (Appendix Table A1).

Among baseline-unemployed workers, the positive effect of free fares relative to no discount on formal-sector employment and earnings began to materialize in the third quarter of the active subsidy period (Figure 3). These positive effects are visually apparent when comparing the raw quarterly trends (panels A and B) and when plotting regression-adjusted quarterly mean differences (panels C and D). According to our benchmark estimates, the treatment effects on quarterly employment and earnings also remain positive and statistically significant at the 0.05 level in the three quarters after the free fares expired (this is the most recent quarter for which we have UI data). The experience of temporarily receiving free fares thus may have generated longer-term improvements in the earning capacity of baseline-unemployed workers. When measuring earnings cumulatively, treatment effects increased linearly over time such that baseline-unemployed workers in the free fares group had earned \$3,933 (28.5%) more total income than their control group counterparts by the eighth quarter after entering the study (Figure 4 panel D).

These subgroup disaggregations, while theoretically motivated, were not fully specified in our pre-analysis plan. The number of additional hypotheses tested may lead us to detect heterogeneity by chance. To address this concern, we complement the above subgroup analysis with a hands-off, machine learning-based approach. Following the method outlined in Chernozhukov et al. (2023), we use the R 'GenericML' package to test for the existence of treatment effect heterogeneity and capture any patterns of heterogeneity across baseline characteristics. To check robustness, we implement the procedure with four alternative covariate sets (described in detail in Appendix B).

The machine learning analysis detects evidence of heterogeneous treatment effects of free fares on cumulative UI earnings in Q1-Q4. The best linear predictor (BLP) of the conditional average treatment effect (CATE) on the ML predictor confirms that the predictions meaningfully sort individuals by their true treatment effects. As shown in Table A4, we reject the null that the heterogeneity loading parameter (HET) is zero, signifying that there exists heterogeneity. Furthermore, this parameter is close to one, suggesting that the ML predictor is well calibrated to the true CATE.

Table 5 reports Group Average Treatment Effects (GATES). Individuals are sorted into four quartiles based on their predicted treatment effects from the ML model, and the table shows the average effect for each quartile. When using the largest set of covariates, the most affected quartile has an average earnings effect of $9, 606, compared to an effect of -$5,593 among those in the bottom quartile. The difference between the average effects of these two groups is highly statistically significant. The algorithm also breaks down the characteristics of the participants in each heterogeneity group, allowing us to examine which covariates are correlated with larger treatment effects. The classification analysis (CLAN) corroborates our finding that being unemployed at baseline was associated with larger impacts on cumulative Q1-Q4 earnings. Figure 5 shows the share of participants in each predicted treatment effect quartile who reported being unemployed at baseline (panel A) and who received unemployment insurance (UI) benefits in the quarter prior to enrollment (panel B). For the self-reported survey measure (panel A), the proportion of unemployed participants rises in the second and third most affected quartiles, and remains elevated, though slightly lower, in the most affected quartile. When using administrative data to measure unemployment (panel B), the most affected quartile has the highest proportion of participants who received UI benefits. Both patterns are consistent with baseline unemployment being a strong predictor of larger treatment effects. We present additional results from this exercise for additional covariates in Table A7.

The results presented thus far indicate that fares yield substantial positive impacts on formal-sector employment and earnings for unemployed workers and for those who are on a temporary leave or layoff from work. These groups are most relevant for testing the theoretical effect of commute costs on the employment decision because they are close to the margin of working. We now present treatment effects on other margins of adjustment among the baseline-unemployed subgroup to better understand the source of the earnings gains for these participants.

5.4 Drivers of earnings gains among the baseline-unemployed

The positive free-fares earnings impacts among the baseline-unemployed appear to be driven mainly by an increased likelihood of employment and by less frequent transitions into and out of the labor force, rather than by increased income when employed. Some evidence on mechanisms come from survey data where administrative data is not available, for example, wages, hours worked, job quality, and job search behavior. As discussed in Appendix D, the follow-up surveys are subject to selection on both observables and unobservables. We report estimates that apply inverse propensity weighting to adjust for selection on observables, but results based on survey data should be interpreted with caution and viewed as exploratory.

Intensive versus extensive margin effects. We find little evidence of intensive-margin effects on earnings. Relative to our preferred estimate of $1,730, the effect of free fares on Q1-Q4 cumulative UI earnings among the unemployed becomes smaller (effect = $677, SE = 860) when conditioning on having non-zero earnings. This estimate does not have a causal interpretation because it conditions on employment which itself is endogenous to treatment, but it at least suggests a small role for effects on the intensive margin of earnings. We also try bounding the intensive margin effect using the method in Lee (2009). This method bounds the effect of the treatment for the "always-takers" who would have positive earnings regardless of treatment (Chen & Roth, 2024). In our setting, the monotonicity assumption is that anyone who would have non-zero earnings without free fares would also have non-zero earnings with free fares. We estimate very wide bounds of [-$1,906 (SE $1,247), $1,494 (SE $1,008)] in levels and [-0.14 (SE 0.12), 0.23 (SE 0.15)] in logs. These bounds are too wide to be informative about the size of the intensive margin effect for the baseline-unemployed, at least without additional assumptions about the characteristics of the always-takers.

The survey data similarly shows little sign of effects on intensive margins of labor supply for the baseline-unemployed. The free fares group reported working slightly more hours per week on average than the control group (Table A5 panel D), but the difference is imprecisely estimated. There is also no detectable impact on the number of paid jobs that participants reported currently holding (panel D) or on the number of days on which they reported working at their main job in the past week (panel B).

Looking back to the UI administrative data, we estimate an 8.9% increase (SE = 5.1%) in the number of quarters during which the baseline-unemployed subgroup had employment in the first four quarters (Table 4 panel A).

In sum, it is unlikely that the free fares treatment caused these participants to take on more jobs, work more hours per week, or work more days per week. Instead, it mainly led to more stable employment in the form of more calendar quarters with any formal-sector work activity.

Wage effects. Hourly wages do not appear to be a significant factor driving the earnings gains of the baseline-unemployed. Taking the self-reported wages from the 15-month survey at face value, the control group earned $13.81 at their main job when they were employed and the 95% interval rules out free fare impacts larger than $1.39 per hour, or 10% of the control mean (Table A5 panel B).[16] The surveys also asked respondents to specify the occupation of their main job if they reported being employed. Free fares had no detectable impact on the likelihood that the person's main occupation ranked above the median annual earnings across all occupations nationwide, conditional on the worker's baseline level of education (Appendix Table A5 panel B).[17] In other words, there is no sign that the treatment caused baseline-unemployed workers to take jobs in higher-paying occupations, adjusted for their skill level, than they would have otherwise taken.

Other measures of job quality. We cannot rule out null effects of free fares on self-reported measures of job satisfaction among the baseline-unemployed participants who reported having a job in the 15-month survey, although the confidence intervals are relatively wide. These results are shown in Appendix Table A5 panel C. Control group respondents gave their main job an average rating of 6.71 out of 10 in terms of how well the job fits their experience and skills, and we rule out free fares impacts larger than plus or minus 10% of the control mean. Free fares do not appear to have led baseline-unemployed workers to move into jobs that better fit their preferences.

We detect a suggestive 4.3 percentage point increase in the reported likelihood of working for an employer that provides commuting benefits to its employees (Appendix Table A5 panel C). The experience of receiving free transit fares may have shifted the preferences of unemployed workers to value commuting benefits more highly as a non-wage job amenity.

Job search intensity and returns to search. To what extent are the earnings gains among the baseline-unemployed attributable to enhanced job search? Our surveys asked an extensive set of questions about job search activities. We use the midline (six-month) follow-up survey to explore the effects of free fares on the job search efforts of the participants who were unemployed at baseline.[18] We focus on the 6-month survey in this analysis because it was the earliest post-treatment measure of job search and thus took place closest in time to when the participant entered the study in a state of unemployment.

[16] This analysis again conditions on an outcome (employment status) and therefore does not have a causal interpretation.

[17] This calculation is according to data from the Current Population Survey 2023 Merged Outgoing Rotation Group. Survey respondents reported their current occupation by selecting from a list of standardized titles from the O*NET database. This enables us to link the person's occupation with Census and Bureau of Labor Statistics data using the Standard Occupational Classification (SOC) code.

[18] The job search questions in the follow-up surveys were displayed for all respondents regardless of their current employment status. For those who reported already having a job, the job search questions asked about their activities searching for a "new job".

We are unable to detect an effect of free fares on the likelihood that baseline-unemployed participants actively searched for work in the past four weeks, as reported six months after entering the study (Appendix Table A6 panel A). Six out of ten control group respondents reported actively searching, and our preferred 95% interval rules out free fares effects outside of -16 to +8 percentage points. Among those who reported actively searching, free fares increased the number of jobs to which they applied in the past four weeks by roughly three to six applications, with the effect reaching statistical significance in certain specifications.

A caveat to these results is that many of the baseline-unemployed participants were no longer unemployed as of the midline survey. The impacts on their reported job search activities in this survey therefore do not fully reflect their search efforts while they were still unemployed. To probe the treatment effects on job search during a contemporaneous state of unemployment, Appendix Table A6 panel B reports impacts among the participants who reported being unemployed in the *midline* survey instead of at baseline. These effects lack a clean causal interpretation because they condition on a post-treatment employment status, but they nonetheless provide suggestive evidence of the effect of fare subsidies on a person's job search effort while they are unemployed. Among the currently unemployed, free fares are associated with a statistically significant 13 to 22 percentage point increase in the likelihood of actively searching for work.

Free public transportation theoretically increases a job-seeker's spatial search radius by reducing the per-mile cost of searching. Yet the midline survey responses show little support for this prediction. Spatial job search is not very prevalent in our sample, as only 26% of the actively-searching control group members reported traveling around to search for work in person in recent weeks (Appendix Table A6 panel A). Free fares yielded negligible point-estimated effects on this likelihood among the baseline-unemployed (panel A) and negative point estimates among the midline-unemployed (panel B). Further, we rule out small increases in the number of Allegheny County municipalities or the number of Pittsburgh neighborhoods in which the person reported searching for work, at least among the baseline-unemployed.

Unemployment duration. Free fares show little sign of reducing the duration of unemployment among the baseline-unemployed. We measure this duration using the midline survey. We calculate each respondent's unemployment duration between baseline and midline as follows: If the person reported being employed at midline (case #1), the duration is the number of days between study enrollment and the start date of their current main job. If they reported not being employed at midline but they have worked since joining the study (case #2), the duration is the number of days between study enrollment and the start date of their most recent job. If they reported not being employed at midline and they have not worked since joining the study (case #3), the duration is the number of days between study enrollment and when they completed the midline survey.

Appendix Figure A2 plots the raw cumulative distribution of the number of days that the baseline-unemployed individuals spent unemployed. There is no clear visual evidence that free fares led to shorter unemployment spells in the first six months of the subsidy. The regression-adjusted impact on mean number of days unemployed is -1.46 days, though the estimate is not precise (SE = 4.18). The sharp increase in the cumulative distribution at around 180 days is due to the mass of individuals who fall into case #3.

Takeaway. Among the baseline-unemployed, we find little empirical support for positive effects of free fares on intensive-margin labor supply, hourly wages, job quality, or the spatial breadth or intensity of job search. The Q1-Q4 formal-sector earnings gains for this group are mostly attributable to movement from zero to non-zero earnings.

5.5 Mobility mechanisms for employment gains among the baseline-unemployed

In this section, we explore treatment effects on geospatial mobility and travel behavior that may help explain the employment increase among the baseline-unemployed. We draw upon rich data on the daily travels of the study participants, which was collected as part of the broader ACDHS program evaluation. Chizeck and Mbonu (2025) provide more detail on these data sources and present an extensive analysis of the effect of fare subsidies on travel and mobility patterns.

A natural channel is commuting costs. As discussed in Section 2, free fares could lower both the time and monetary costs of traveling to potential jobs. Our survey data provide some insight into this channel, though only for respondents who reported being employed at the time of the survey. The responses to these commuting questions therefore provide only partial insight into the effect of our intervention on commute costs; the employed respondents may systematically differ from the non-employed respondents in their potential costs of traveling to work due to selection effects in the work decision.

There is little evidence that free fares led to a change in commute times. Free fares did not substantially affect daily round-trip commute times, though the estimates are noisy. Our benchmark 95% interval is wide, ruling out free-fares effects outside of -50 to +70 minutes on this outcome (Appendix Table A5, panel E). Free fares also do not appear to have led the baseline-unemployed to take jobs in locations that are faster to commute to from their home; there is no detectable effect on the average travel time between participants' home addresses and their employer address as listed in UI records (Appendix Table A3).[19]

At the same time, we find some evidence that the intervention reduced commuting costs in monetary terms. Our surveys did not ask participants how much money they spent on *getting to work*. However, free fares did reduce self-reported weekly spending on all transit trips by \$19.33 (58%) among the baseline-unemployed. This reduction in spending, together with the fact that 54% of control group respondents reported using public transit to get to work (Appendix Table A5 panel E), make it plausible that the treatment reduced the monetary commute costs that the baseline-unemployed sample members faced in their consideration set as they decided whether or not to re-enter the labor market. To put these changes in perspective, the average control group member that was unemployed at baseline spent about \$23 per month on transit over the study period, corresponding to roughly 8.5 trips. In contrast, the free fare group received a subsidy worth approximately \$51 per month (\$918 in total over 18 months). These magnitudes are non-trivial: the monthly value of the free fare subsidy represented about 30% of average SNAP benefits in Allegheny County, underscoring that the intervention meaningfully reduced recurring transportation expenses.

Free fares likely also changed the primary mode of travel to work. Our benchmark specification estimates a 13.1 percentage point (24%) increase in the likelihood of using the bus as one's primary mode of commuting among the baseline-unemployed who were employed as of the 15-month survey (Appendix Table A5 panel E). This increase in bus usage is accompanied by suggestive decreases in rates of taking a car, walking, and biking to get to work.

Beyond commuting, free fares increased overall mobility among the baseline-unemployed. This subgroup increased its total spatial mobility along several dimensions in response to free fares. According to GPS data from participants' smartphones, this group experienced positive impacts on the total distance they traveled and the number of unique places they visited per day, as well as their total number of trips taken per week (Table 6). In contrast, the rest of the sample experienced *negative* point-estimated effects on these outcomes. Furthermore, according to text message-based travel diary surveys, the baseline-unemployed experienced a positive impact on the likelihood of reporting going to work yesterday and no impact on the likelihood of leaving the house at all yesterday, contrasting with the robust *negative* impacts on these measures for the rest of the sample. They also had an outsized transit ridership response to free fares, taking 3.49 additional

[19]This calculation is limited to the participants who had at least one UI employer in Q1-Q4 with a non-missing street address. Travel times are calculated using Google Maps API for a trip that starts on a recent Wednesday at 8 am. The null effect applies to both car-based trips and public transit trips.

transit trips per week, compared with only 0.139 additional trips among those who were employed at baseline (Table 6). These results hint at a relationship between increased total mobility and employment gains among the jobless, although it is unclear whether this increased mobility is a cause (e.g. spatial job search) or a consequence (e.g. work-related travel) of their increased employment.

5.6 Heterogeneity across other sample characteristics

Our extensive set of baseline characteristics from administrative and baseline survey data enables us to disaggregate treatment effects on Q1-Q4 formal-sector employment and earnings by many other relevant sample subgroups.[20] These results are presented in Figures 6 and 7. In general, some types of non-employment (retired, temporary lay-off, unemployed, other) tend to have the largest treatment effects, while others (student, disabled, care taker, temporary leave) have lower or negative treatment effects. Looking across all 9,544 sample members, the earnings impact of free fares did not meaningfully differ between between Whites and non-Whites or between those with only a high school education and those with more than a high school education. Earnings effects were positive for females and negative for males.

We also note that the positive effect of free fares on earnings do not hold when using an alternative indicator of baseline unemployment: receipt of UI benefits. Free fares caused an estimated *decrease* of $4,219 in cumulative Q1 - Q4 earnings among those who received any UI benefits in the quarter before enrollment (Figure 7). This marked difference in impacts between definitions of unemployment is due to the dynamics of UI receipt among low-income workers. Among participants who reported being unemployed in the baseline survey, only 4% received UI benefits in the quarter prior to enrollment and only 5.7% received UI in the 4 quarters before enrollment. This aligns with research showing lower rates of UI benefit eligibility and take-up among poorer workers.[21] Additionally, the self-reported unemployed who received UI benefits in the quarter before enrollment had mean earnings of $21,287 in the year before entering the study, compared with earnings of only $4,829 among the self-reported unemployed who did *not* receive UI benefits. Unemployed SNAP adults who claim UI benefits are thus positively selected in ways that make them less responsive to the

[20]Note that the baseline survey does not suffer from any non-response bias as it was mandatory for all participants.

[21]See for example P. M. Anderson and Meyer (1997) and Lachowska et al. (2022). Low-income workers are less likely to qualify for UI during spells of unemployment because they often do not satisfy the minimum earnings criteria in the quarters before job loss. They are also less likely to apply for UI benefits when eligible, which studies have attributed to information frictions, hassle costs (O'Leary et al., 2022; Shaefer, 2010), and place-based economic factors (Kuka & Stuart, 2024).

work-supporting effects of free fares.

A data-driven approach to uncovering heterogeneous treatment effects supports much of the findings above. Following the machine learning algorithm outlined in Chernozhukov et al., 2023, we run a classification analysis that compares the average characteristics of participants in the most and least affected heterogeneity groups, as predicted by the model. Table A7 presents these results, ordered by the p-value of the difference in means between the two groups. The covariates showing statistically significant differences are primarily related to proxies for labor market engagement and baseline access to or need for public transportation. Participants that were employed at any point in the year prior to enrollment tend to experience larger treatment effects. Relying on a car for mobility, and living *outside* the PRT frequent service walkshed are both associated with *larger* treatment effects. This pattern again likely reflects the fact that these participants are marginal users of public transit – that is, they were less reliant on public transit at baseline and were thus more likely to be induced to increase their ridership by the intervention.

We also explore heterogeneous effects for various subgroups among the baseline-unemployed, to explore moderators of the positive employment and earnings impacts that this group experienced as a whole. The results are presented in Figures 8 and 9. In Figure 9, having a history of homelessness, having no employment in the past year, and having no more than a high school degree are all associated with less positive earnings impacts than the average baseline-unemployed participant. In contrast, receipt of UI benefits in the quarter before enrollment was associated with relatively larger estimated earnings gains.

Several other treatment effect disaggregations in Figure 9 are noteworthy in light of the spatial mismatch theory that motivates our study. Participants who lived within walking distance of the highest-frequency public transit service had a *smaller* estimated earnings response to free fares than the baseline-unemployed average. This may reflect the fact that these individuals already enjoyed relatively good transit access, and likely relied heavily on public transit prior to the intervention, such that the marginal benefit of removing fare costs was limited.[22] Those who lived in census tracts with relatively poor transit access to jobs had *above*-average earnings impacts.[23]

[22]For example, the baseline-unemployed participants who lived within the PRT seven-day frequent service walkshed reported taking 5.4% more PRT trips per week in the baseline survey than the average unemployed person. They were also 3.4% less likely to report having access to a car.

[23]We use 2021 LEHD LODES data and a GIS network dataset to calculate the percentage of all jobs in Allegheny County that are accessible from each census tract via public transit within 60 minutes, with no more than 20 minutes of walking. See Figure 1 panel C and the footnote to this figure for more detail on the calculation.

6 Cost effectiveness of free fares

In this section, we assess the cost-effectiveness of an 18-month free transit pass in improving the work outcomes of SNAP recipients. We focus only on the free fares treatment for the baseline-unemployed subgroup because that is where we see strong effects. We also calculate the marginal value of public funds (MVPF). Further details on these calculations are in Appendix C.

The direct cost of free fares to the government includes foregone fare revenue, administrative costs, and any marginal costs of additional ridership for PRT operations. The free-fare subsidy lasted for approximately 18 months for the average baseline-unemployed participant.[24] Eighteen months' worth of free fares cost PRT an estimated $424.71 in foregone revenue per baseline-unemployed participant. The program cost $5.12 to administer per person. We assume that there is no marginal operating expense to PRT for an additional passenger boarding. The program thus had a direct cost of $429.83 per person.

Free fares increased the earnings of baseline-unemployed participants by an average of $3,933 in the first two years (Figure 4 panel D), for a return on investment (ROI) of $3,933 / $429.83 = 9.15. This metric of cost-effectiveness compares favorably with other programs that show evidence of increasing the earnings of unemployed adults, such as wage insurance for dislocated workers (ROI of 6.15 over four years), individualized case management for low-income adults (ROI of 2.27 over two years), sectoral-focused job training (ROI of 6.43 over 63 months), and temporary subsidized job placements with wraparound supportive services (ROI of 0.37 over four years).[25]

Marginal value of public funds. The MVPF is the ratio of society's willingness to pay for free fares to the net fiscal cost of the policy (Hendren & Sprung-Keyser, 2020). The MVPF numerator includes the subsidy recipients' private willingness to pay for free

[24] Recall that participants had access to free fares for varying lengths of time because they signed up over a three-month period and the subsidy expired on June 30, 2024 for everyone. This expiration date was 559 days after study enrollment for the average baseline-unemployed sample member. We round this to 18 months because it usually took several days for participants to receive their farecards after enrolling in the study.

[25] *Wage insurance:* Hyman et al. (2024) find that eligibility for wage insurance through the U.S. Trade Adjustment Assistance program increased workers' earnings by an average of $18,260 over the first four years following displacement from work, at a cost of $2,970 per eligible worker. *Individualized case management:* Evans et al. (2025) find that the Padua program in Texas increased the earnings of baseline non-employed participants by $421 per month as measured after 24 months, at a per-participant cost of $22,950. *Sectoral-focused training:* The Per Scholas program increased trainees' cumulative earnings by $28,661 after 63 months at a cost of $4,459 per person (Schaberg & Greenberg, 2020). *Subsidized job placements:* The ReHire Colorado program increased participants' earnings by $2,177 over four years at a per-person cost of $5,932 (Barham et al., 2025).

fares plus society's willingness to pay for any downstream externalities of the policy. The denominator includes the mechanical cost of free fares plus any fiscal externalities associated with the effects of the policy. Our MVPF calculation incorporates the willingness to pay for the subsidy itself, as well as the program's effects on earnings, UI benefit income (Appendix Table A1), and income from various means-tested transfers (Appendix Figure A4).

Table 7 presents the results. When measuring costs and benefits over the first two years, an 18-month free transit pass for an unemployed SNAP recipient generates tax revenue that exceeds the direct cost of the subsidy. The program thus pays for itself and the MVPF is "infinite" in the framework of Hendren and Sprung-Keyser (2020). This infinite MVPF is larger than the average MVPF of the job training programs (0.44) and the UI benefit enhancement programs (0.61) listed in Table 2 of Hendren and Sprung-Keyser (2020). Free fares stand out as one of few workforce development policies to date that fully pays for itself via increased tax revenue. Our MVPF also exceeds those of other SNAP-related policies such as reducing eligibility renewal burdens (2.1) and removing work requirements (0.9).[26] Free transit fares generate additional social welfare benefits by causing recipients to take fewer car trips, thus reducing the negative externalities associated with automobile travel. Given these environmental benefits, the MVPF of free fares remains greater than one when the subsidy is provided to all SNAP adults, not only those who are unemployed (See Chizeck and Mbonu (2025) for this full-sample MVPF calculation).

7 Discussion

Poor urban residents rely heavily on public transportation, and there are concerns that fare prices constrain the labor market activity of this population. In this paper, we test the effect of transit fare discounts on the employment outcomes of 9,544 working-age adults who receive SNAP benefits in one large U.S. county. We conduct a randomized trial that assigns each person to receive either free fares, half-price fares, or regular-price fares for 16 to 19 months. We measure an array of employment-related outcomes using UI administrative records and three follow-up surveys.

For the full sample, fare discounts had a negligible average treatment effect on cumulative earnings during the active subsidy period. However, free fares produced substantial earnings gains among the participants who were unemployed when they first received the subsidy. These gains persisted for at least three calendar quarters after the subsidy expired. The half-fare treatment, in contrast, did not yield a detectable improvement in earnings for

[26]The MVPF's of these and other policies are summarized in the Policy Impacts MVPF library: https://policyimpacts.org/policy-impacts-library/

this group. The earnings gains among the baseline-unemployed were primarily driven by the extensive margin of labor supply rather than by increased wages or greater hours worked when employed.

Our results support the basic theoretical prediction that a reduction in daily commute costs will induce marginal workers to enter the labor market. At the same time, we find little empirical support for other components of spatial mismatch theory. Public transportation costs do not seem to hinder the intensity or efficiency of job search in our setting. This result contrasts with prior research showing that transportation subsidies increase job search activity among unemployed adults in Washington, D.C. (Phillips, 2014) and among youth in developing countries (Franklin, 2018; Banerjee & Sequeira, 2023; Abebe et al., 2021). This is likely because in more recent times and in more developed economies, job search is mostly conducted online or by phone. We also find no meaningful differences in treatment effects between White and Black participants. This runs counter to prior work showing that spatial frictions in housing and labor markets can have differential employment effects along racial lines (Gobillon et al., 2014; Miller, 2023). In any case, our findings demonstrate that low-income job-seekers are not able to achieve economically-optimal use of public transportation under status quo prices. This basic fact highlights the presence of transportation-related frictions in the labor market, although the micro-foundations of these frictions warrant further study.

To summarize, free fares are a cost-effective form of work support when targeted to the low-income unemployed. While fare-free transit may have other economic benefits for the broader population of low-income adults, this policy best achieves the goal of increasing earned income when it is targeted to those who are close to the margin of paid work. At a time of ongoing policy interest in promoting employment among recipients of public assistance, we show that the SNAP program could increase the earnings of its unemployed adult caseload by offering them free public transportation passes. Two caveats are that targeting the unemployed in a real-world policy environment may be difficult because unemployment is not verifiable in administrative data, and the use of fare-free transit as a work support policy is only feasible in areas that have adequate public transportation service to begin with.

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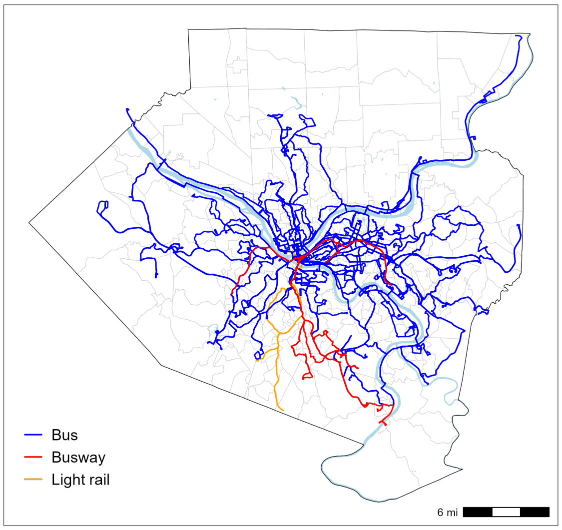
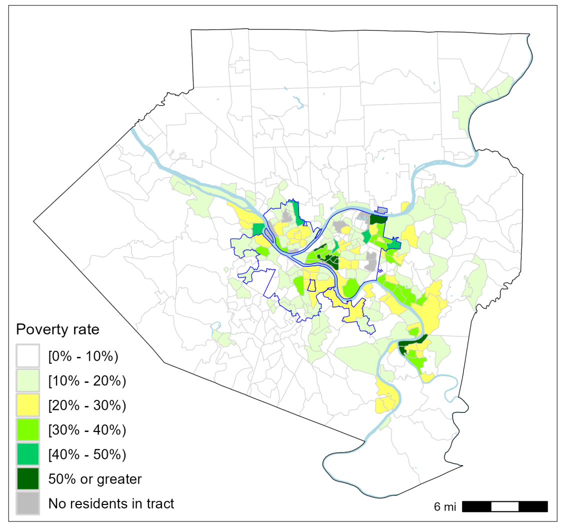
Figures

Figure 1: Socioeconomic and transportation context of Allegheny County, Pennsylvania

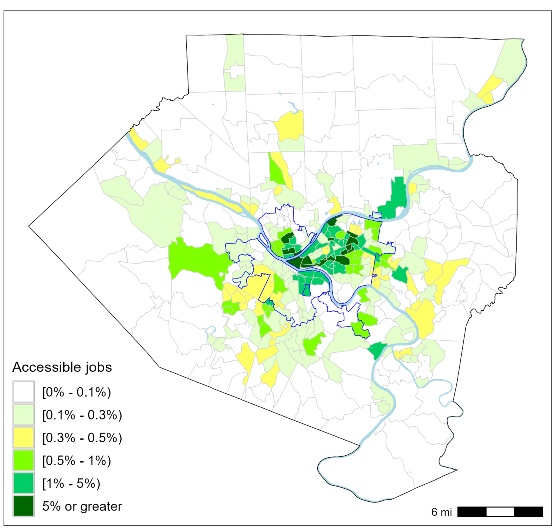
(a) Pittsburgh Regional Transit (PRT) service routes



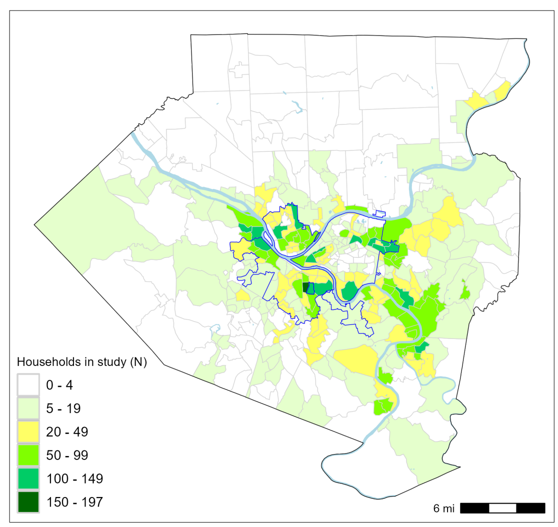
(b) Share of residents below poverty level, by census tract



(c) Percentage of jobs that are accessible via public transit, by census tract

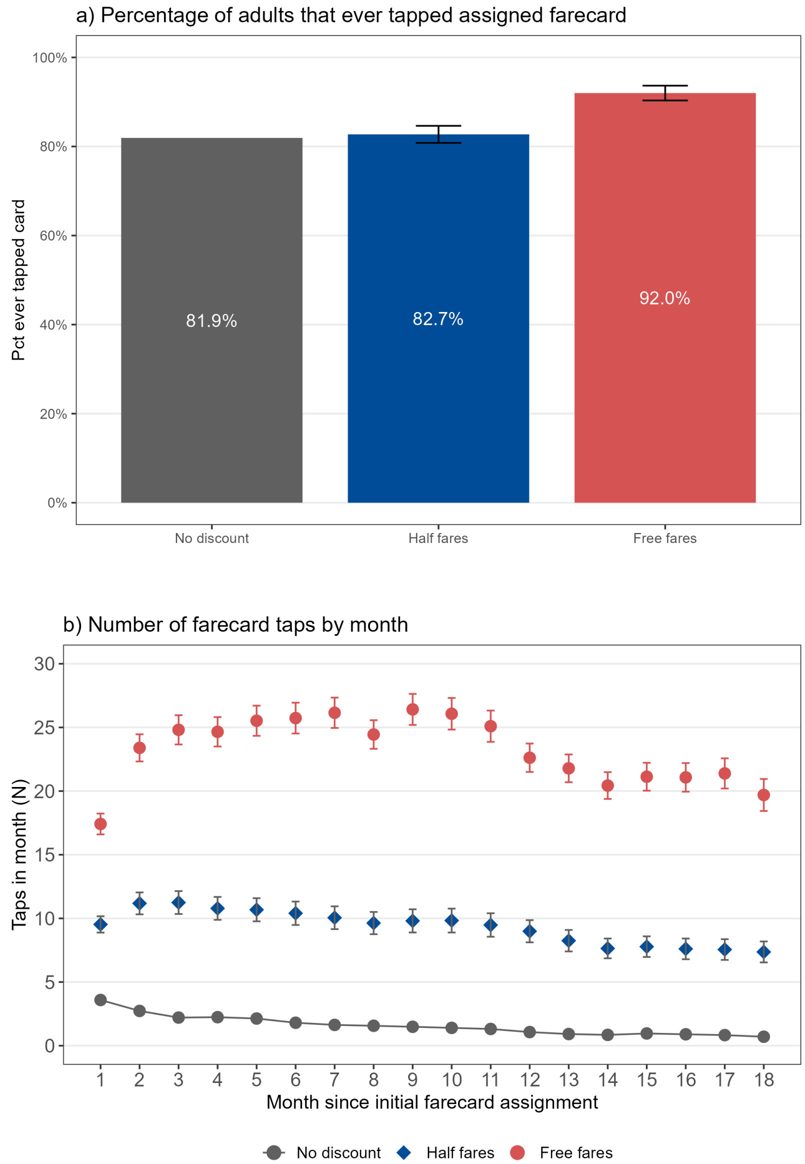


(d) Number of participating households by census tract



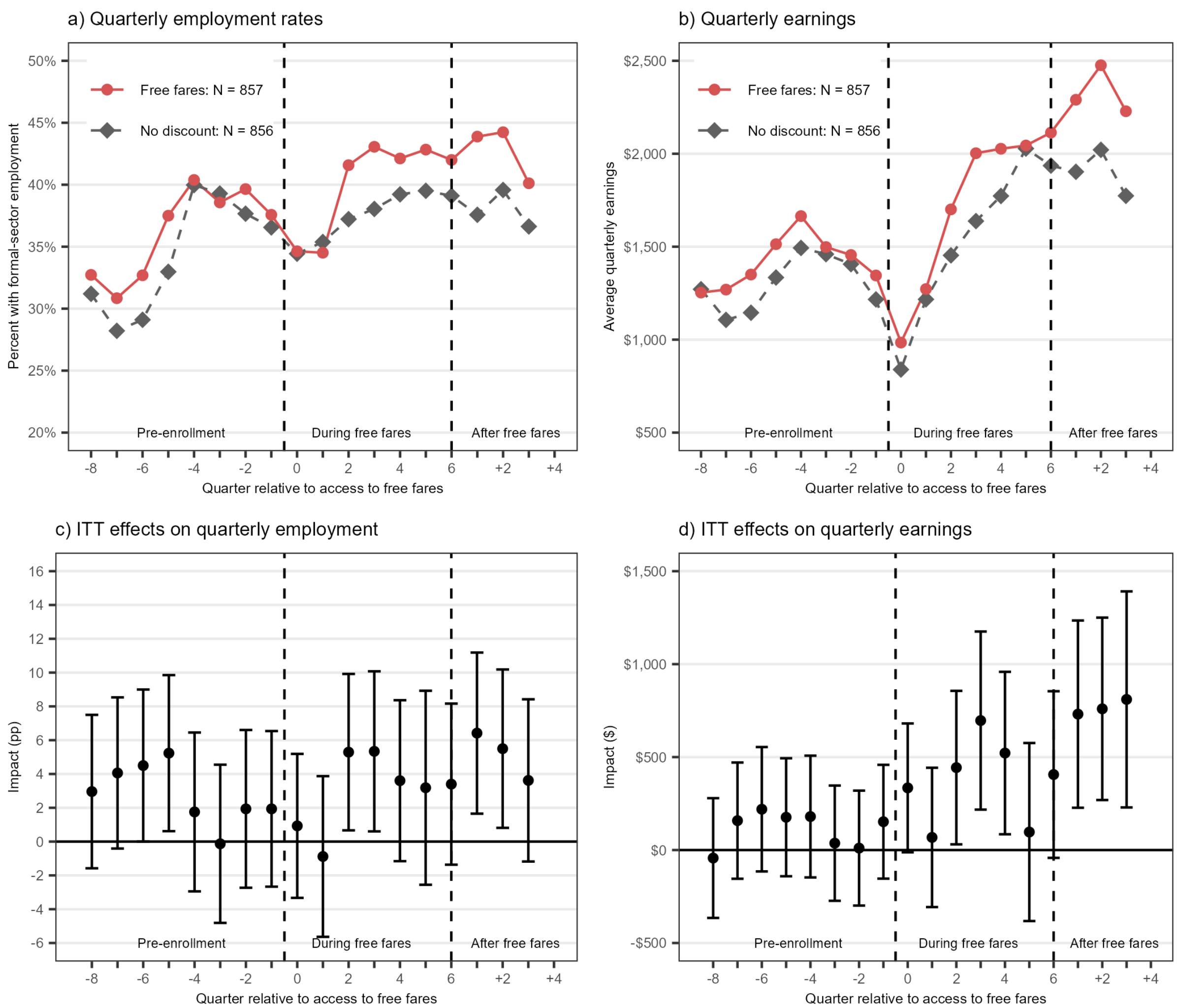
Notes: Data in Panel (b) comes from American Community Survey Table S1701 2022 5-year estimates. Panel (c) maps the percentage of all jobs in Allegheny County that are accessible via public transportation from each census tract. A job is defined as accessible from the origin census tract if it can be reached in less than 60 minutes via a combination of walking and public transportation, with no more than 20 minutes of total walking time in the journey. Job locations are aggregated to the census block level using 2021 Census LEHD LODES Workplace Area Characteristics primary job counts. If a destination census block is accessible from a given origin tract, then all jobs within the census block are considered accessible from the origin tract. Travel times between origin tract centroids and destination block centroids are calculated using a GIS network dataset that incorporates Pittsburgh Regional Transit General Transit Feed Specification data to obtain transit service timetables. The network dataset allows walking on all roads except limited access highways and highway on/off ramps. The travel time calculations assume that the trip begins at 7:30 am on a Wednesday morning. The blue boundary in panels (b), (c), and (d) outlines the city of Pittsburgh.

Figure 2: Treatment take-up



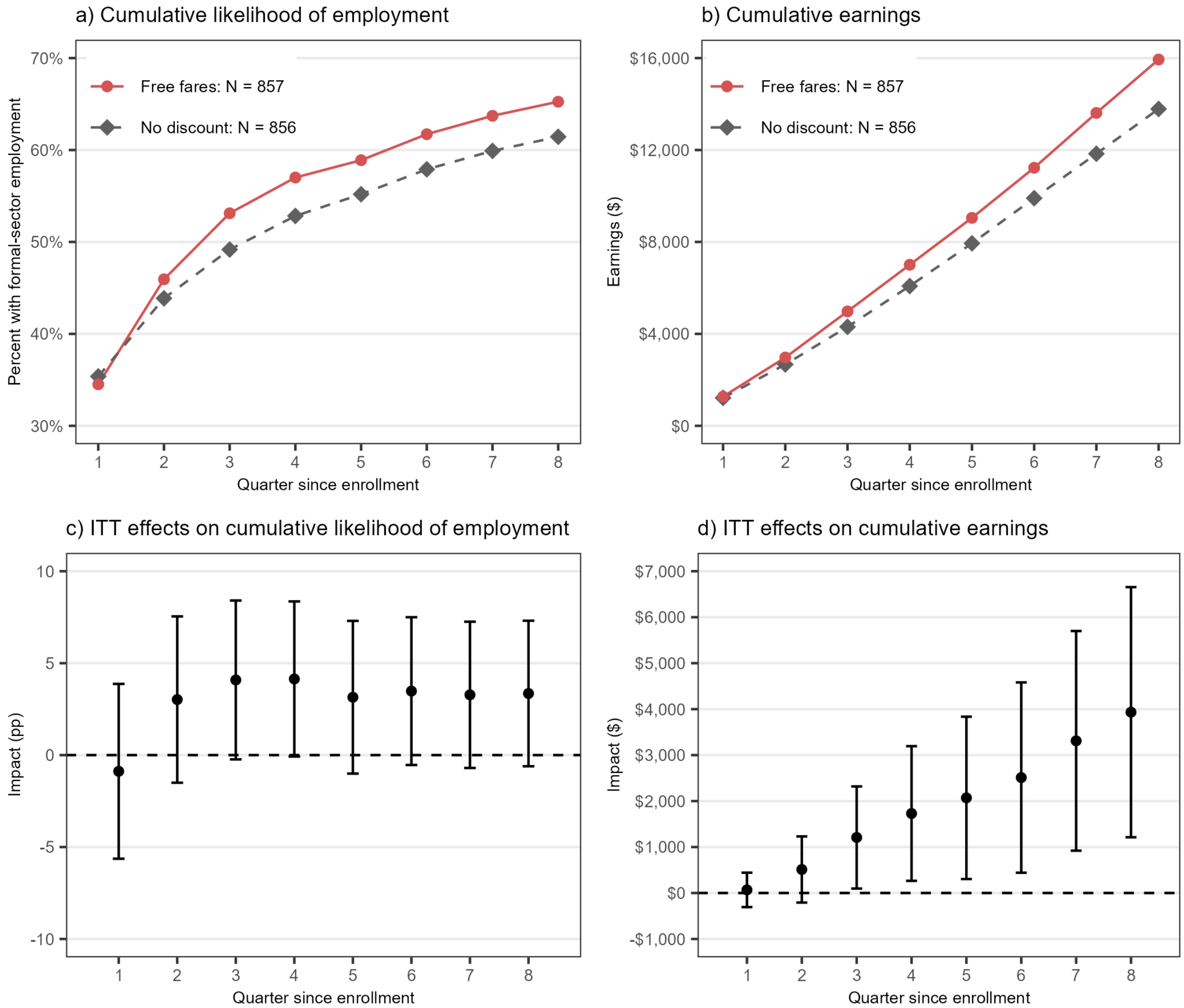
Notes: Figure presents rates of treatment take-up by way of using the study-issued farecards. Panel A presents the percentage of participants in each of the three study arms that tapped their assigned farecard at least once during the study. Panel B presents the number of times that the participants tapped their study-issued farecard in each month. Calculations are based on data from Pittsburgh Regional Transit (PRT) fare transaction records. The analysis excludes 357 participants who were not assigned a ConnectCard. It also excludes 14 participants whose study-issued ConnectCard number was not recorded properly in the study database. The error bars in both panels represent 95% confidence intervals of the effect of being assigned to the given study group relative to no discount. The effects adjust for the following baseline covariates: Age (years), female (y/n), Black (y/n), more than high school education (y/n), currently employed (y/n), PRT trips taken last week (N), and lives within the PRT 7-day frequent service walkshed (y/n).

Figure 3: Formal-sector employment and earnings in Pennsylvania, free fares versus no discount, among the baseline-unemployed



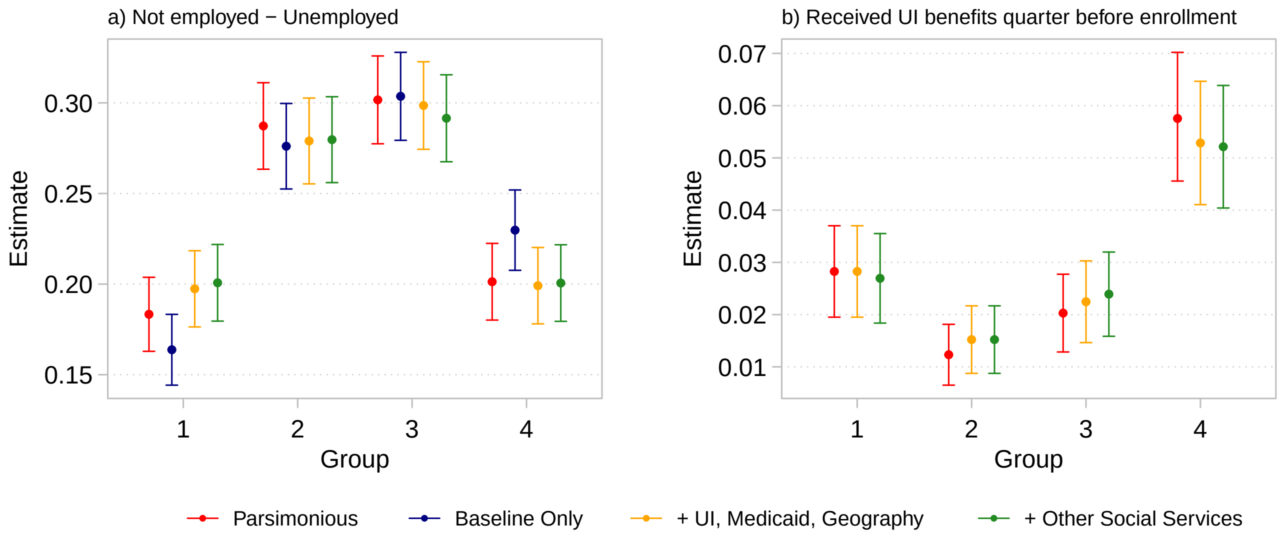
Notes: Panels a) and b) show raw quarterly employment rates and mean earnings over time among the free fares and control group members who were unemployed at baseline. The data comes from Pennsylvania unemployment insurance (UI) administrative records. The treatment effects in panels c) and d) adjust for the following baseline covariates: Age (years), female (y/n), Black (y/n), more than high school education (y/n), currently employed (y/n), PRT trips taken last week (N), and lives within the PRT 7-day frequent service walkshed (y/n). The effects in the period after time zero also adjust for the outcome in the four quarters before enrollment. Treated participants had access to free fares for either 5 or 6 full calendar quarters, depending on when they joined the study. Error bars represent the 95% confidence intervals using robust standard errors. The p-value from a test that all pre-treatment differences in employment (earnings) are jointly 0 is 0.247 (0.683).

Figure 4: Cumulative formal-sector employment and earnings in Pennsylvania, free fares versus no discount, among the baseline-unemployed



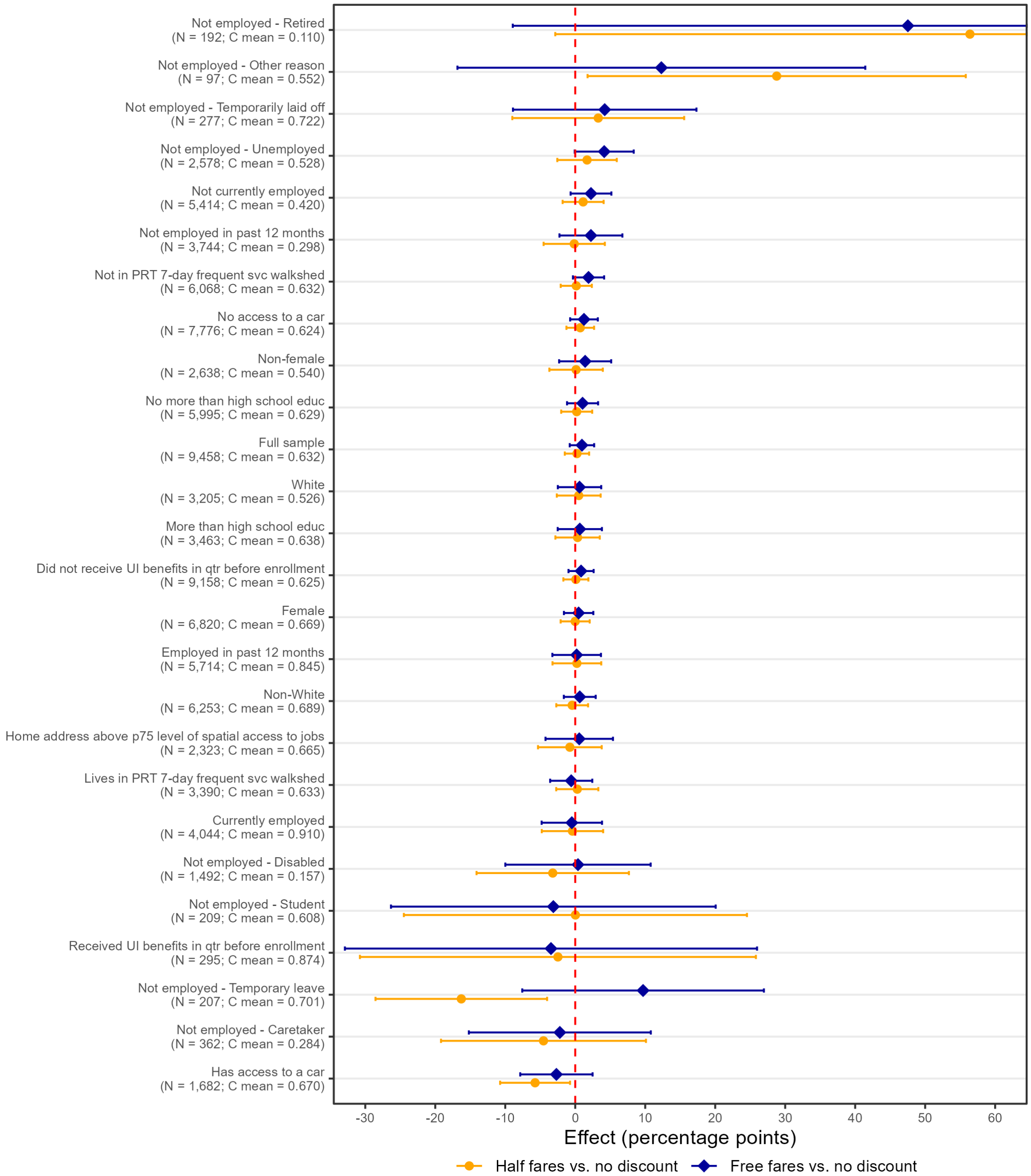
Notes: Figure shows cumulative earnings and the cumulative likelihood of having any paid employment since joining the study, among the free fares and control group members who were unemployed at baseline. The data comes from Pennsylvania unemployment insurance (UI) administrative records. The treatment effects in panel b) adjust for the following baseline covariates: Age (years), female (y/n), Black (y/n), more than high school education (y/n), currently employed (y/n), PRT trips taken last week (N), lives within the PRT 7-day frequent service walkshed (y/n), and earnings in the four quarters before enrollment. Error bars represent the 95% confidence intervals using robust standard errors.

Figure 5: Classification analysis of cumulative UI earnings comparing the control group to the free fares group



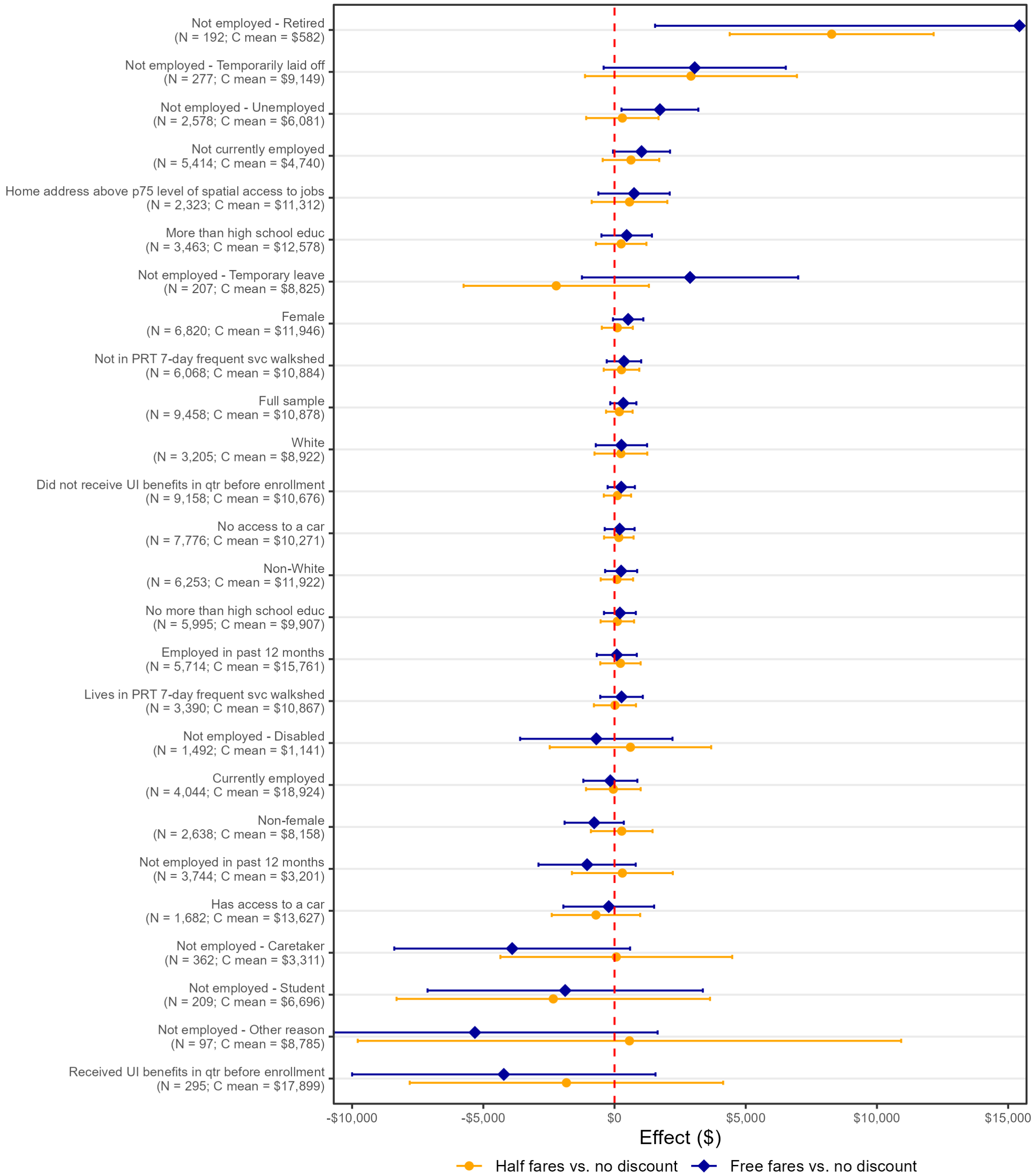
Notes: Figure displays the classification analysis (CLAN) computed using the method outlined in Chernozhukov et al., 2023. Panel a) displays the average proportion of participants who reported being unemployed in the baseline survey for each heterogeneity group. Panel b) displays the average proportion of participants who received UI benefits in the quarter before enrollment for each heterogeneity group. Group 1 has the lowest predicted effect and Group 4 has the highest. We use four different sets of covariates to train the models; 'Parsimonious' uses covariates related to employment from both the baseline survey and administrative data. 'Baseline Only' includes only information from the baseline survey, '+ UI, Medicaid, Geographic' additionally includes unemployment history, geographic features of participants' residences, and Medicaid health care utilization, '+ Other Social Services' further adds historical involvement in other social services. Missing values are imputed using the sample-wide median within experimental groups, and indicator variables are included for whether an entry has a missing value for each covariate.

Figure 6: Heterogeneous impacts on likelihood of having any formal-sector employment in Pennsylvania in Q1-Q4



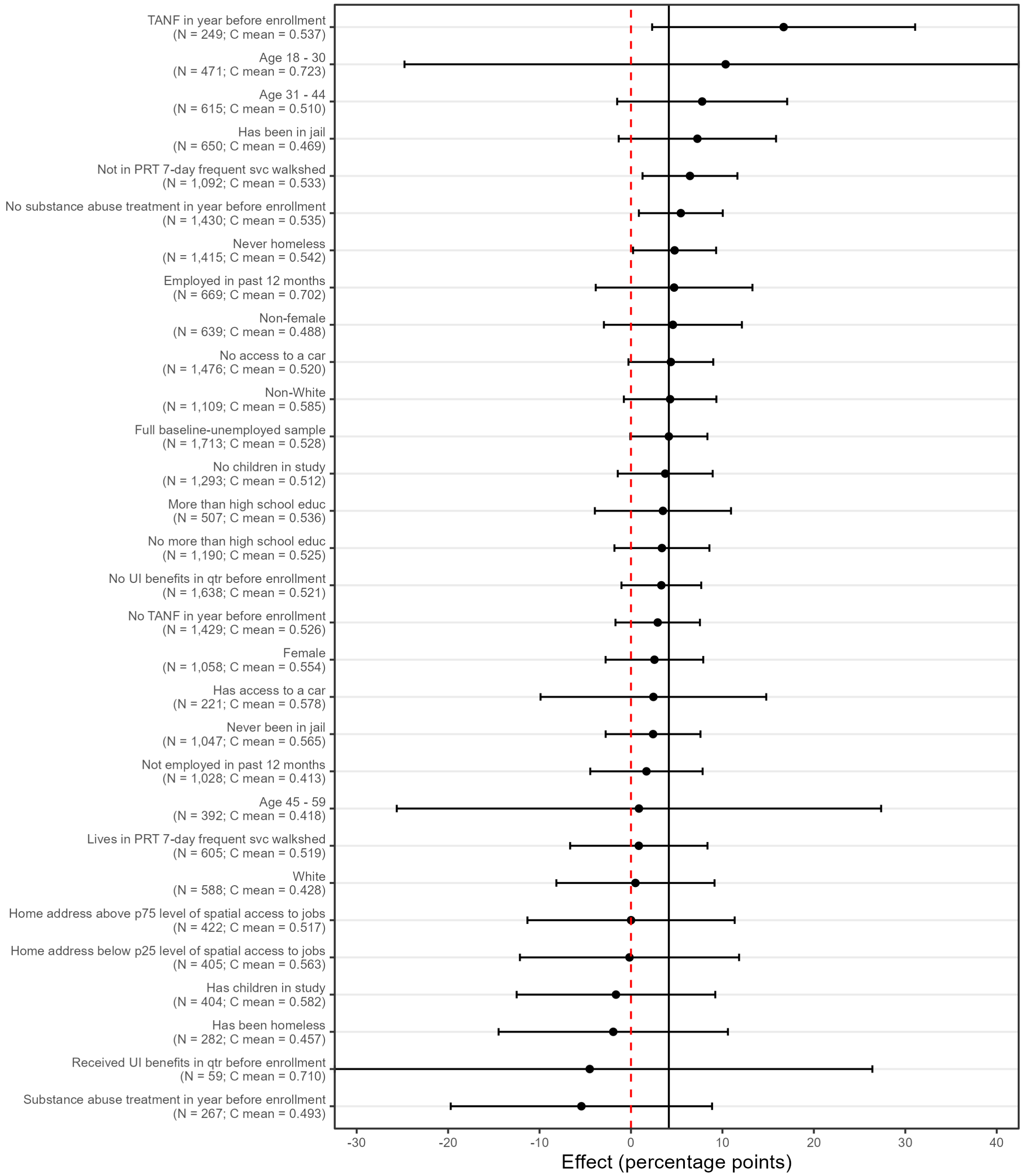
Notes: Figure presents intent-to-treat effects on the likelihood of being employed at any point the first four full calendar quarters after the quarter of study enrollment. Employment is measured from Pennsylvania unemployment insurance (UI) records. Treatment effects are disaggregated by various baseline subgroups. The effects adjust for the following baseline covariates: Age (years), female (y/n), Black (y/n), more than high school education (y/n), currently employed (y/n), PRT trips taken last week (N), lives within the PRT 7-day frequent service walkshed (y/n), and the outcome measured in the four quarters before the person enrolled in the study. N's report the number of observations in the subgroup across the three study arms. Error bars represent 95% confidence intervals using robust standard errors.

Figure 7: Heterogeneous impacts on cumulative Q1-Q4 formal-sector earnings in Pennsylvania



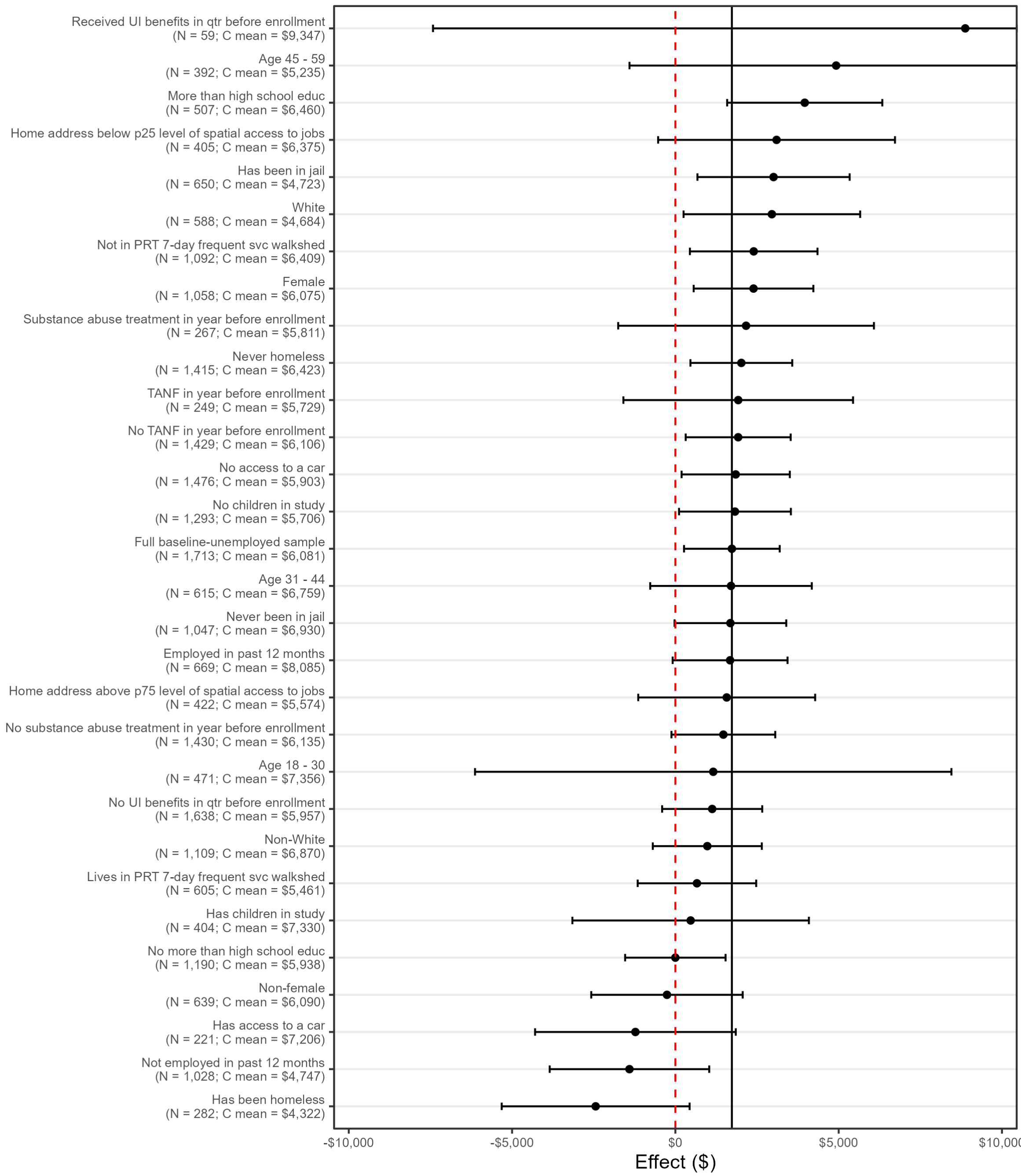
Notes: Figure presents ITT effects on cumulative earnings over the first four full calendar quarters after the quarter of study enrollment. Earnings are measured from Pennsylvania unemployment insurance (UI) records. Treatment effects are disaggregated by various baseline subgroups. The effects adjust for the following baseline covariates: Age (years), female (y/n), Black (y/n), more than high school education (y/n), currently employed (y/n), PRT trips taken last week (N), lives within the PRT 7-day frequent service walkshed (y/n), and the outcome measured in the four quarters before the person enrolled in the study. N's report the number of observations in the subgroup across the three study arms. Error bars represent 95% confidence intervals using robust standard errors.

Figure 8: Heterogeneous impacts of free fares versus no discount on likelihood of having any employment in Q1-Q4, within the baseline-unemployed subgroup



Notes: Figure presents the effect of being assigned to free fares relative to no discount on the likelihood of being employed at any point during the first four full calendar quarters after the quarter of study enrollment. Employment is measured from Pennsylvania unemployment insurance (UI) records. Treatment effects are disaggregated by various baseline subgroups among the participants who reported being unemployed in the baseline survey. The effects adjust for the following baseline covariates: Age (years), female (y/n), Black (y/n), more than high school education (y/n), currently employed (y/n), PRT trips taken last week (N), lives within the PRT 7-day frequent service walkshed (y/n), and the outcome measured in the four quarters before the person enrolled in the study. The solid black vertical line represents the treatment effect for the entire baseline-unemployed sample. Error bars represent 95% confidence intervals using robust standard errors.

Figure 9: Heterogeneous impacts of free fares versus no discount on cumulative Q1-Q4 earnings, within the baseline-unemployed subgroup



Notes: Figure presents the effect of being assigned to free fares relative to no discount on cumulative earnings over the first four full calendar quarters after the quarter of study enrollment. Earnings are measured from Pennsylvania unemployment insurance (UI) records. Treatment effects are disaggregated by various baseline subgroups among the participants who reported being unemployed in the baseline survey. The effects adjust for the following baseline covariates: Age (years), female (y/n), Black (y/n), more than high school education (y/n), currently employed (y/n), PRT trips taken last week (N), lives within the PRT 7-day frequent service walkshed (y/n), and the outcome measured in the four quarters before the person enrolled in the study. The solid black vertical line represents the treatment effect for the entire baseline-unemployed sample. Error bars represent 95% confidence intervals using robust standard errors.

Tables

Table 1: Study milestone dates

Date	Milestone
November 17, 2022	Study enrollment begins.
February 13, 2023	Study enrollment ends.
May 17, 2023	Six-month follow-up (midline) survey begins.
October 17, 2023	Eleven-month follow-up (endline) survey begins. Allegheny County DHS announces that fare discounts will be extended beyond 12 months for all 50% and 100% discount group members
February 17, 2024	Fifteen-month follow-up (post-endline) survey begins.
May 15, 2024	Control group and 50% discount group members are invited to be the first Allegheny County residents to enroll in a new, permanent half-fare discount program called "AlleghenyGo".
June 3, 2024	The new "AlleghenyGo" program becomes publicly available for all Allegheny County SNAP beneficiaries ages 6 to 64. Allegheny County DHS stops providing replacement farecards for study participants whose card is lost, stolen, or damaged.
June 30, 2024	All study-issued farecards for the 100% discount group are deactivated.

Table 2: Baseline sample characteristics

	Entire study-eligible population	No discount	Half fares	Free fares	Half fares vs. control: Diff.	Half fares vs. control: t-stat	Free fares vs. control: Diff.	Free fares vs. control: t-stat
A. Demographics								
Female	0.605	0.717	0.726	0.721	0.008	0.743	0.004	0.320
Age (years)	40.80	39.64	39.56	39.42	-0.079	-0.254	-0.214	-0.688
Black	0.438	0.588	0.591	0.588	0.003	0.274	<0.001	-0.024
Hispanic	0.012	0.032	0.033	0.035	0.001	0.284	0.003	0.621
Highest education								
Less than high school degree	0.031	0.072	0.084	0.088	0.012	1.72	0.016	2.30
High school degree	0.787	0.560	0.552	0.532	-0.008	-0.634	-0.028	-2.22
More than high school degree	0.181	0.364	0.358	0.375	-0.006	-0.474	0.011	0.917
B. Transportation								
PRT trips last week (N)	-	10.12	9.99	10.00	-0.134	-0.413	-0.118	-0.354
PRT spending last week ($)	-	30.36	30.02	29.32	-0.343	-0.425	-1.04	-1.30
Lives in PRT 7-day frequent service walkshed	0.250	0.357	0.360	0.359	0.003	0.262	0.003	0.216
Has no access to a car	-	0.819	0.829	0.818	0.010	1.02	-0.002	-0.166
C. Employment (from baseline survey)								
Currently employed	-	0.432	0.424	0.425	-0.009	-0.692	-0.007	-0.589
Employed in past 12 months	-	0.611	0.598	0.603	-0.013	-1.06	-0.008	-0.646
Status if not employed								
Unemployed	-	0.479	0.478	0.472	-0.001	-0.074	-0.006	-0.379
Temporarily laid off (you expect to get back your previous job)	-	0.055	0.052	0.046	-0.003	-0.387	-0.009	-1.16
On a temporary leave of absence	-	0.044	0.039	0.033	-0.005	-0.689	-0.011	-1.65
Student	-	0.043	0.036	0.037	-0.007	-1.03	-0.005	-0.768
Homemaker	-	0.058	0.073	0.072	0.015	1.86	0.015	1.78
Unable to work due to illness or injury	-	0.265	0.271	0.288	0.006	0.431	0.023	1.52
Retired	-	0.041	0.034	0.031	-0.007	-1.13	-0.009	-1.51
Other non-employment reason	-	0.017	0.018	0.019	<0.001	0.206	0.003	0.567
Hours worked per week at main job (N; among the employed)	-	30.41	30.91	30.96	0.501	1.19	0.556	1.31
Hourly wage at main job ($; among the employed)	-	13.59	13.39	13.46	-0.194	-1.40	-0.128	-0.912
Modes of commuting to main job last week (among the employed)								
Public transportation	-	0.866	0.888	0.886	0.022	1.77	0.020	1.60
Personal car	-	0.090	0.092	0.097	0.001	0.127	0.007	0.592
Carpool	-	0.065	0.060	0.074	-0.005	-0.534	0.009	0.943
Ridesharing app (like Uber or Lyft)	-	0.179	0.207	0.219	0.028	1.88	0.040	2.61
Walk	-	0.208	0.183	0.177	-0.025	-1.66	-0.031	-2.05
Bike	-	0.027	0.025	0.022	-0.002	-0.276	-0.006	-0.934
Hours spent searching for work last week (N)	-	8.59	8.79	8.84	0.202	0.590	0.255	0.718
D. Employment in four quarters prior to enrollment (from UI records)								
Had any paid employment	0.500	0.641	0.647	0.631	0.006	0.494	-0.011	-0.858
Number of quarters with paid employment (N)	1.52	1.98	2.02	1.99	0.043	0.974	0.010	0.222
Total earnings ($)	7,451	8,987	9,102	9,001	115.5	0.369	14.76	0.046
Received any UI benefits	0.046	0.058	0.067	0.057	0.009	1.46	<0.001	-0.151
Total UI benefits received ($)	170.4	176.9	221.1	191.6	44.18	1.60	14.66	0.542
Test for joint orthogonality								
F-stat					1.058		0.801	
p-value					0.396		0.782	
Total sample size		**3,149**	**3,241**	**3,154**				

Notes: Table presents mean baseline characteristics for the study sample. The demographics and transportation characteristics come from the baseline survey that all participants were required to complete before enrolling in the study. The employment characteristics in Panel D come from Pennsylvania unemployment insurance (UI) records. Baseline survey questions that permitted unbounded continuous-valued responses are winsorized at the 99th percentile. The joint F test is conducted using randomization inference. Robust standard errors are in parentheses. The second column shows characteristics of the entire population that was eligible to participate in the study (Allegheny County residents ages 18 to 64 who received SNAP in September 2022) ***p <0.01, **p <0.05, *p <0.1

Table 3: ITT effect of fare discounts on formal-sector employment outcomes in Pennsylvania

Outcome	Control mean	Treatment effects: Half fares	Free fares	Free vs. half fares
A. Full sample (N = 9,461)				
Pre-registered primary outcome: Earnings in Q3 ($)	2,767	55.38	177.7**	122.3
		(79.49)	(79.57)	(80.55)
Had any paid employment in Q1-Q4	0.632	0.002	0.010	0.007
		(0.009)	(0.009)	(0.009)
Number of quarters with employment in Q1-Q4 (N)	2.04	0.020	0.042	0.022
		(0.031)	(0.031)	(0.030)
Cumulative earnings in Q1-Q4 ($)	10,878	183.4	335.2	151.7
		(258.4)	(254.0)	(256.2)
B. Employed at baseline (N = 4,074)				
Pre-registered primary outcome: Earnings in Q3 ($)	4,734	-33.79	99.55	133.3
		(161.8)	(159.7)	(160.9)
Had any paid employment in Q1-Q4	0.910	-0.004	-0.005	<0.001
		(0.022)	(0.022)	(0.022)
Number of quarters with employment in Q1-Q4 (N)	3.18	0.037	0.047	0.010
		(0.079)	(0.077)	(0.079)
Cumulative earnings in Q1-Q4 ($)	18,924	-44.98	-159.8	-114.9
		(531.5)	(525.6)	(538.6)
C. Not employed at baseline (N = 5,470)				
Pre-registered primary outcome: Earnings in Q3 ($)	1,267	159.9	321.5*	161.5
		(166.4)	(179.8)	(172.6)
Had any paid employment in Q1-Q4	0.420	0.011	0.023	0.011
		(0.015)	(0.015)	(0.014)
Number of quarters with employment in Q1-Q4 (N)	1.17	0.017	0.085	0.068
		(0.055)	(0.054)	(0.053)
Cumulative earnings in Q1-Q4 ($)	4,740	626.5	1,030*	403.3
		(550.0)	(554.1)	(515.4)

Notes: Table presents estimates of the effect of being assigned to each treatment status (half fares or free fares) on formal-sector employment outcomes. The data comes from Pennsylvania unemployment insurance (UI) administrative records. Quarters are measured relative to the calendar quarter when the person enrolled in the study; Q1 is the first complete quarter after the quarter of enrollment. Estimates are from a regression of the outcome on indicators for each treatment status, adjusting for the following baseline covariates: Age (years), female (y/n), Black (y/n), more than high school education (y/n), currently employed (y/n), PRT trips taken last week (N), lives within the PRT 7-day frequent service walkshed (y/n), and the outcome measured in the four complete quarters prior to study enrollment. Robust standard errors are in parentheses. ***p <0.01, **p <0.05, *p <0.1; † refers to comparable thresholds for sharpened FDR q-values

Table 4: ITT effect of fare discounts on formal-sector employment outcomes in Pennsylvania, among those non-employed at baseline

		Treatment effects		
Outcome	Control mean	Half fares	Free fares	Free vs. half fares
A. Unemployed (N = 2,605)				
Pre-registered primary outcome: Earnings in Q3 ($)	1,638	61.14 (211.4)	696.5*** (244.4)	635.3*** (240.2)
Had any paid employment in Q1-Q4	0.528	0.017 (0.022)	0.041* (0.022)	0.025 (0.021)
Number of quarters with employment in Q1-Q4 (N)	1.50	0.013 (0.077)	0.134* (0.077)	0.121 (0.075)
Cumulative earnings in Q1-Q4 ($)	6,081	298.2 (703.6)	1,730** (747.3)	1,431** (710.7)
B. On a temporary leave or temporary layoff (N = 490)				
Pre-registered primary outcome: Earnings in Q3 ($)	2,271	560.5 (407.1)	849.5** (401.1)	289.0 (454.8)
Had any paid employment in Q1-Q4	0.713	-0.033 (0.046)	0.059 (0.048)	0.092* (0.049)
Number of quarters with employment in Q1-Q4 (N)	2.03	0.014 (0.157)	0.419** (0.165)	0.405** (0.175)
Cumulative earnings in Q1-Q4 ($)	9,005	615.3 (1,295)	2,842** (1,335)	2,227 (1,466)
C. Unable to work for health reasons (N = 1,503)				
Pre-registered primary outcome: Earnings in Q3 ($)	286.8	-43.67 (443.5)	-581.7 (446.4)	-538.0* (282.2)
Had any paid employment in Q1-Q4	0.157	-0.032 (0.056)	0.004 (0.053)	0.036 (0.048)
Number of quarters with employment in Q1-Q4 (N)	0.357	-0.046 (0.184)	0.141 (0.178)	0.187 (0.166)
Cumulative earnings in Q1-Q4 ($)	1,141	606.8 (1,570)	-694.4 (1,482)	-1,301 (882.4)
D. Student, homemaker, retired, or other non-employment reason (N = 872)				
Pre-registered primary outcome: Earnings in Q3 ($)	1,165	-378.6 (413.6)	-1,139*** (392.6)	-760.1* (404.0)
Had any paid employment in Q1-Q4	0.353	0.049 (0.041)	0.034 (0.041)	-0.015 (0.034)
Number of quarters with employment in Q1-Q4 (N)	0.993	0.044 (0.163)	-0.035 (0.161)	-0.079 (0.141)
Cumulative earnings in Q1-Q4 ($)	4,067	219.6 (1,488)	-2,896** (1,346)	-3,115** (1,347)

Notes: Table presents estimates of the effect of being assigned to each treatment status (half fares or free fares) on formal-sector employment outcomes for subgroups of participants who reported being non-employed at baseline. The subgroups are mutually exclusive and jointly cover all reasons for non-employment listed in the baseline survey. The data comes from Pennsylvania unemployment insurance (UI) administrative records. Quarters are measured relative to the calendar quarter when the person enrolled in the study; Q1 is the first complete quarter after the quarter of enrollment. Estimates are from a regression of the outcome on indicators for each treatment status, adjusting for the following baseline covariates: Age (years), female (y/n), Black (y/n), more than high school education (y/n), currently employed (y/n), PRT trips taken last week (N), lives within the PRT 7-day frequent service walkshed (y/n), and the outcome measured in the four complete quarters prior to study enrollment. Robust standard errors are in parentheses. ***p <0.01, **p <0.05, *p <0.1; † refers to comparable thresholds for sharpened FDR q-values

Table 5: Group Average Treatment Effects of UI earnings in first four quarters after enrollment, comparing the control group to the free fares group

	25% Most (Group 4)	25% Least (Group 1)	Difference
Parsimonious	2,836.79	-3,441.23	6,288.03
	(2,221.22; 3,451.85)	(-4,065.92; -2,821.22)	(5,385.02; 7,167.17)
	[0.00]	[0.00]	[0.00]
Baseline Only	2,181.91	-1,927.02	4,079.32
	(1,642.18; 2,727.64)	(-2,469.81; -1,388.03)	(3,303.73; 4,868.53)
	[0.00]	[0.00]	[0.00]
+ UI, Medicaid, Geography	3,329.68	-4,136.8	7,475.33
	(2,548.89; 4,107.64)	(-4,910.65; -3,356.03)	(6,355.66; 8,598.48)
	[0.00]	[0.00]	[0.00]
+ Other Social Services	3,543.45	-4,455.7	7,984.74
	(2,708.39; 4,386.98)	(-5,286.88; -3,612.5)	(6,762.17; 9,202.02)
	[0.00]	[0.00]	[0.00]

Notes: Table presents Group Average Treatment Effects (GATES) of cumulative earnings, comparing the control group to the free fares group, estimated using the method outlined in Chernozhukov et al. (2023). Median confidence intervals are in parenthesis. P-values are in brackets. We use four different covariate sets for the models; 'Parsimonious' includes the set of variables that are only related to employment outcomes from both administrative data and the baseline survey. 'Baseline Only' includes only information from the baseline survey, '+UI, Medicaid, Geographic' additionally includes unemployment history, geographic features of participants' residences, and Medicaid health care utilization, '+Other Social Services' further adds historical involvement in other social services. Missing values are imputed using the sample-wide median within experimental groups, and indicator variables are included for whether an entry has a missing value for each covariate..

Table 6: Effect of free fares on mobility outcomes by baseline employment status

Outcome	Employed				Not employed				Not employed - Unemployed		
	N	Control mean	Effect		N	Control mean	Effect		N	Control mean	Effect
A. From smartphone GPS data											
Number of trips per week (N)											
Car trips	128	2.12	-1.99		185	1.76	-1.54		90	1.98	2.90
			(1.77)	[0.292]			(2.33)	[0.115]			(3.45)
Public transportation trips	128	0.558	0.139		185	0.450	2.40***		90	0.445	3.49***
			(1.16)	[0.750]			(0.802)	[0.237]			(1.20)
Walk or bike trips	128	0.764	-0.106		185	0.664	0.433		90	0.857	-0.319
			(0.961)	[0.351]			(0.657)	[0.897]			(1.17)
Total trips	128	3.45	-2.62		185	2.88	0.307		90	3.29	4.79*
			(2.66)	[0.293]			(2.16)	[0.036]			(2.78)
Unique POI's visited per day (N)	128	1.68	-0.204		185	1.35	0.037		90	1.57	0.326*
			(0.201)	[0.588]			(0.162)	[0.098]			(0.176)
Time spent traveling per day (hours)	128	1.34	-0.152		185	1.28	-0.278*		90	1.43	0.014
			(0.143)	[0.007]			(0.159)	[0.007]			(0.249)
Total distance traveled per day (miles)	128	13.99	-1.09		185	10.64	0.643		90	12.87	6.38**
			(1.60)	[0.259]			(2.14)	[0.171]			(2.65)
B. From travel diaries											
Number of places visited yesterday (N)	2,059	3.43	-0.550***		2,538	3.90	-0.723**		1,187	4.65	-1.17**
			(0.169)	[0.219]			(0.304)	[0.039]			(0.503)
Likelihood of taking at least one trip yesterday											
Car trip	2,076	0.365	0.006		2,566	0.330	-0.009		1,201	0.319	0.002
			(0.016)	[0.642]			(0.013)	[0.997]			(0.019)
Public transportation trip	2,073	0.623	0.008		2,562	0.537	0.009		1,198	0.572	0.015
			(0.016)	[0.733]			(0.015)	[0.597]			(0.022)
Walk or bike trip	2,073	0.477	-0.068***		2,558	0.463	-0.052***		1,196	0.480	-0.024
			(0.017)	[0.776]			(0.014)	[0.080]			(0.021)
Left the house for work yesterday	2,067	0.601	-0.025		2,548	0.244	-0.012		1,190	0.294	0.013
			(0.016)	[0.840]			(0.013)	[0.148]			(0.019)
Did not leave the house yesterday	2,067	0.090	0.029***		2,548	0.170	0.018*		1,190	0.156	0.003
			(0.009)	[0.940]			(0.010)	[0.181]			(0.014)

Notes: This table reports heterogeneity in the effect of free fares versus no discount on mobility outcomes by the person's baseline employment status. All regressions adjust for the following baseline covariates: Age (years), female (y/n), Black (y/n), more than high school education (y/n), currently employed (y/n), PRT trips taken last week (N), and lives within the PRT 7-day frequent service walkshed (y/n). The regressions in Panel B also adjust for the outcome measured in the year prior to enrollment. The numbers in brackets are p-values of the difference in treatment effects between the two baseline sub-groups that are on either side of the bracketed number. Robust standard errors are in parentheses. ***p <0.01, **p <0.05, *p <0.1

Table 7: Marginal value of public funds (MVPF) of 18-month free public transportation pass for an unemployed SNAP recipient

	Measuring WTP by revealed preference	Measuring WTP by ex post benefits
Willingness to pay		
Value of free fares	\$569.34 [\$303.48, \$835.20]	-
Increased labor earnings	-	\$2,101.46 [\$215.30, \$3,987.62]
Change in UI benefit income	-	\$49.79 [\$-197.69, \$293.67]
Change in public assistance income	-	\$262.76 [\$-1,461.71, \$1,987.22]
Net cost		
Direct cost of fare subsidies	\$429.82	\$429.82
Increased income tax revenue	-\$782.61 [-\$1,496.34, -\$68.88]	-\$782.61 [-\$1,496.34, -\$68.88]
Change in UI benefit spending	\$49.79 [\$-197.69, \$293.67]	\$49.79 [\$-197.69, \$293.67]
Change in public assistance spending	\$269.10 [\$-1,682.87, \$2,221.07]	\$269.10 [\$-1,682.87, \$2,221.07]
MVPF	∞ **[0.11, ∞]**	∞ **[-0.50, ∞]**

Note: All values are per person. The subsidy lasts for 18 months and the marginal costs and benefits are measured over the first two years from the start of the subsidy. An MVPF of infinity means that the denominator is negative, i.e., the fiscal externalities exceed the cost of the subsidy. The 95% confidence intervals in brackets are based on the intervals of the underlying treatment effect estimates, using whichever interval bounds make the overall MVPF the smallest (for the 95% lower bound) or largest (for the 95% upper bound).

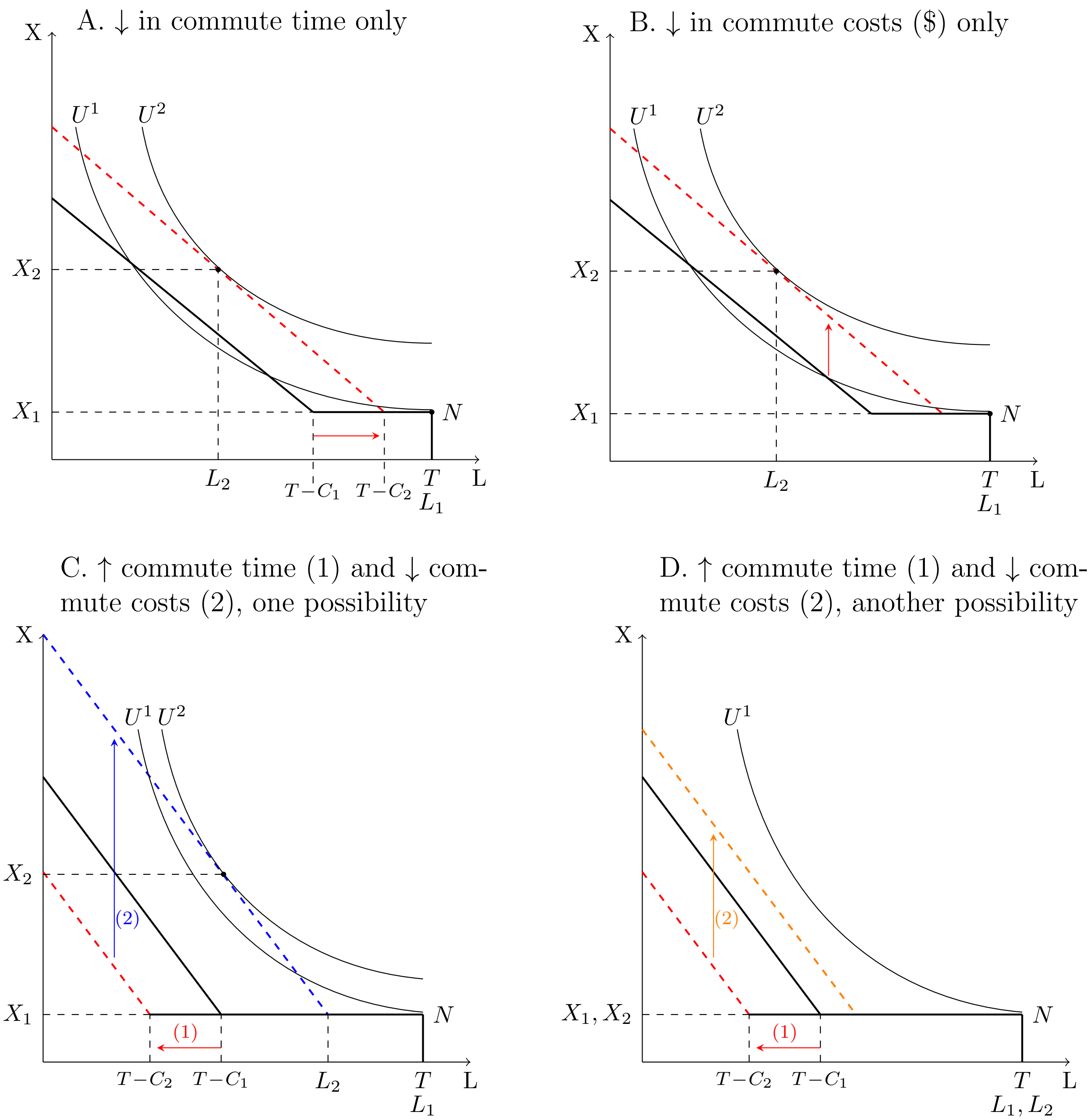
Faring Well in the Labor Market: The Employment Effects of Public Transportation Fare Subsidies

Online Appendix

Seth Chizeck and Oluchi Mbonu

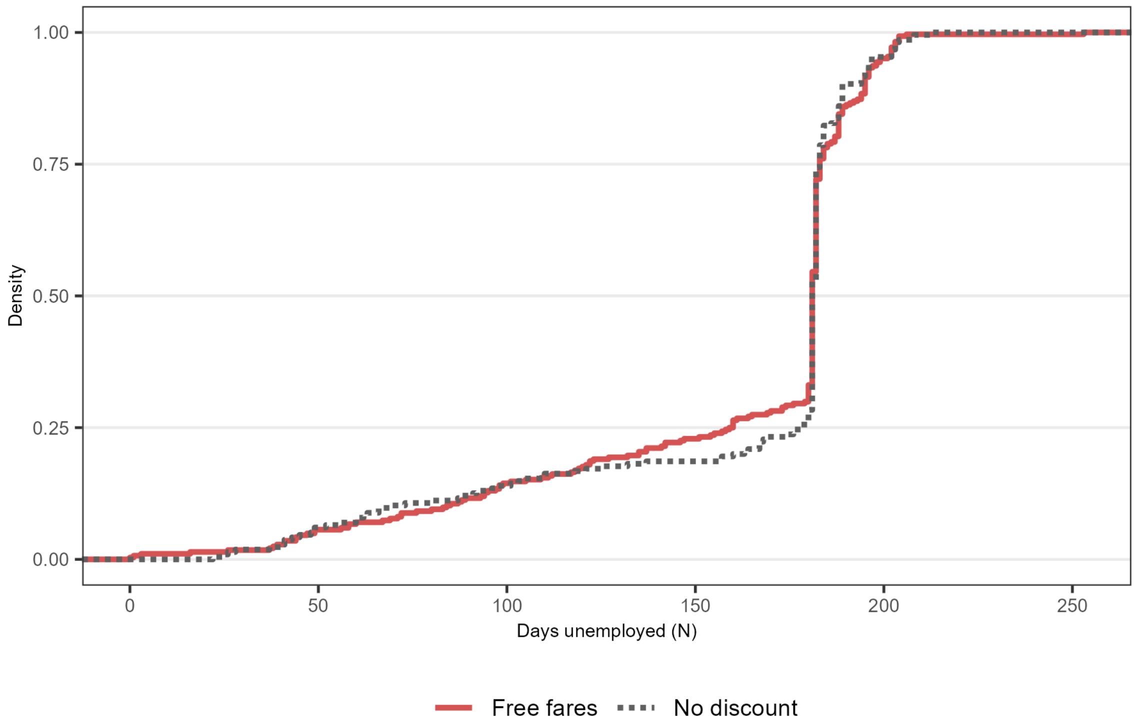
A Additional figures and tables

Figure A1: Theoretical effect of changes in commute time and commute costs on labor force participation



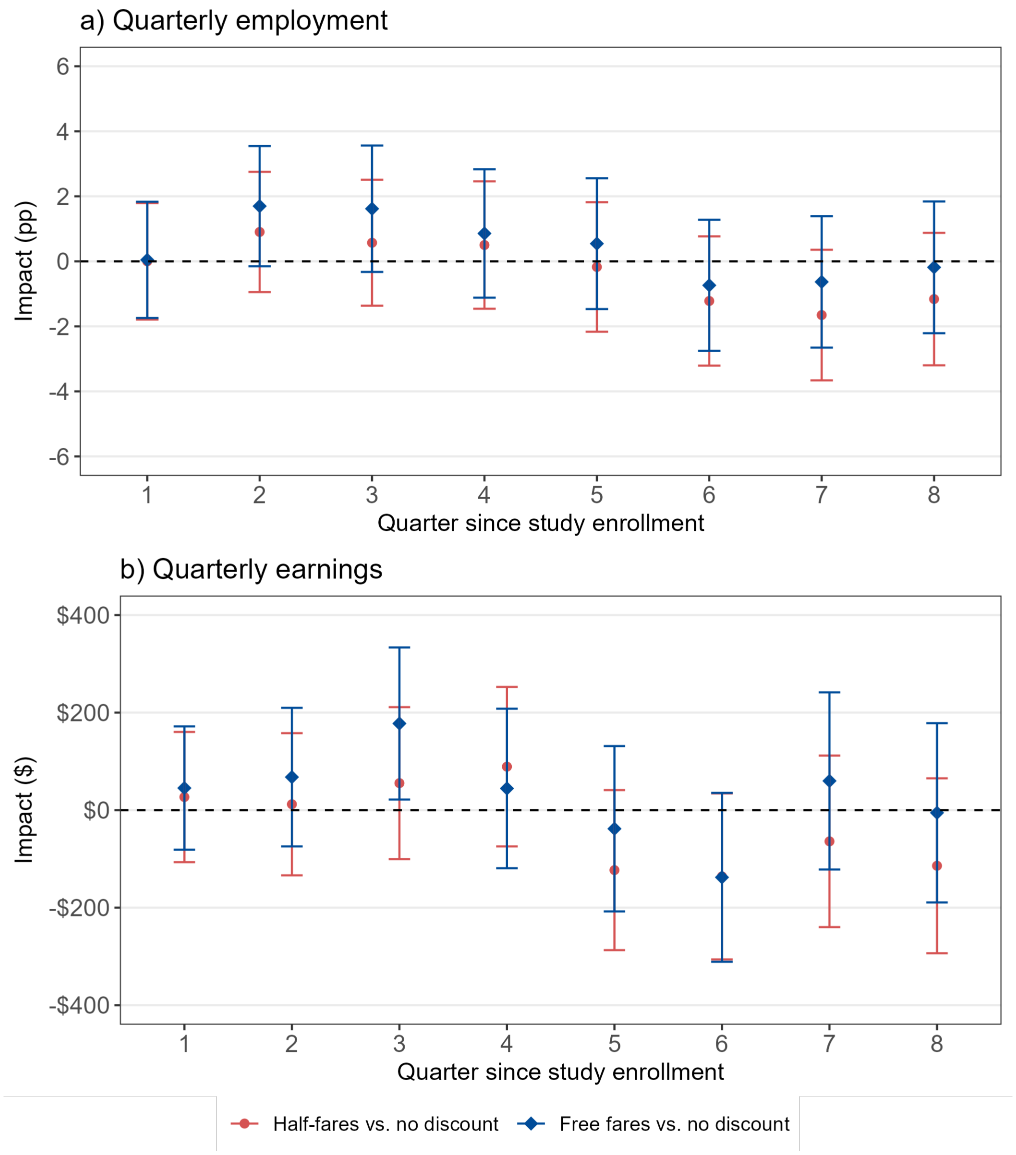
Notes: This figure depicts four scenarios for the effect of free fares on the labor force participation of an unemployed worker. The worker is endowed with non-labor income N and has T total hours in the day to devote to work (measured in terms of consumption good X) and leisure time L. The person faces commute time C if she chooses to work and faces commute costs net of her daily wage. In panel A, the treatment reduces commute time from C_1 to C_2 and moves the worker to an interior solution. In panel B, the treatment reduces commute costs and again moves her to an interior solution. In panels C and D, the treatment *increases* commute time (arrow 1) and *decreases* commute costs (arrow 2). The net effect on the worker's labor force participation decision is ambiguous. In panel C, the reduction in monetary commute costs dominates the increase in time costs, so the worker moves into employment. In panel D, the increase in time costs dominates, so she remains unemployed.

Figure A2: Cumulative distribution of number of days unemployed, among those who were unemployed at baseline



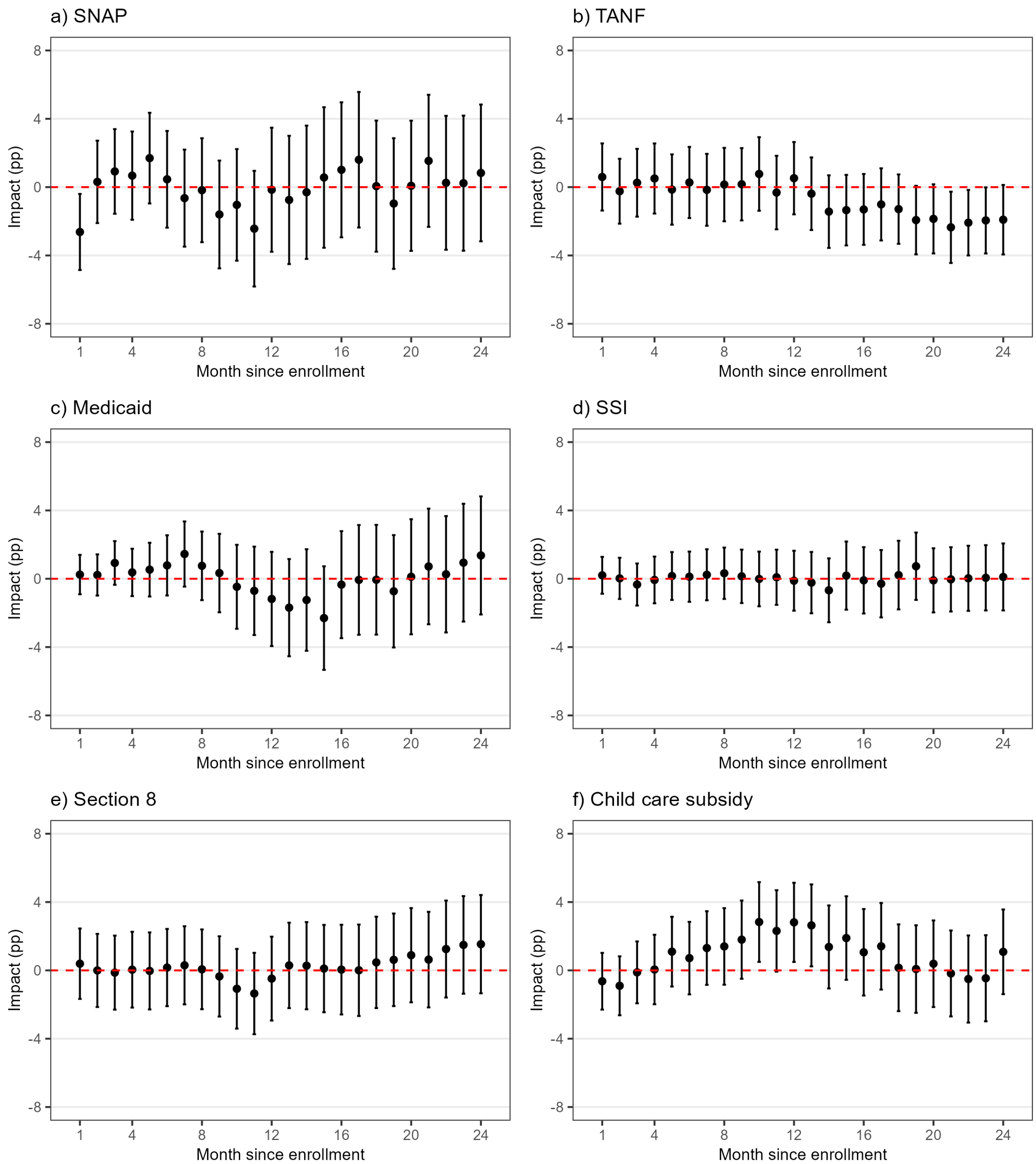
Notes: Figure presents the cumulative distribution of the number of days that the baseline-unemployed participants were unemployed between study enrollment and the midline survey. This survey took place six months after the person joined the study.

Figure A3: ITT effects on quarterly formal-sector employment and earnings in Pennsylvania, for the full sample



Notes: Figure shows estimates of the effect of being assigned to each fare discount, relative to no discount, on quarterly employment and earnings. The data comes from Pennsylvania unemployment insurance (UI) administrative records. The treatment effects adjust for the following baseline covariates: Age (years), female (y/n), Black (y/n), more than high school education (y/n), currently employed (y/n), PRT trips taken last week (N), lives within the PRT 7-day frequent service walkshed (y/n), and the outcome in the four quarters before enrollment. Error bars represent 95% confidence intervals using robust standard errors.

Figure A4: ITT effect on monthly likelihood of receiving public benefits over time, among those who were unemployed at baseline



Notes: Figure presents estimates of the effect of being assigned to free fares relative to no discount on the monthly likelihood of receiving various public benefits over time. The analysis is limited to the participants who were unemployed at baseline. Data comes from Allegheny County Department of Human Services (ACDHS) and Pennsylvania Department of Human Services (PADHS) administrative records. Estimates are from monthly cross-sectional regressions of the outcome in the given month (i.e. received the benefit or not) on indicators for each treatment status, adjusting for the following baseline covariates: Age (years), female (y/n), Black (y/n), more than high school education (y/n), currently employed (y/n), PRT trips taken last week (N), lives within the PRT 7-day frequent service walkshed (y/n), and the outcome measured in the 12 months before the person enrolled in the study. Error bars represent 95% confidence intervals using robust standard errors.

Table A1: Robustness of ITT effect of free fares on formal-sector employment outcomes in Pennsylvania in first four quarters after enrollment

Outcome	N	Control mean	(1)	(2)	(3)	(4)	(5)	(6)
A. Full sample								
Primary outcome: Earnings in Q3 ($)	6,244	2,767	163.1 (104.8)	167.7* (93.94)	177.7** (79.57)	201.1** (78.30)	199.4*** (80.67)	145.7* (75.86)
Had any paid employment in Q1-Q4	6,241	0.632	0.013 (0.012)	0.013 (0.010)	0.010 (0.009)	0.016* (0.008)	0.017 (0.009)	-
Cumulative earnings in Q1-Q4 ($)	6,241	10,878	296.6 (373.0)	322.1 (323.4)	335.2 (254.0)	412.5* (250.3)	437.3*** (261.2)	245.5 (245.2)
Received any UI benefits in Q1-Q4	6,241	0.068	<0.001 (0.006)	<0.001 (0.006)	-0.001 (0.006)	-0.002 (0.006)	<0.001 (0.006)	-
Cumulative UI benefits in Q1-Q4 ($)	6,241	243.5	-10.83 (29.72)	-9.82 (29.45)	-16.81 (29.13)	-15.41 (28.34)	-10.76** (28.35)	-20.25 (24.94)
B. Employed at baseline								
Had any paid employment in Q1-Q4	2,701	0.910	0.006 (0.011)	<0.001 (0.013)	-0.005 (0.022)	0.008 (0.009)	0.008 (0.009)	-
Cumulative earnings in Q1-Q4 ($)	2,701	18,924	236.2 (612.1)	304.3 (628.8)	-159.8 (525.6)	498.0 (450.5)	426.6*** (477.6)	-69.55 (504.3)
Received any UI benefits in Q1-Q4	2,701	0.108	0.006 (0.012)	0.003 (0.013)	<0.001 (0.012)	0.003 (0.011)	0.004 (0.012)	-
Cumulative UI benefits in Q1-Q4 ($)	2,701	380.9	3.12 (55.53)	-6.65 (59.59)	-33.26 (56.48)	-4.08 (52.72)	-3.18 (53.65)	-34.10 (50.75)
C. Not employed at baseline								
Had any paid employment in Q1-Q4	3,602	0.420	0.024 (0.017)	0.019 (0.016)	0.023 (0.015)	0.018 (0.013)	0.024 (0.013)	-
Cumulative earnings in Q1-Q4 ($)	3,602	4,740	511.0 (346.6)	501.0 (367.7)	1,030* (554.1)	353.1 (271.2)	471.9*** (286.1)	297.2 (524.9)
Received any UI benefits in Q1-Q4	3,602	0.037	-0.004 (0.006)	-0.008 (0.007)	-0.007 (0.007)	-0.006 (0.006)	-0.005 (0.006)	-
Cumulative UI benefits in Q1-Q4 ($)	3,602	138.6	-18.28 (30.63)	-32.15 (30.95)	-21.65 (32.31)	-20.84 (30.21)	-18.02*** (29.46)	-28.27 (25.60)
D. Not employed at baseline - Unemployed								
Had any paid employment in Q1-Q4	1,713	0.528	0.042* (0.024)	0.046* (0.024)	0.041* (0.022)	0.026 (0.020)	0.036 (0.021)	-
Cumulative earnings in Q1-Q4 ($)	1,713	6,081	925.5 (562.5)	1,338** (591.7)	1,730** (747.3)	735.1 (468.0)	851.1*** (494.0)	1,011 (683.4)
Received any UI benefits in Q1-Q4	1,713	0.050	<0.001 (0.011)	-0.005 (0.012)	-0.004 (0.010)	<0.001 (0.010)	<0.001 (0.010)	-
Cumulative UI benefits in Q1-Q4 ($)	1,713	172.5	-0.973 (51.84)	-13.12 (58.71)	-31.07 (50.03)	-7.36 (52.09)	-2.41 (50.00)	-35.68 (40.81)
E. Not employed at baseline - On temporary leave or temporary layoff								
Had any paid employment in Q1-Q4	320	0.713	0.044 (0.050)	0.051 (0.052)	0.059 (0.048)	0.013 (0.045)	0.051 (0.045)	-
Cumulative earnings in Q1-Q4 ($)	320	9,005	2,925* (1,586)	4,041** (1,750)	2,842** (1,335)	2,124* (1,238)	3,082*** (1,396)	2,258* (1,275)
Received any UI benefits in Q1-Q4	320	0.109	-0.023 (0.034)	-0.025 (0.034)	-0.015 (0.032)	-0.038 (0.036)	-0.023 (0.033)	-
Cumulative UI benefits in Q1-Q4 ($)	320	442.2	-123.3 (163.8)	-126.2 (186.6)	-46.30 (194.3)	-172.8 (175.0)	-126.2*** (163.6)	-36.12 (151.2)
F. Not employed at baseline - Disabled								
Had any paid employment in Q1-Q4	996	0.157	0.028 (0.024)	0.032 (0.037)	0.004 (0.053)	0.009 (0.021)	0.022 (0.021)	-
Cumulative earnings in Q1-Q4 ($)	996	1,141	368.9 (348.0)	948.5* (525.1)	-694.4 (1,482)	218.9 (246.4)	300.4*** (313.3)	-2,392 (1,526)
Received any UI benefits in Q1-Q4	996	0.006	-0.003 (0.005)	-0.001 (0.004)	<0.001 (0.004)	-0.002 (0.004)	-0.003 (0.005)	-
Cumulative UI benefits in Q1-Q4 ($)	996	40.70	-19.23 (29.80)	-10.85 (27.22)	-1.38 (24.69)	-13.78 (27.53)	-20.11*** (29.58)	0.700 (16.48)
No covariates			X					
Includes benchmark covariates				X	X			X
Includes 4 qtr lagged outcome					X			
Post-double LASSO covariate selection						X		
Causal forest							X	
Continuous outcomes winsorized at p99								X

Table A1: Robustness of ITT effect of free fares on formal-sector employment outcomes in Pennsylvania in first four quarters after enrollment (cont'd)

	N	Control mean	(1)	(2)	(3)	(4)	(5)	(6)
G. Not employed at baseline - Student, homemaker, retired, or other reason								
Had any paid employment in Q1-Q4	573	0.353	0.035 (0.041)	0.019 (0.041)	0.034 (0.041)	0.010 (0.034)	0.016 (0.034)	-
Cumulative earnings in Q1-Q4 ($)	573	4,067	-517.3 (701.4)	-660.5 (756.4)	-2,896** (1,346)	-982.9 (613.3)	-808.9*** (600.8)	-2,779** (1,303)
Received any UI benefits in Q1-Q4	573	0.007	0.003 (0.008)	<0.001 (0.009)	0.012 (0.010)	0.004 (0.008)	0.003 (0.008)	-
Cumulative UI benefits in Q1-Q4 ($)	573	10.85	39.29 (36.80)	28.65 (30.97)	38.43 (35.63)	40.99 (38.43)	37.38*** (36.76)	22.99 (26.05)
No covariates			X					
Includes benchmark covariates				X	X			X
Includes 4 qtr lagged outcome					X			
Post-double LASSO covariate selection						X		
Causal forest							X	
Continuous outcomes winsorized at p99								X

Notes: Table presents the robustness of the effect of being assigned to free fares relative to no discount on employment outcomes. The data comes from Pennsylvania unemployment insurance (UI) administrative records. Quarters are measured relative to the calendar quarter when the person enrolled in the study; Q1 is the first complete quarter after the quarter of enrollment. The benchmark covariates include: Age (years), female (y/n), Black (y/n), more than high school education (y/n), currently employed (y/n), PRT trips taken last week (N), lives within the PRT 7-day frequent service walkshed (y/n), and the outcome measured in the four complete quarters prior to study enrollment. Robust standard errors are in parentheses. ***p <0.01, **p <0.05, *p <0.1

Table A2: Robustness of ITT effect of free fares on self-reported employment outcomes from post-endline (15-month) survey

Outcome	N	Control mean	(1)	(2)	(3)	(4)	(5)
A. Full sample							
Currently employed	2,579	0.523	-0.023 (0.020)	-0.020 (0.018)	-0.012 (0.016)	-0.015 (0.016)	-0.003 (0.025)
Hours worked per week (N)	2,455	17.86	-1.72** (0.862)	-1.66** (0.808)	-1.41* (0.732)	-1.49** (0.745)	-2.42** (1.19)
Hourly wage at main job ($; among the employed)	1,199	14.29	-0.437 (0.270)	-0.266 (0.334)	-0.503* (0.262)	-0.416 (0.263)	-0.043 (0.485)
Total pretax monthly earnings ($)	2,360	655.0	-86.87* (44.56)	-74.13* (40.63)	-58.57 (39.31)	-75.94*** (40.31)	-85.72 (78.33)
B. Employed at baseline							
Currently employed	1,147	0.795	-0.039 (0.025)	-0.023 (0.028)	-0.035 (0.024)	-0.037 (0.024)	-0.019 (0.041)
Hours worked per week (N)	1,071	28.07	-2.58** (1.28)	-1.97 (1.37)	-2.28** (1.09)	-2.43** (1.10)	-5.58** (2.16)
Hourly wage at main job ($; among the employed)	812	14.64	-0.719** (0.317)	-0.871** (0.357)	-0.556* (0.306)	-0.669 (0.308)	-0.448 (0.440)
Total pretax monthly earnings ($)	1,011	1,045	-92.52 (72.53)	-99.38 (77.77)	-80.52 (92.88)	-82.66*** (93.27)	-74.29 (137.8)
C. Not employed at baseline							
Currently employed	1,432	0.301	-0.002 (0.025)	0.004 (0.025)	0.005 (0.023)	<0.001 (0.022)	0.004 (0.037)
Hours worked per week (N)	1,384	9.88	-0.939 (0.978)	-0.606 (1.04)	-0.301 (0.839)	-0.581 (0.838)	0.602 (1.45)
Hourly wage at main job ($; among the employed)	387	13.55	0.156 (0.503)	0.439 (0.536)	-0.016 (0.510)	0.211 (0.507)	-0.309 (0.753)
Total pretax monthly earnings ($)	1,349	360.2	-78.74 (50.27)	-55.71 (50.23)	-73.38 (61.65)	-107.5*** (61.53)	-37.51 (90.74)
D. Not employed at baseline - Unemployed							
Currently employed	647	0.404	0.024 (0.039)	0.035 (0.039)	0.034 (0.038)	0.022 (0.038)	-0.015 (0.053)
Hours worked per week (N)	617	13.40	0.313 (1.70)	0.647 (1.70)	0.724 (1.50)	0.680 (1.47)	2.12 (1.92)
Hourly wage at main job ($; among the employed)	237	13.81	-0.026 (0.603)	0.101 (0.656)	-0.072 (0.633)	-0.003 (0.601)	-0.826 (0.977)
Total pretax monthly earnings ($)	595	480.2	-59.57 (88.12)	-56.11 (84.66)	-65.75 (130.4)	-121.3*** (127.4)	-144.1 (239.8)
E. Not employed at baseline - On temporary leave or temporary layoff							
Currently employed	110	0.510	-0.069 (0.096)	-0.037 (0.109)	-0.005 (0.100)	-0.081 (0.096)	-0.037 (0.102)
Hours worked per week (N)	102	15.08	-1.71 (3.59)	-0.939 (3.99)	-1.29 (3.85)	-2.23 (3.55)	-0.939 (3.71)
Hourly wage at main job ($; among the employed)	52	14.35	-2.02 (1.50)	-1.97 (1.69)	-2.95 (1.86)	-2.13** (1.56)	-1.97 (1.45)
Total pretax monthly earnings ($)	101	472.0	22.84 (187.4)	186.1 (199.4)	51.04 (250.7)	64.69*** (232.7)	126.2 (150.3)
F. Not employed at baseline - Disabled							
Currently employed	419	0.090	<0.001 (0.029)	0.025 (0.043)	-0.006 (0.030)	0.002 (0.028)	-0.053 (0.083)
Hours worked per week (N)	415	2.87	-0.254 (0.958)	0.991 (1.25)	-0.031 (0.938)	-0.225 (0.951)	-1.21 (2.04)
Hourly wage at main job ($; among the employed)	37	12.03	3.48* (1.76)	0.170 (3.00)	1.94 (2.21)	4.93*** (2.24)	-11.52 (16.89)
Total pretax monthly earnings ($)	412	113.0	-22.00 (45.43)	1.12 (54.66)	-37.76 (45.78)	-20.37*** (45.49)	-23.09 (46.50)
No covariates			X				
Includes benchmark covariates				X			X
Post-double LASSO covariate selection					X		
Causal forest						X	
Nonresponse weights							X

Table A2: Robustness of ITT effect of free fares on self-reported employment outcomes from post-endline (15-month) survey (cont'd)

	N	Control mean	(1)	(2)	(3)	(4)	(5)
G. Not employed at baseline - Student, homemaker, retired, or other reason							
Currently employed	256	0.264	0.009	0.023	0.016	0.009	0.041
			(0.056)	(0.064)	(0.051)	(0.052)	(0.059)
Hours worked per week (N)	250	9.49	-2.79	-0.760	-1.37	-2.50**	-0.137
			(2.19)	(2.34)	(2.02)	(1.98)	(2.09)
Hourly wage at main job ($; among the employed)	61	12.87	0.679	0.565	1.50	0.800	-5.30
			(1.44)	(3.09)	(1.58)	(1.49)	(3.60)
Total pretax monthly earnings ($)	241	402.7	-204.2	-132.4	-328.3*	-397.9***	-276.0*
			(128.6)	(118.4)	(198.3)	(225.0)	(166.7)
No covariates			X				
Includes benchmark covariates				X			X
Post-double LASSO covariate selection					X		
Causal forest						X	
Nonresponse weights							X

Notes: Table presents the robustness of the effect of being assigned to free fares relative to no discount on self-reported employment outcomes from the post-endline survey. The survey took place 15 months after the person joined the study. Continuous-valued outcomes that allowed unbounded response values are winsorized at the 99th percentile. Sample sizes vary across outcomes due to differing survey item response rates (most questions did not force a response). The benchmark covariates include: Age (years), female (y/n), Black (y/n), more than high school education (y/n), currently employed (y/n), PRT trips taken last week (N), and lives within the PRT 7-day frequent service walkshed (y/n). Robust standard errors are in parentheses. ***p <0.01, **p <0.05, *p <0.1

Table A3: Effect of free fares on one-way travel time from home address to employer address, by baseline employment status

Outcome	N	Control mean	(1)	(2)	(3)	(4)
A. Employed at baseline						
One-way commute time by car (mins)	1,303	26.74	0.811	1.05	0.456	0.416
			(2.11)	(2.26)	(2.44)	(2.39)
One-way commute time by public transit (mins)	1,303	66.13	2.79	3.10	1.23	0.686
			(4.40)	(4.79)	(5.14)	(4.93)
B. Not employed at baseline						
One-way commute time by car (mins)	851	28.63	5.07	3.79	3.94	3.97
			(3.14)	(3.62)	(3.73)	(3.68)
One-way commute time by public transit (mins)	851	74.92	9.24	6.25	5.94	7.45
			(6.98)	(8.05)	(8.22)	(7.57)
C. Not employed at baseline - Unemployed						
One-way commute time by car (mins)	530	30.15	3.49	-0.373	-0.053	-0.016
			(4.12)	(5.22)	(5.45)	(5.40)
One-way commute time by public transit (mins)	530	78.84	3.77	-5.20	-5.25	-3.17
			(8.98)	(11.85)	(12.16)	(10.98)
No covariates			X			
Includes benchmark covariates				X	X	X
Weighted by employer share of earnings					X	X
Winsorizing outcome at p99						X

Notes: Table presents the effect of being assigned to free fares relative to no discount on the one-way travel time between the participant's home address and the address of their place of employment. The home address comes from the study enrollment form. The employer address comes from the participant's Pennsylvania unemployment insurance (UI) records from the first four complete quarters after they enrolled in the study. Travel times are calculated using the Google Maps distance matrix API. The calculation accounts for traffic conditions and transit service schedules, based on a trip that begins at 8 am on Wednesday, May 7th, 2025. For participants who worked for more than one employer in Q1-Q4, their outcome is the average of the travel times across all of their employers during this time period. The effects in columns (1) and (2) use an unweighted average, and the effects in columns (3) and (4) weight the average by the employer's share of the person's total earnings in Q1-Q4. Column N indicates the number of participants across the 100% discount and no-discount study arms that have non-missing data for the given outcome. Only 40% of employers have an address in the UI data. Public transit travel times are coded as missing if the place of employment cannot be reached by public transportation. Robust standard errors are in parentheses. ***p <0.01, **p <0.05, *p <0.1

Table A4: Best Linear Predictor of UI earnings in the first four quarters after enrollment, comparing the control group to the free fares group

	ATE	HET
Parsimonious	-106.78	1.11
	(-400.33,185.14)	(1.02,1.19)
	[0.47]	[0.00]
Baseline Only	37.47	1.3
	(-212.2,286.33)	(1.21,1.39)
	[0.76]	[0.00]
+ UI, Medicaid, Geography	-116.04	0.96
	(-492.79,253.91)	(0.87,1.05)
	[0.54]	[0.00]
+ Other Social Services	-119.6	0.95
	(-524.02,284.41)	(0.86,1.04)
	[0.57]	[0.00]

Notes: Table presents results from the Best Linear Predictor (BLP) of the conditional average treatment effect on the ML proxies for models using different covariate sets, estimated using the method outlined in Chernozhukov et al. (2023). ATE are the average treatment effects and HET are the heterogeneity loading parameters. All other definitions are the same as in Table 5

Table A5: Effects of free fares on self-reported employment outcomes at 15 months after enrollment, among those unemployed at baseline

Outcome	N	Control mean	Unweighted No covariates (1)	Unweighted Benchmark covariates (2)	Weighted Benchmark covariates (3)
A. Current work status					
Working full-time	647	0.215	0.038 (0.034)	0.041 (0.033)	0.055 (0.039)
Working part-time	647	0.189	-0.012 (0.031)	-0.002 (0.031)	-0.068 (0.052)
Not working, but would like to work	647	0.309	-0.011 (0.037)	-0.028 (0.037)	<0.001 (0.051)
Temporarily laid off (you expect to get back your previous job)	647	0.022	<0.001 (0.012)	0.003 (0.011)	-0.045 (0.038)
On a temporary leave of absence from work	647	0.025	-0.007 (0.012)	-0.010 (0.013)	-0.017 (0.020)
Student, at school, or in training	647	0.029	0.014 (0.015)	0.007 (0.015)	-0.021 (0.041)
Unable to work due to illness or injury	647	0.175	-0.008 (0.030)	<0.001 (0.030)	-0.007 (0.044)
Homemaker	647	0.062	-0.013 (0.018)	-0.013 (0.019)	-0.071 (0.045)
Retired	647	0.011	<0.001 (0.008)	-0.002 (0.010)	0.012 (0.010)
Employed in past 12 months	639	0.596	-0.004 (0.039)	-0.002 (0.040)	-0.051 (0.054)
B. Main job characteristics (among the employed)					
Hours worked per week (N)	272	28.45	2.48 (1.83)	2.75 (2.16)	7.21** (2.95)
Days worked at main job in past 7 days (N)	295	3.88	-0.064 (0.232)	-0.152 (0.255)	0.090 (0.415)
Hourly wage ($)	237	13.81	-0.026 (0.603)	0.101 (0.656)	-0.826 (0.977)
Occupation is above CPS median earnings	236	0.184	-0.027 (0.050)	0.016 (0.058)	0.096 (0.068)
Employer benefits provided					
Health insurance	295	0.203	0.053 (0.049)	0.046 (0.050)	0.003 (0.055)
Contribution to a retirement account	295	0.154	0.043 (0.045)	0.035 (0.045)	0.039 (0.037)
Commuter benefits	295	0.008	0.033* (0.017)	0.043** (0.020)	0.025** (0.012)
C. Satisfaction with main job (among the employed)					
Rating of aspects of main job (1-10)					
Fit with your experience and skills	270	6.71	0.114 (0.330)	-0.058 (0.344)	-0.192 (0.543)
Opportunities for promotion over next 3 years	268	5.26	-0.196 (0.360)	-0.406 (0.396)	-0.852* (0.473)
Satisfied with aspects of main job					
Pay	270	0.319	0.005 (0.057)	0.038 (0.061)	0.134 (0.087)
Other aspects of job besides pay	268	0.328	0.021 (0.058)	0.037 (0.063)	0.076 (0.081)
All aspects of job overall	270	0.445	-0.015 (0.061)	-0.004 (0.067)	0.100 (0.093)
D. Total labor supply and earnings					
Number of paid jobs currently held (N)	607	0.438	-0.020 (0.052)	-0.006 (0.052)	-0.327 (0.251)
Hours worked per week (N)	617	13.40	0.313 (1.70)	0.647 (1.70)	2.12 (1.92)

Table A5: Effects of free fares on self-reported employment outcomes at 15 months after enrollment, among those unemployed at baseline *(continued)*

Outcome	N	Control mean	Unweighted No covariates (1)	Unweighted Benchmark covariates (2)	Weighted Benchmark covariates (3)
Total pretax monthly earnings ($)	595	480.2	-59.57 (88.12)	-56.11 (84.66)	-144.1 (239.8)
E. Commuting (among the employed)					
Do you work from home for main job?					
No	270	0.798	-0.010 (0.050)	0.031 (0.055)	-0.016 (0.071)
Yes	270	0.101	-0.028 (0.035)	-0.039 (0.041)	0.021 (0.060)
Sometimes	270	0.101	0.038 (0.040)	0.008 (0.043)	-0.005 (0.058)
Primary commute mode to main job last week					
Bus	241	0.543	0.134** (0.063)	0.131* (0.070)	0.093 (0.103)
Light rail	241	0.019	-0.004 (0.017)	0.012 (0.019)	0.013 (0.014)
Personal car	241	0.181	-0.085* (0.045)	-0.067 (0.045)	0.058 (0.075)
Carpool	241	0.029	<0.001 (0.022)	0.012 (0.024)	-0.038 (0.045)
Walk or bike	241	0.124	-0.036 (0.040)	-0.062 (0.046)	-0.052 (0.050)
Ridesharing app (e.g. Uber or Lyft)	241	0.057	0.002 (0.030)	0.007 (0.031)	0.025 (0.063)
Round-trip commute time on typical day (minutes)	191	84.65	10.96 (29.89)	10.25 (30.49)	-19.41 (61.14)

Notes: Table presents estimates of the effect of being assigned to free fares relative to no discount on self-reported employment outcomes among the participants who reported being unemployed in the baseline survey. The outcome data comes from the post-endline survey, which took place 15 months after the person enrolled in the study. The benchmark covariates include: Age (years), female (y/n), Black (y/n), more than high school education (y/n), PRT trips taken last week (N), and lives within the PRT 7-day frequent service walkshed (y/n). Column N indicates the number of individuals across the free fares and control groups that responded to the survey item. Sample sizes vary across outcomes due to differing survey item response rates. Outcome data is winsorized at the 99th percentile if it comes from a survey question that permitted an unbounded numeric response. Robust standard errors are in parentheses. ***p <0.01, **p <0.05, *p <0.1; † refers to comparable thresholds for sharpened FDR q-values

Table A6: Effects of free fares on self-reported job search activities at six months after enrollment, among the unemployed

Outcome	N	Control mean	Unweighted No covariates (1)	Unweighted Benchmark covariates (2)	Weighted Benchmark covariates (3)
A. Among those unemployed at baseline					
Actively searched for job in past 4 weeks	282	0.603	-0.051 (0.059)	-0.036 (0.061)	-0.081 (0.075)
Job search activities among active searchers					
Jobs applied to in past 4 weeks (N)	152	7.74	4.51* (2.48)	3.32 (2.08)	6.13** (2.81)
Time spent searching for a job last week (hours)	154	12.83	-0.763 (3.10)	-1.40 (3.05)	-4.46 (3.94)
Traveled around to search in person in past 4 weeks	155	0.264	0.001 (0.071)	-0.004 (0.071)	<0.001 (0.082)
Allegheny County municipalities where you have searched for work in past 4 weeks (N)	127	2.18	-0.544 (0.332)	-0.446 (0.365)	-0.056 (0.485)
Pittsburgh neighborhoods where you have searched for work in past 4 weeks (N)	107	1.32	-0.671** (0.330)	-0.676* (0.355)	-0.597 (0.378)
Not actively searching due to transportation problems (among non-active searchers)	119	0.104	-0.006 (0.057)	0.015 (0.062)	0.028 (0.040)
B. Among those unemployed at midline					
Actively searched for job in past 4 weeks	159	0.726	0.134** (0.065)	0.158** (0.063)	0.224** (0.088)
Job search activities among active searchers					
Jobs applied to in past 4 weeks (N)	120	12.84	1.46 (3.70)	2.07 (3.22)	5.78* (3.17)
Time spent searching for a job last week (hours)	121	10.76	4.93 (2.99)	4.69 (3.03)	0.326 (2.81)
Traveled around to search in person in past 4 weeks	125	0.377	-0.141* (0.084)	-0.135 (0.085)	-0.102 (0.106)
Allegheny County municipalities where you have searched for work in past 4 weeks (N)	94	2.07	-0.207 (0.406)	0.228 (0.414)	0.467 (0.484)
Pittsburgh neighborhoods where you have searched for work in past 4 weeks (N)	81	1.34	-0.647* (0.366)	-0.607 (0.398)	-0.380 (0.342)
Not actively searching due to transportation problems (among non-active searchers)	32	0.300	-0.217 (0.134)	0.165 (0.555)	-0.030 (0.340)

Notes: Table presents estimates of the effect of being assigned to free fares relative to no discount on self-reported job search activities. The outcome data comes from the midline survey, which took place 6 months after the person enrolled in the study. Panel A shows the results among those who reported being unemployed in the baseline survey. Panel B shows the results among those who reported being unemployed in the midline survey. The benchmark covariates include: Age (years), female (y/n), Black (y/n), more than high school education (y/n), PRT trips taken last week (N), and lives within the PRT 7-day frequent service walkshed (y/n). Column N indicates the number of individuals across the free fares and control groups that responded to the survey item. Sample sizes vary across outcomes due to differing survey item response rates. Outcome data is winsorized at the 99th percentile if it comes from a survey question that permitted an unbounded numeric response. Robust standard errors are in parentheses. ***p <0.01, **p <0.05, *p <0.1; † refers to comparable thresholds for sharpened FDR q-values

Table A7: Classification Analysis of UI earnings in first six quarters after study enrollment, comparing the control group to the free fares group

	25% Most (Group 4)	25% Least (Group 1)	Difference
UI employment 3 quarters before enrollment	0.731 (0.707,0.754) [0.000]	0.609 (0.583,0.635) [0.000]	0.122 (0.087,0.156) [0.000]
UI employment 2 quarters before enrollment	0.733 (0.709,0.756) [0.000]	0.625 (0.6,0.651) [0.000]	0.108 (0.074,0.142) [0.000]
UI employment 1 quarter before enrollment	0.771 (0.749,0.793) [0.000]	0.672 (0.647,0.697) [0.000]	0.1 (0.067,0.134) [0.000]
UI earnings 2 quarters before enrollment	4249.419 (4018.208,4478.9) [0.000]	3392.887 (3169.131,3615.871) [0.000]	850.152 (522.943,1174.572) [0.000]
UI earnings 3 quarters before enrollment	3948.889 (3723.103,4175.077) [0.000]	3146.974 (2930.862,3362.998) [0.000]	806.809 (490.785,1114.534) [0.000]
Gets around with a car	0.29 (0.266,0.313) [0.000]	0.222 (0.201,0.244) [0.000]	0.066 (0.034,0.099) [0.000]
Age	37.009 (36.57,37.451) [0.000]	38.223 (37.789,38.656) [0.000]	-1.231 (-1.849,-0.613) [0.000]
UI earnings 1 quarter before enrollment	4359.698 (4119.831,4600.441) [0.000]	3733.062 (3509.567,3956.086) [0.000]	621.233 (295.396,948.034) [0.000]
High school education	0.55 (0.524,0.577) [0.000]	0.48 (0.453,0.506) [0.000]	0.071 (0.033,0.108) [0.000]
Currently employed	0.64 (0.615,0.666) [0.000]	0.572 (0.546,0.599) [0.000]	0.069 (0.032,0.105) [0.000]
Lives in PRT 5-day svc walkshed	0.861 (0.843,0.879) [0.000]	0.904 (0.889,0.92) [0.000]	-0.043 (-0.067,-0.019) [0.001]
Lives in PRT 7-day svc walkshed	0.823 (0.802,0.843) [0.000]	0.869 (0.851,0.887) [0.000]	-0.047 (-0.073,-0.02) [0.001]
Received UI benefits 1 quarter before enrollment	0.052 (0.04,0.064) [0.000]	0.027 (0.018,0.036) [0.000]	0.025 (0.01,0.04) [0.001]
Lives in PRT 6-day svc walkshed	0.839 (0.819,0.858) [0.000]	0.882 (0.865,0.899) [0.000]	-0.044 (-0.07,-0.018) [0.001]
No access to a car	0.697 (0.672,0.721) [0.000]	0.753 (0.73,0.775) [0.000]	-0.055 (-0.089,-0.022) [0.001]
More than high school education	0.388 (0.362,0.414) [0.000]	0.447 (0.421,0.473) [0.000]	-0.059 (-0.096,-0.022) [0.002]

Table A7: Classification Analysis of UI earnings in first six quarters after study enrollment, comparing the control group to the free fares group *(Continued)*

	25% Most (Group 4)	25% Least (Group 1)	Difference
Not employed - Disabled	0.038	0.063	-0.026
	(0.028,0.048)	(0.05,0.075)	(-0.042,-0.01)
	[0.000]	[0.000]	[0.002]
UI benefits 1 quarter before enrollment	118.53	58.053	60.105
	(85.366,151.794)	(34.389,81.846)	(19.413,100.567)
	[0.000]	[0.000]	[0.004]
Employed in past 12 months	0.83	0.79	0.041
	(0.81,0.85)	(0.768,0.811)	(0.012,0.07)
	[0.000]	[0.000]	[0.006]
Gets around with public transportation	0.873	0.903	-0.03
	(0.855,0.89)	(0.887,0.919)	(-0.054,-0.007)
	[0.000]	[0.000]	[0.011]
Not employed - Caretaker	0.035	0.054	-0.017
	(0.026,0.045)	(0.042,0.065)	(-0.033,-0.002)
	[0.000]	[0.000]	[0.025]
Owns a car	0.111	0.086	0.024
	(0.094,0.127)	(0.071,0.101)	(0.002,0.046)
	[0.000]	[0.000]	[0.031]
UI benefits 3 quarters before enrollment	58.901	31.405	27.231
	(37.278,80.109)	(15.267,47.374)	(0.558,53.965)
	[0.000]	[0.000]	[0.045]
Female	0.894	0.87	0.024
	(0.877,0.91)	(0.852,0.887)	(0,0.048)
	[0.000]	[0.000]	[0.048]
No. children	2.549	2.433	0.121
	(2.459,2.64)	(2.341,2.524)	(-0.009,0.249)
	[0.000]	[0.000]	[0.068]
Race - White	0.26	0.288	-0.03
	(0.237,0.283)	(0.264,0.312)	(-0.063,0.004)
	[0.000]	[0.000]	[0.080]
Received UI benefits 3 quarters before enrollment	0.034	0.023	0.011
	(0.024,0.044)	(0.015,0.031)	(-0.001,0.023)
	[0.000]	[0.000]	[0.083]
Race - Black	0.665	0.634	0.031
	(0.64,0.69)	(0.609,0.659)	(-0.005,0.066)
	[0.000]	[0.000]	[0.091]
Not employed - Temporarily laid off	0.027	0.038	-0.011
	(0.019,0.036)	(0.028,0.048)	(-0.024,0.002)
	[0.000]	[0.000]	[0.111]
Less than high school education	0.057	0.071	-0.014
	(0.045,0.069)	(0.057,0.085)	(-0.032,0.005)
	[0.000]	[0.000]	[0.143]
Gets around with rideshare	0.289	0.266	0.024
	(0.266,0.313)	(0.243,0.289)	(-0.01,0.057)
	[0.000]	[0.000]	[0.163]
Received UI benefits 2 quarters before enrollment	0.033	0.024	0.009
	(0.024,0.043)	(0.016,0.032)	(-0.004,0.021)
	[0.000]	[0.000]	[0.170]

Table A7: Classification Analysis of UI earnings in first six quarters after study enrollment, comparing the control group to the free fares group *(Continued)*

	25% Most (Group 4)	25% Least (Group 1)	Difference
Not employed - Student	0.022	0.03	-0.008
	(0.014,0.029)	(0.021,0.039)	(-0.02,0.004)
	[0.000]	[0.000]	[0.195]
Not employed - Other reason	0.007	0.012	-0.005
	(0.003,0.012)	(0.006,0.018)	(-0.012,0.003)
	[0.002]	[0.000]	[0.205]
Race - Other	0.054	0.063	-0.009
	(0.042,0.066)	(0.05,0.075)	(-0.026,0.009)
	[0.000]	[0.000]	[0.320]
No. public transportation trips last week	10.099	10.878	-0.761
	(9.047,11.249)	(9.68,12.093)	(-2.367,0.87)
	[0.000]	[0.000]	[0.349]
Race - Hispanic	0.038	0.032	0.006
	(0.028,0.048)	(0.023,0.041)	(-0.008,0.02)
	[0.000]	[0.000]	[0.376]
Not employed - Retired	0.004	0.002	0.001
	(0,0.007)	(0,0.005)	(-0.002,0.005)
	[0.025]	[0.083]	[0.405]
UI benefits 2 quarters before enrollment	63.119	50.777	12.851
	(40.813,85.521)	(30,71.129)	(-17.649,42.847)
	[0.000]	[0.000]	[0.407]
Gets around with carpool	0.077	0.069	0.008
	(0.063,0.091)	(0.055,0.082)	(-0.012,0.027)
	[0.000]	[0.000]	[0.438]
Lives in PRT 7-day frequent svc walkshed	0.327	0.334	-0.007
	(0.302,0.352)	(0.309,0.359)	(-0.042,0.028)
	[0.000]	[0.000]	[0.696]
Not employed - Temporary leave	0.025	0.026	-0.001
	(0.016,0.033)	(0.018,0.035)	(-0.013,0.01)
	[0.000]	[0.000]	[0.809]
Gets around by walking	0.326	0.329	-0.003
	(0.301,0.351)	(0.305,0.354)	(-0.038,0.031)
	[0.000]	[0.000]	[0.850]
Has children enrolled in study	0.786	0.784	0
	(0.764,0.807)	(0.762,0.806)	(-0.03,0.031)
	[0.000]	[0.000]	[0.977]
Not employed - Unemployed	0.201	0.201	0
	(0.179,0.222)	(0.18,0.222)	(-0.03,0.03)
	[0.000]	[0.000]	[0.984]

Notes: Table presents estimates from classification analysis (CLAN) computed using the method outlined in Chernozhukov et al., 2023 for the treatment effect of UI earnings comparing the control group to the full fares group. All estimates are from the machine learning model that uses the full set of baseline covariates available (from the baseline survey and the administrative data). Median confidence intervals are in parenthesis and p-values are in brackets.

B Machine Learning Covariates

Our analysis applies machine learning in two contexts: first, to estimate average treatment effects, and second, to test for heterogeneity in those effects.

Machine Learning for Treatment Effect Estimation We implement two separate machine learning-based methods of estimating treatment effects to test the robustness of our benchmark OLS estimates that use pre-specified covariates. In one specification, we select optimal controls using a post-double LASSO procedure (Belloni et al., 2014). In another, we estimate average treatment effects nonparametrically using generalized random forests that are trained on the full set of available covariates (Athey et al., 2019). The LASSO regressions do not incorporate any covariate interactions or polynomial terms.

The set of potential controls for these machine learning methods includes age; demographics; highest education; all items from the baseline survey; indicators for the calendar month and year of enrollment; indicators for sharing a home address with another study participant; measures of socioeconomic need and transit accessibility of the person's residential location; quarterly UI employment, earnings and benefit receipt in the 12 quarters preceding study enrollment; various measures of Medicaid-funded health care utilization in the year before enrollment; criminal justice involvement in the year before enrollment; and receipt of various social services such as SNAP, TANF, SSI, Medicaid, Section 8, child care subsidies, and homeless shelters in the year before enrollment.

The results of these machine learning specifications are shown in Appendix Table A1 for the UI-based employment outcomes and Appendix Table A2 for the employment outcomes measured from the 15-month survey.

Machine Learning for Heterogeneity Tests To explore treatment effect heterogeneity, we apply the methodology outlined in Chernozhukov et al. (2023). We use four sets of covariates (constructed from the list above) to train the predictive model and present results for each covariate set:

1. *Parsimonious set*: A core set of covariates that are plausibly related to employment outcomes from the baseline survey and administrative data.

2. *Baseline Only*: All study application and baseline survey variables. This covariate set has no missing values as all participants were required to complete the baseline survey before enrollment.

3. *+ UI, Medicaid, Geography*: Includes the "Baseline Only" set plus administrative data on UI employment history (including UI benefits receipt), geographic features of the person's baseline residence (including access to public transit) and Medicaid-funded health care utilization.

4. *+ Other Social Services*: Includes the "+ UI, Medicaid, Geography" set plus historical involvement in other social services (TANF, SNAP, SSI, Section 8, etc.)

For both treatment effect estimation and heterogeneity tests, we exclude covariates that have missing data for more than 20% of observations. We then impute any missing values using the median value of the control variable within each study arm. We also include indicator variables for the missingness of each variable as an additional covariate, as recommended in Zhao and Ding (2024).

C Additional details on cost effectiveness calculations

In this appendix, we calculate the costs and benefits of providing an 18-month free transit pass to unemployed SNAP recipients. The costs and benefits are measured over the first two years from the start of the program.

C.1 Program costs

The direct cost of free fares to the government includes foregone fare revenue, administrative costs, and any marginal costs of additional ridership on PRT operating expenses.

Free fares cause PRT to lose the fare revenue that it would otherwise earn under regular prices. The additional ridership in response to free fares does not count towards foregone revenue because this ridership does not exist under the counterfactual of regular prices. The baseline-unemployed control group members took an average of 3.12 transit trips per week as measured from smartphone location data (Table 6 panel B). However, some of these trips would have been deemed a "free transfer" under regular prices because the trip took place within three hours of the previous trip.[27] When counting only payable trips, the control group took 1.98 trips per week, or 154.44 trips over 18 months. The policy thus cost PRT 154.44 × \$2.75 = \$424.71 in foregone fare revenue per person.

ACDHS hired one part-time employee to manage the fare discount program. This person worked 25 hours per week at \$25 per hour. The program served a total of 9,544 adults, for a total 18-month administrative cost per participant of (25 × \$25 × 52 × 1.5) / 9,544 = \$5.11.

We assume that PRT incurs no marginal expense to serve one additional passenger. PRT's buses and light rail vehicles were only 22% full on average at the time that study participants boarded. PRT therefore has substantial capacity to handle additional riders at current service levels. Other marginal costs could in theory include more time spent idling at each transit stop to allow more riders to board, and increased fuel costs per mile when more people are aboard a bus. For context, PRT's average operating cost per passenger was \$12.03 in fiscal year 2023.[28]

Summing these costs yields a total direct cost of \$424.71 + \$5.11 = \$429.82 per person.

C.2 Marginal value of public funds

We now calculate the marginal value of public funds (MVPF) of providing 18 months' worth of free public transportation to unemployed SNAP recipients. The MVPF is the ratio of society's willingness to pay for free fares to the net fiscal cost of the policy (Hendren & Sprung-Keyser, 2020). We abstract from any general equilibrium effects that could arise

[27]PRT riders are not required to pay for boardings that take place within three hours of the previous boarding. In particular, riders are always required to pay for the first boarding of the day. Any boardings that take place within three hours of the first boarding are free. Riders then must pay for the next boarding after the end of this initial three-hour window, and a new three-hour free transfer window begins at that time. This logic repeats until the system resets at 3 am the next day.

[28]https://www.rideprt.org/siteassets/inside-the-pa/transparency/annual-service-report/01.08.24_final_asr_fy2023.pdf

if the policy were implemented at larger scale. Such effects could include increased SNAP benefit enrollment to qualify for the fare discount or the cost of providing more frequent transit service to meet higher ridership demand.

C.2.1 Willingness to pay

The MVPF numerator includes the subsidy recipients' private willingness to pay (WTP) for free fares, plus society's WTP for any externalities of the policy.

Recipients' private WTP. When valuating recipients' own WTP, a key question is whether or not they fully understood the benefits of free transit fares ex ante. If they fully understood the benefits, then their WTP is based on revealed preference: the number of transit trips they take under free fares. If they initially misjudged the benefits of free fares, however, then we should instead use an ex post valuation of their WTP that is based on any downstream benefits the person derives from the subsidy.

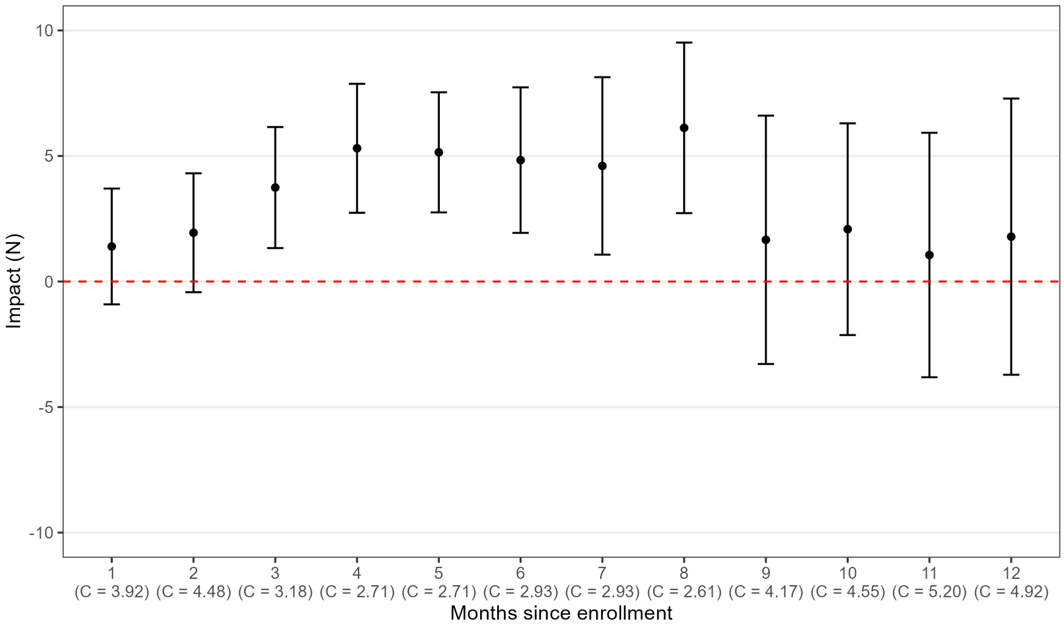
Our data gives some indications that the baseline-unemployed participants did not fully understand the value of free fares at the beginning of the study. The causal effect of free fares on public transportation ridership increased in the first four months of the study before leveling off (Appendix Figure C1). This suggests a period of learning or habit formation in which recipients gradually came to understand the value of the treatment and adjusted their behavior accordingly.[29] Furthermore, free fares had a larger impact on daily PRT ridership among the participants who reported taking zero transit trips at baseline than among those who reported taking non-zero trips (Appendix Figure C2). The larger ridership effect among people with no baseline trips may indicate that they were not making optimal use of transit to begin with, perhaps due to information frictions or behavioral biases.

On the other hand, each of our follow-up surveys included the question "Would you be willing to pay $X for a month of unlimited PRT trips?", where X is a random integer between 1 and 97 (a regular-price monthly pass costs $97.50). There are no systematic changes in the shape of these unincentivized WTP curves for the fare discount recipients across the three survey waves. This implies that participants' understanding of the value of transit trips did not evolve over time, at least beyond the first survey at six months. Also, two-thirds of control group respondents said they would be willing to pay $22 to $25, which corresponds to the monetary value of the number of payable transit trips that the free fares group actually took per year ($283). Put differently, the majority of control group members valued free transit trips at the treatment group's actual level of usage, which means it may be liquidity constraints rather than inaccurate valuations that prevent our sample from using transit optimally.

Given the mixed evidence on the extent to which participants were optimizing ex ante, we calculate two versions of private WTP: 1) The revealed-preference approach, and 2) The ex post approach based on the personal benefits derived from the policy.

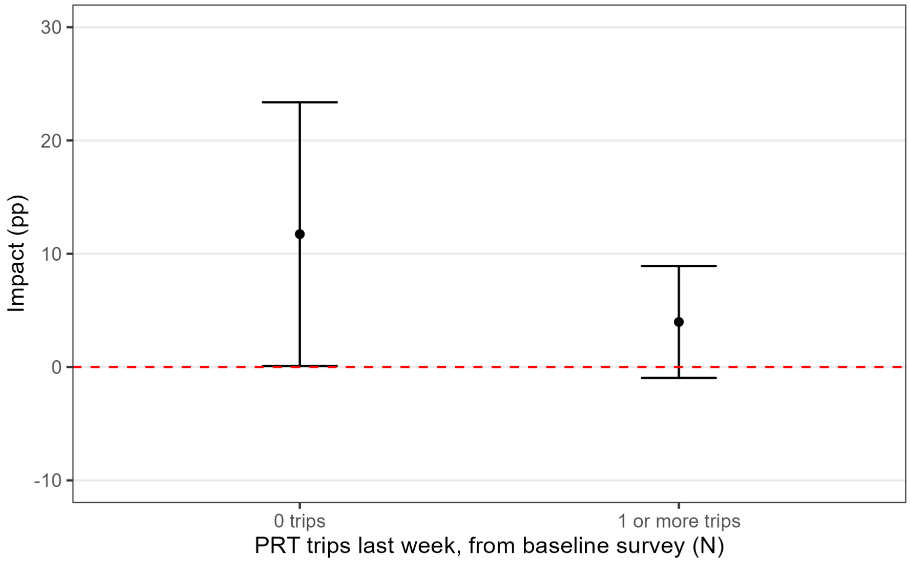
[29] If the ridership effect had instead jumped immediately to its plateau level, it could imply that transit ridership is limited more by liquidity constraints than by information frictions.

Figure C1: Effect of free fares on number of public transportation trips per week over time, among the baseline-unemployed



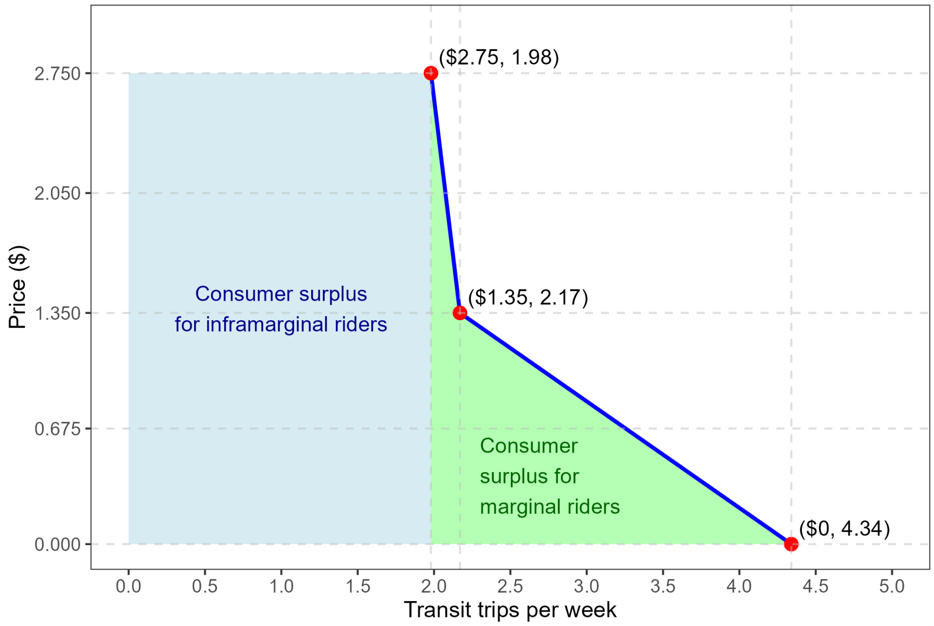
Notes: Figure presents the effect of being assigned to free fares relative to no discount on the number of public transportation trips taken per week over time. Data comes from Google Maps location history (GPS) data. Treatment effects are estimated by running repeated cross-sectional regressions by month. The regressions adjust for the following baseline covariates: Age (years), female (y/n), Black (y/n), more than high school education (y/n), currently employed (y/n), PRT trips taken last week (N), lives within the PRT 7-day frequent service walkshed (y/n), and the outcome measured in the 365 days before the person joined the study. Error bars show 95% confidence intervals using robust standard errors. See Chizeck and Mbonu (2025) for more information about how we measured public transit ridership from smartphone GPS data.

Figure C2: Effect of free fares on daily likelihood of taking at least one public transportation trip, by baseline level of ridership, among the baseline-unemployed



Notes: Figure presents the effect of being assigned to free fares relative to no discount on the likelihood of taking at least one public transportation trip on a given day. The analysis is limited to the baseline-unemployed sample. The effects are disaggregated by whether the person reported taking a non-zero number of public transit trips last week in the baseline survey. The outcome is measured from SMS travel diary surveys. The regressions adjust for the following baseline covariates: Age (years), female (y/n), Black (y/n), more than high school education (y/n), currently employed (y/n), PRT trips taken last week (N), and lives within the PRT 7-day frequent service walkshed (y/n). The regressions also include normalized weights for the number of travel diaries that each person completed. Error bars show 95% confidence intervals using robust standard errors. See Chizeck and Mbonu (2025) for more information about how we measured public transit ridership from travel diary surveys.

Figure C3: Transit demand curve based on effects of fare discounts on number of payable PRT trips per week among the baseline-unemployed sample



Notes: Figure presents the demand curve that is implied by the effects of fare discounts on the number of payable public transit trips per week among the baseline-unemployed sample. A trip is payable if it is not a free transfer, meaning it did not take place within three hours of the previous trip. The control group took 1.98 payable trips per week according to GPS data. Half fares added 0.19 payable trips per week (SE = 0.683) and free fares added another 2.17 payable trips per week (SE = 0.502).

Revealed-preference approach: We abstract from any insurance value of the fare subsidies for risk-averse individuals. This imposes an upper bound valuation of $1 per dollar of subsidy. In fact, the average baseline-unemployed participant valued the subsidy at less than its resource cost, as shown by the demand curve that is traced out by our three fare prices (Appendix Figure C3). The demand curve linearly interpolates between the three observed price effects. Free fares provide consumer surplus of 1.98 $\times$ \$2.75 = \$5.45 for the 1.98 payable weekly trips that the person would take under regular prices, 0.19 $\times$ \$2.05 = \$0.39 for the 0.19 additional payable weekly trips induced when fares decrease by half to \$1.35, and 2.17 $\times$ \$0.675 = \$1.46 for the 2.17 additional payable weekly trips induced when fares become free, for a total WTP of (\$5.45 + \$0.39 + \$1.46) $\times$ 52 $\times$ 1.5 = \$569.34 per capita over the 18-month subsidy period.

Ex post benefits approach: The baseline-unemployed participants gained welfare from higher post-tax earnings. We assume that their earnings are subject to a flat employee payroll tax rate of 7.65%, a flat Pennsylvania state income tax of 3.07%, and a combined marginal federal income tax of 10%. We reduce the valuation of their labor earnings by a factor of 0.6 due to reduced leisure (Mas & Pallais, 2019). We sum the quarterly earnings effects $\hat{\beta}^{t,earnings}$ through eight quarters (T = 8), discounted at quarterly gross rate 1 + r where we set r = 0.01. Any effects that persist beyond eight quarters would make this valuation even higher. The net present value WTP for higher earnings is:

$$(1 - 0.0765 - 0.0307 - 0.1) \times 0.6 \times \sum_{t=1}^{T=8} \frac{\hat{\beta}^{t,earnings}}{(1+0.01)^{t-1}} = \$2,101.46,$$

Participants also derive welfare from any social insurance income. We estimate treatment effects on the quarterly amount of UI benefits received by baseline-unemployed participants over the first eight quarters (Appendix Table A1 panel D reports the effects for the first four quarters). We also estimate effects on their monthly likelihood of receiving SNAP, Temporary Assistance for Needy Families (TANF), Supplemental Security Income (SSI), Medicaid, Section 8 rental housing, and child care benefits over the first 24 months after study enrollment (Appendix Figure A4). The effects of free fares on these measures of benefit receipt are generally small and statistically insignificant. We nonetheless incorporate the point estimates and confidence intervals into the MVPF calculation to give a more complete picture of the policy's costs and benefits.

UI benefits in Pennsylvania are subject to federal income tax but not state or local taxes (Pennsylvania Department of Labor and Industry, 2025). The net present value WTP for the eight-quarter stream of effects on UI benefit income is

$$(1 - 0.1) \times \sum_{t=1}^{T=8} \frac{\hat{\beta}^{t,UIbenefits}}{(1+0.01)^{t-1}} = \$47.79,$$

We impute the monthly monetary value of the other social insurance programs as follows. These benefits are generally not taxable, and we ignore any insurance value of the benefit beyond the transfer value:

- *SNAP:* \$154/month[30]
- *TANF*: \$403/month [31]
- *SSI:* \$914/month[32]
- *Medicaid:* \$83.58/month[33]
- *Section 8 rental housing subsidy:* \$637/month[34]

[30] This was the average monthly benefit amount per person in 2022 (U.S. Department of Agriculture, 2025).
[31] This is the maximum monthly benefit for a 3-person household in Pennsylvania
[32] This was the maximum monthly benefit in 2023 for an individual with no countable income (Social Security Administration, 2025).
[33] This was the average monthly out-of-pocket health care spending per capita in the U.S. among people age 19 to 64 in 2020 (Centers for Medicare and Medicaid Services, 2025)
[34] The average cost of a Housing Choice Voucher (i.e. Section 8 voucher) to the Allegheny County government was \$9,207 per household per year in 2024, according to ACDHS administrative data. We follow Hendren and Sprung-Keyser (2020) in taking a WTP estimate from Reeder (1985), whose estimates suggest recipients are willing to pay 83% of the cost of the voucher. This implies a monthly WTP of \$9,207 × 0.83 / 12 = \$637.

- *Child care subsidy:* \$1,485/month[35]

The net present value WTP for the 24-month stream of effects on the receipt of these benefits is

$$\sum_{t=1}^{T=24} \frac{1}{(1+0.01)^{t-1}} \times \Big[\hat{\beta}^{t,P(SNAP)}(\$154) + \hat{\beta}^{t,P(TANF)}(\$403) + \hat{\beta}^{t,P(SSI)}(\$914)$$
$$+ \hat{\beta}^{t,P(Medicaid)}(\$83.58) + \hat{\beta}^{t,P(Section8)}(\$637) + \hat{\beta}^{t,P(Childcare)}(\$1,485)\Big] = \$262.76$$

C.2.2 Net cost to the government

The MVPF denominator includes the direct cost to the government of providing free fares for 18 months, plus any fiscal externalities associated with the effects of the policy. The direct cost is \$429.82 per person, as calculated in Section C.1 above. The government collects additional tax revenue on participants' increased earnings over the first two years (eight quarters). The net present value of this revenue is

$$(0.0765 + 0.0307 + 0.1) \times \sum_{t=1}^{T=8} \frac{\hat{\beta}^{t,earnings}}{(1+0.01)^{t-1}} = \$782.61,$$

The per-person fiscal impact on UI benefit payments and other public assistance expenditures over the first two years is[36]

$$(1-0.1) \times \sum_{t=1}^{T=8} \frac{\hat{\beta}^{t,UIbenefits}}{(1+0.01)^{t-1}} + \sum_{t=1}^{T=24} \frac{1}{(1+0.01)^{t-1}} \times \Big[\hat{\beta}^{t,P(SNAP)}(\$154) + \hat{\beta}^{t,P(TANF)}(\$403) +$$
$$\hat{\beta}^{t,P(SSI)}(\$914) + \hat{\beta}^{t,P(Medicaid)}(\$379.75) + \hat{\beta}^{t,P(Section8)}(\$767.25) + \hat{\beta}^{t,P(Childcare)}(\$1,485)\Big]$$
$$= \$316.89$$

The total marginal cost to the government per person over the first two years is \$429.82 - \$782.61 + \$316.89 = -\$35.90. The fiscal externalities thus exceed program costs and the program pays for itself. The MVPF is defined as "infinite" in this case (Hendren & Sprung-Keyser, 2020).

[35] The federal Child Care Development Fund program served an average of 802,500 families per month in 2021 (Office of Child Care, 2025a) at a total annual cost of \$14.3 billion (Office of Child Care, 2025b), for an estimated per-family monthly value of \$14.3 billion / 802,500 / 12 = \$1,485.

[36] The monthly Medicaid expenditure per person is taken from the Pennsylvania adult spending per enrollee in 2021 (Kaiser Family Foundation, 2025). The monthly Section 8 spending is \$9,207 / 12 following the estimate from Jacob and Ludwig (2012).

C.2.3 MVPF results

The MVPF results are summarized in Table 7. When measuring costs and benefits over the first two years, an 18-month free transit pass for an unemployed SNAP recipient has an MVPF of infinity regardless of whether private WTP is measured using revealed preference or using ex post benefits.

D Follow-up survey non-response

D.1 Survey response rates and reweighting for selection into response

All study participants were invited to complete three follow-up surveys: a midline at six months after enrollment, an endline at 11 months, and a post-endline at 15 months. The majority of questions in these surveys did not force a response. The final question asked the participant to check a box that said "I have completed the survey". We consider a participant to have completed the survey if they checked this box, regardless of how many questions they answered within the survey. Each participant was randomly offered either $10 or $20 for completing the survey. Those who completed the survey immediately received a digital reward via email for the offered amount.

We focus our non-response analysis on the post-endline (15-month) survey because it had the highest overall response rate of the three survey waves and it took place at the very end of the active fare subsidy period. Table D1 presents the post-endline survey completion rates by study arm and survey incentive amount. Overall, 42.6% of our 9,544 study participants completed the survey. Response rates increased with the subsidy level: 36.1% among the control group, 41.8% among the half fares group, and 49.8% among the free fares group. The $20 incentive group was 5.8 percentage points more likely than the $10 incentive group to complete the survey.

Table D1: Post-endline survey completion rates

Discount group	Total	$20 incentive	$10 incentive	$20 versus $10 diff.
No discount	0.361	0.397	0.325	0.072***
				(0.017)
Half fares	0.418	0.441	0.396	0.045***
				(0.017)
Free fares	0.498	0.525	0.471	0.054***
				(0.018)
Total	**0.426**	**0.455**	**0.397**	**0.058*** **
				(0.010)

Notes: This table presents the post-endline (15-month follow-up) survey completion rates, disaggregated by fare discount group and the survey incentive amount that was offered to the participant. Participants were randomly offered either $10 or $20 for completing the survey. The majority of questions in the survey did not force a response. The final question in the survey asked participants to check a box to indicate that they have completed the survey. We consider a participant to have completed the survey if they checked this box, regardless of how many questions they answered within the survey. Robust standard errors are in parentheses. ***p <0.01, **p <0.05, *p <0.1

Table D2 reports average baseline characteristics of the post-endline survey respondents and non-respondents. The respondents were more likely to be female, White, and have more than a high school degree. They were also slightly more likely to be currently employed and had greater total formal-sector earnings in the calendar quarter prior to joining the study. For several characteristics, the magnitude of the standardized difference in means (in the rightmost column of Table D2) exceeds 0.20, a rule-of-thumb threshold for substantial baseline imbalance (Imbens & Wooldridge, 2009). The omnibus F-test for all characteristics in the table is also significant at the $p < 0.05$ level.

We construct inverse propensity weights to account for selective survey response on observable characteristics. Separately by fare discount group, we use a logit regression to predict survey response based on characteristics measured prior to study enrollment and in the post-enrollment time period before they received the survey. The logit model includes the following predictors: age, one indicator for gender (female), one indicator for race (Black), the number of PRT trips taken last week as reported in the baseline survey, indicators for living in each of the four PRT walksheds at baseline (5-day, 6-day, 7-day, and 7-day frequent service), the number of children in the household as reported in the baseline survey, an indicator for not having car access at baseline, two indicators for educational attainment (less than high school and high school), indicators for each self-reported employment status in the baseline survey, an indicator for having any employment in the past 12 months in the baseline survey. We also include controls for quarterly UI employment and earnings from the twelfth quarter before study enrollment through the fourth quarter after study enrollment, three indicators for having any UI employment in each of the three years before random assignment, the average UI earnings in each of the three years before random assignment, the number of months in which the person received Medicaid, SNAP, TANF, and SSI benefits in the 60 months before enrollment, and indicators for Medicaid, SNAP, TANF, and SSI receipt in each of the 12 months after enrollment. Finally, we control for whether the person completed the midline survey and the endline survey, their randomized incentive amount for completing the post-endline survey ($10 or $20), and whether they ever used their assigned farecard for a PRT boarding.

We impute missing values of each predictor using the median value of the variable by study arm. We omit any variables that have missing values for more than 20% of the sample. The resulting non-response weight is the inverse of the predicted probability that the person completed the post-endline survey. We winsorize the weights at the 99th percentile.

Table D2: Selection into post-endline survey completion on baseline characteristics

	Respondent mean	Non-respondent mean	Difference	t-stat	Diff./SD
A. Demographics (from baseline survey)					
Female	0.782	0.683	0.099***	10.89	0.226
Age	39.37	39.64	-0.270	-1.05	-0.022
Race					
Black	0.536	0.622	-0.086***	-8.32	-0.175
White	0.384	0.308	0.076***	7.55	0.160
Other	0.057	0.046	0.012**	2.47	0.053
Hispanic	0.039	0.030	0.009**	2.38	0.051
Children in household (N)	1.14	1.13	0.006	0.206	0.004
Highest education					
Less than high school	0.062	0.093	-0.032***	-5.75	-0.118
High school	0.487	0.587	-0.100***	-9.59	-0.202
More than high school	0.444	0.316	0.128***	12.53	0.265
B. Transportation (from baseline survey)					
Owns a car	0.067	0.051	0.017***	3.29	0.070
PRT trips last week (N)	9.37	10.45	-1.08***	-4.07	-0.084
PRT spending last week ($)	27.18	31.62	-4.44***	-6.94	-0.143
C. Employment (from baseline survey)					
Employed past 12 months	0.613	0.598	0.014	1.38	0.029
Currently employed	0.443	0.417	0.026**	2.52	0.053
Hours worked per week at main job (N)	30.17	31.15	-0.984***	-2.79	-0.089
Hourly wage at main job ($; among the employed)	13.64	13.38	0.260**	2.23	0.072
D. Employment in quarter prior to enrollment (from UI records)					
Total earnings ($)	2,406.78	2,227.21	179.58**	2.57	0.054
Received nonzero UI benefits	0.035	0.029	0.007*	1.78	0.038
Test for joint orthogonality					
F stat			1.927		
p-value			0.014		
N	**3,689**	**5,855**			

Notes: This table compares the mean baseline characteristics between the participants who completed the post-endline (15 month) survey and those who did not. The majority of questions in the survey did not force a response. The final question in the survey asked participants to check a box to indicate that they have completed the survey. We consider a participant to have completed the survey if they checked this box, regardless of how many questions they answered within the survey. The joint F test is done using randomization inference. ***p <0.01, **p <0.05, *p <0.1

D.2 Randomization balance among post-endline respondents

Among post-endline survey respondents, baseline characteristics are generally balanced between the no-discount group and the free fares group, regardless of whether we apply the non-response weights described above. Table D3 presents average baseline characteristics for the survey respondents in these two groups, along with the weighted and unweighted differences in means and the corresponding test statistics. In the unweighted sample, the control group is more educated and worked fewer hours per week when employed. In the weighted sample, the only marginally significant differences are that the free fares group has slightly more children in their household and was more likely to be employed in the year before joining the study.

Table D3: Randomization balance among post-endline survey respondents

			Unweighted		Weighted	
	Control mean	Free fares mean	Diff.	t-stat	Diff.	t-stat
A. Demographics (from baseline survey)						
Female	0.796	0.785	-0.011	-0.702	-0.002	-0.070
Age	38.75	39.43	0.685	1.48	-1.17	-1.50
Race						
Black	0.549	0.565	0.016	0.849	0.023	0.782
White	0.380	0.356	-0.024	-1.28	-0.045	-1.58
Other	0.056	0.057	<0.001	0.111	0.015	1.06
Hispanic	0.039	0.041	0.003	0.351	0.010	0.745
Children in household (N)	1.14	1.22	0.087*	1.67	0.137*	1.69
Highest education						
Less than high school	0.051	0.071	0.020**	2.14	0.011	0.582
High school	0.481	0.495	0.013	0.693	0.003	0.094
More than high school	0.461	0.426	-0.034*	-1.78	-0.014	-0.494
B. Transportation (from baseline survey)						
Owns a car	0.076	0.064	-0.011	-1.14	-0.013	-1.03
PRT trips last week (N)	9.48	9.31	-0.167	-0.383	-0.437	-0.502
PRT spending last week ($)	27.43	26.81	-0.622	-0.600	-1.33	-0.711
C. Employment (from baseline survey)						
Employed past 12 months	0.628	0.622	-0.006	-0.322	0.052*	1.75
Currently employed	0.451	0.446	-0.005	-0.257	0.008	0.266
Hours worked per week at main job (N; among the employed)	29.34	30.83	1.49**	2.43	1.35	1.44
Hourly wage at main job ($; among the employed)	13.79	13.56	-0.226	-1.04	0.091	0.263
D. Employment in quarter prior to enrollment (from UI records)						
Total earnings ($)	2,415	2,510	95.82	0.728	217.5	1.09
Received nonzero UI benefits	0.031	0.030	-0.001	-0.210	0.006	0.607

Notes: Table presents mean baseline characteristics among the free fares and control group members who completed the post-endline (15 month) survey. The majority of questions in the survey did not force a response. The final question in the survey asked participants to check a box to indicate that they have completed the survey. We consider a participant to have completed the survey if they checked this box, regardless of how many questions they answered within the survey. Baseline survey items that permitted unbounded continuous-valued responses are winsorized at the 99th percentile. ***p <0.01, **p <0.05, *p <0.1

D.3 Selection into survey response on formal-sector employment treatment effects

The effect of free fares on employment outcomes measured from administrative UI records are similar between the full sample and the unweighted and weighted samples of survey respondents. Table D4 reports effects on cumulative formal-sector employment and earnings during the first four quarters after enrollment. The effects are disaggregated by baseline employment status (panels B and C) and are reported separately for the full study sample and only those who completed the survey. The point-estimated effects often differ in sign and magnitude between the full sample and the unweighted sample of survey respondents. In panel A, the non-response weights bring the effect on cumulative earnings among the survey respondents closer to the full-sample effect. In panels B and C, however, the non-response weights do not lead to closer alignment between the full-sample effect and the effect among survey respondents.

Table D4: ITT effect of free fares on formal-sector employment outcomes in Pennsylvania in first four quarters after enrollment, comparison of results among all participants and only the post-endline survey respondents

	All participants		Post-endline respondents			
Outcome	Control mean	Effect	Unweighted control mean	Unweighted effect	Weighted control mean	Weighted effect
A. Full sample						
Had any paid employment	0.632	0.010 (0.009)	0.648	0.014 (0.015)	0.611	0.018 (0.023)
Number of quarters with employment (N)	2.04	0.042 (0.031)	2.08	0.060 (0.053)	1.98	0.039 (0.079)
Cumulative earnings ($)	10,878	335.2 (254.0)	11,173	-64.82 (425.1)	10,382	207.5 (603.7)
B. Employed at baseline						
Had any paid employment	0.910	-0.005 (0.022)	0.923	0.029 (0.020)	0.915	0.081 (0.051)
Number of quarters with employment (N)	3.18	0.047 (0.077)	3.22	0.189** (0.092)	3.21	0.302* (0.172)
Cumulative earnings ($)	18,924	-159.8 (525.6)	19,292	-603.5 (848.7)	18,647	382.9 (823.9)
C. Not employed at baseline						
Had any paid employment	0.420	0.023 (0.015)	0.430	0.034 (0.026)	0.387	0.035 (0.041)
Number of quarters with employment (N)	1.17	0.085 (0.054)	1.18	0.117 (0.081)	1.08	0.049 (0.136)
Cumulative earnings ($)	4,740	1,030* (554.1)	4,752	1,042* (535.9)	4,316	792.5 (891.8)

Notes: Table presents estimates of the effect of being assigned to free fares versus no discount on formal-sector employment outcomes, comparing the effects among the full study sample and only among those who completed the post-endline survey. The data comes from Pennsylvania unemployment insurance (UI) administrative records. The outcomes are measured over the first four complete calendar quarters after the quarter in which the person enrolled in the study. All estimates adjust for the following baseline covariates: Age (years), female (y/n), Black (y/n), more than high school education (y/n), currently employed (y/n), PRT trips taken last week (N), lives within the PRT 7-day frequent service walkshed (y/n), and the outcome measured in the four complete quarters prior to study enrollment. The weighted effects among the post-endline survey respondents include inverse propensity weights based on the person's predicted likelihood of completing the survey. Robust standard errors are in parentheses. ***p <0.01, **p <0.05, *p <0.1

D.4 Bounding effects on post-endline survey outcomes to account for non-response bias

As noted in Section D.1, the post-endline survey response rate varied substantially across the three study arms, which raises the possibility of selective nonresponse biasing the results from this survey. Table D5 presents bounds on the free-fares ITT effects estimated on focal employment outcomes from the survey. We report three sets of bounds: Lee (2009), Kling and Liebman (2004), and Horowitz and Manski (1998).

Across all survey questions and sample groupings in Table D5, the free fares group was more likely to respond than the control group. For the Lee bounds, we trim outcomes among the free fares group until the free fares group's response rate to the given survey question equals that of the control group. The lower bounds trim the free fares participants with the largest response values; upper bounds trim the free fares participants with the smallest response values. We break ties using the estimated propensity to respond to the given survey question and trim participants who were least likely to respond. We estimate the Lee bounds using a regression that includes the benchmark set of baseline covariates and inverse propensity weights for nonresponse to the given survey question.

The Kling-Liebman bounds assume that non-respondents have response values that are one standard deviation away from the mean value. The lower bounds assume that the free fares (control) group non-respondents have outcomes one standard deviation below (above) the mean. The upper bounds assume that the free fares (control) group non-respondents have outcomes one standard deviation above (below) the mean. We estimate the Kling-Liebman bounds using a regression with the benchmark set of baseline covariates.

The Horowitz-Manski upper bounds assume that all non-respondents in the free fares group had the highest response value that is observed across the free fares and control groups, and all non-respondents in the control group had the lowest observed value across the two groups. The lower bound assumes the opposite, meaning that all non-respondents in the free fares group had the lowest observed outcome and all non-respondents in the control group had the highest observed outcome. Horowitz-Manski bounds represent the worst case of item-level non-response bias in either direction, showing what the impact estimate would be if those who answered the survey question gave either maximally higher or maximally lower response values than those who did not answer the question. We estimate the Horowitz-Manski bounds using a regression with the benchmark set of baseline covariates.

As shown in Table D5, the bounds on the full-sample and subgroup effects are generally wide and do not preclude substantial effect sizes in either the positive or negative direction. The Manski bounds in particular are too wide to be informative for the effects on continuous-valued outcomes.

Table D5: Bounds on ITT effects on self-reported employment outcomes from post-endline survey

				Lee		Kling-Liebman		Horowitz-Manski	
	Free fares response rate	Control response rate	Weighted ITT effect Benchmark covariates	Lower bound	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound
A. Full sample									
Currently employed	47.3%	34.5%	-0.003	-0.068**	0.062**	-0.599***	0.582***	-0.598***	0.584***
			(0.025)	(0.027)	(0.027)	(0.010)	(0.010)	(0.010)	(0.010)
Hours worked per week (N)	44.8%	33.1%	-2.42**	-10.74***	-0.495	-26.11***	24.85***	-110.9***	94.17***
			(1.19)	(1.11)	(1.24)	(0.397)	(0.410)	(1.28)	(1.37)
Hourly wage at main job ($; among the employed)	21.3%	16.7%	-0.043	-1.90***	2.49***	-7.61***	7.44***	-22.58***	22.42***
			(0.485)	(0.389)	(0.474)	(0.066)	(0.069)	(0.139)	(0.143)
Total pretax monthly earnings ($)	43.0%	31.9%	-85.72	-546.8***	-10.96	-1,340***	1,277***	-4,053***	3,465***
			(78.33)	(66.42)	(82.08)	(19.74)	(20.39)	(46.81)	(50.36)
B. Employed at baseline									
Currently employed	49.2%	35.9%	-0.019	-0.059	0.220***	-0.551***	0.613***	-0.549***	0.614***
			(0.041)	(0.043)	(0.033)	(0.016)	(0.015)	(0.016)	(0.015)
Hours worked per week (N)	45.8%	33.6%	-5.58**	-10.15***	4.01**	-24.76***	25.99***	-110.6***	93.69***
			(2.16)	(2.12)	(2.04)	(0.684)	(0.675)	(1.96)	(2.14)
Hourly wage at main job ($; among the employed)	34.0%	26.2%	-0.448	-2.01***	1.59***	-6.78***	6.28***	-19.76***	19.29***
			(0.440)	(0.490)	(0.424)	(0.124)	(0.136)	(0.263)	(0.279)
Total pretax monthly earnings ($)	43.2%	31.7%	-74.29	-645.5***	161.3	-1,300***	1,328***	-4,068***	3,482***
			(137.8)	(94.58)	(141.0)	(34.17)	(34.45)	(71.08)	(78.88)
C. Not employed at baseline									
Currently employed	46.0%	33.4%	0.004	-0.158***	0.064*	-0.611***	0.570***	-0.610***	0.571***
			(0.037)	(0.040)	(0.038)	(0.014)	(0.014)	(0.013)	(0.014)
Hours worked per week (N)	44.0%	32.7%	0.602	-9.84***	1.50	-26.27***	24.29***	-109.5***	94.03***
			(1.45)	(1.14)	(1.50)	(0.522)	(0.531)	(1.84)	(1.90)
Hourly wage at main job ($; among the employed)	12.0%	9.5%	-0.309	-1.99***	3.07***	-8.18***	8.19***	-24.45***	24.47***
			(0.753)	(0.551)	(0.835)	(0.080)	(0.080)	(0.169)	(0.168)
Total pretax monthly earnings ($)	42.8%	32.0%	-37.51	-390.4***	-31.38	-1,346***	1,234***	-3,991***	3,419***
			(90.74)	(80.92)	(90.15)	(25.90)	(26.80)	(66.94)	(69.76)
D. Unemployed at baseline									
Currently employed	43.4%	32.1%	-0.015	-0.108**	0.039	-0.589***	0.610***	-0.588***	0.612***
			(0.053)	(0.052)	(0.052)	(0.021)	(0.020)	(0.020)	(0.020)
Hours worked per week (N)	40.8%	31.2%	2.12	-7.12***	2.66	-25.44***	26.12***	-109.3***	98.25***
			(1.92)	(1.72)	(2.02)	(0.822)	(0.792)	(2.72)	(2.71)
Hourly wage at main job ($; among the employed)	15.8%	11.9%	-0.826	-2.46***	1.41**	-8.00***	7.82***	-23.72***	23.56***
			(0.977)	(0.807)	(0.694)	(0.124)	(0.132)	(0.261)	(0.272)
Total pretax monthly earnings ($)	39.4%	30.0%	-144.1	-607.1***	-140.4	-1,353***	1,287***	-4,027***	3,556***
			(239.8)	(198.3)	(221.1)	(41.17)	(42.15)	(99.04)	(101.2)

Notes: Table presents estimates of the effect of being assigned to free fares versus no discount on self-reported employment outcomes from the post-endline survey. The survey took place 15 months after study enrollment. All estimates adjust for the following baseline covariates: Age (years), female (y/n), Black (y/n), more than high school education (y/n), currently employed (y/n), PRT trips taken last week (N), and lives within the PRT 7-day frequent service walkshed (y/n). The weighted effects include inverse propensity weights based on the person's predicted likelihood of responding to the given survey item. Robust standard errors are in parentheses. ***p <0.01, **p <0.05, *p <0.1

D.5 Assessing selection on unobservables

Recent research has demonstrated that traditional methods for addressing survey non-response bias may not be adequate if non-response is driven by subject characteristics that the researcher cannot observe, such as the subject's potential answers to the questions in the survey (Dutz et al., 2025; Coffman et al., 2019). Our randomized survey incentive payments enable us to test for certain types of unobservable selection effects on the dimension of the incentive amount (i.e. the time value of money). Significant differences in response rates and response values between the two incentive groups would provide evidence of such selection effects.

The higher incentive group was significantly more likely than the low incentive group to respond to each survey question shown in Table D6. The differences in item-level response rates in the table range from 3.8 to 6.0 percentage points. We next leverage these randomly-induced differences in response rates to test for selection bias by comparing the mean response values to these survey questions between the two incentive groups. Table D7 compares the mean answers in the low and high incentive groups and tests whether the difference is zero. Respondents in the high incentive group reported a 3.1 percentage point higher employment rate than the respondents in the low incentive group. The high incentive respondents also reported working 1.58 more hours per week.

Comparing the mean answer among the *marginal responders* (i.e. those who respond to high but not low incentives) with the mean answer among the *always-responders* (i.e. those who respond to low and high incentives) provides a more direct test of selection into survey response on the answer to the given survey item. To make this comparison, we follow the methods in Coffman et al. (2019). We consider the responders in the \$10 incentive group to be always-responders. We calculate the mean answer among marginal responders as $y_{marg} = \frac{r_{20}}{r_{20}-r_{10}} \cdot y_{20} - \frac{r_{10}}{r_{20}-r_{10}} \cdot y_{10}$, where r_{20} is the item response rate among the \$20 incentive group, r_{10} is the item response rate among the \$10 incentive group, and y_{20} and y_{10} are the mean response values among the respective incentive groups.

The results are shown in the rightmost column in Table D7. The size of the mean differences between the marginal and always-responders and the standard errors of these differences are both inflated by the relatively small differences in response rates between the low and high incentive groups. As in Coffman et al. (2019), the lack of a large response to incentives makes it difficult to assess how different the marginal responders are from the always-responders in terms of their responses to the survey questions. Nonetheless, certain differences in response values reach conventional levels of statistical significance; for example, the marginal responders work an estimated 11.4 more hours per week than the always-responders and are 20.8 percentage points less likely to commute by bus. Furthermore, some of these significant differences persist or become even larger when correcting for selection on *observable* characteristics (D7 panel B). This persistence implies that nonresponse weights for selection on observables are not sufficient to correct for selection on the person's response value to the survey question itself (i.e. selection on unobservables) in our setting.

Based on these results, we are not able to rule out substantial selection bias on unobservables in the self-reported employment outcomes from the post-endline survey, even after correcting for selection on observable traits. Dutz et al. (2025) provide guidance for correcting survey selection on unobservables. They conclude that bounding exercises with minimal assumptions tend to yield wide bounds when the overall survey response rate is fairly low, as is the case in our study. Bounds with stronger assumptions can be more informative, but this depends on the particular study context. We therefore do not attempt to further correct our survey results for selection on unobservables. We interpret our survey-based findings as merely exploratory and worthy of further research, perhaps using methods that contain multiple dimensions of exogenous variation in the likelihood of answering the survey

Table D6: Post-endline survey item response rates for high and low incentive groups

	High incentive ($20)		Low incentive ($10)		
	Number invited	Response rate	Number invited	Response rate	$20 vs. $10 diff.
Employed	4,771	0.436	4,773	0.376	0.060*** (0.010)
Not working, but would like to work	4,771	0.436	4,773	0.376	0.060*** (0.010)
Hourly wage at main job ($; among the employed)	4,771	0.209	4,773	0.164	0.046*** (0.008)
Weekly work hours (N)	4,771	0.415	4,773	0.358	0.057*** (0.010)
Total pretax monthly earnings ($)	4,771	0.402	4,773	0.343	0.060*** (0.010)
Satisfied with main job overall (among the employed)	4,771	0.227	4,773	0.182	0.045*** (0.008)
Primary commute mode to main job last week (among the employed)					
Bus	4,771	0.209	4,773	0.166	0.043*** (0.008)
Personal car	4,771	0.209	4,773	0.166	0.043*** (0.008)
Round-trip commute time on typical day (minutes; among the employed)	4,771	0.164	4,773	0.125	0.038*** (0.007)
Actively searched for job in past 4 weeks	4,771	0.348	4,773	0.295	0.054*** (0.010)
I have finished the survey	**4,771**	**0.455**	**4,773**	**0.397**	**0.058*** (0.010)**

Notes: This table compares post-endline (15-month follow-up) survey response rates between the high ($20) and low ($10) incentive groups across all three study arms. Participants were randomly offered either $10 or $20 for completing the survey. The majority of questions in the survey did not force a response, such that participants were able to complete the survey without answering all questions. Robust standard errors are in parentheses. ***p <0.01, **p <0.05, *p <0.1

Table D7: Comparing post-endline survey response values of high and low incentive groups

	High incentive ($20)		Low incentive ($10)			
	Number of respondents	Mean	Number of respondents	Mean	$20 vs. $10 difference	Marginal responders vs. always-responders difference
A. Without inverse propensity weights for survey non-response						
Employed	2,078	0.520	1,793	0.489	0.031* (0.016)	0.227* (0.125)
Not working, but would like to work	2,078	0.172	1,793	0.181	-0.009 (0.012)	-0.069 (0.093)
Hourly wage at main job ($; among the employed)	999	14.19	782	13.76	0.422* (0.216)	1.94* (1.01)
Weekly work hours (N)	1,980	17.52	1,707	15.94	1.58** (0.684)	11.41** (5.56)
Total pretax monthly earnings ($)	1,920	622.6	1,635	549.9	72.68** (33.77)	488.5** (248.9)
Satisfied with main job overall (among the employed)	1,083	0.471	867	0.469	0.001 (0.023)	0.007 (0.118)
Primary commute mode to main job last week (among the employed)						
Bus	997	0.605	792	0.648	-0.043* (0.023)	-0.208* (0.120)
Personal car	997	0.146	792	0.116	0.030* (0.016)	0.147* (0.087)
Round-trip commute time on typical day (minutes; among the employed)	781	89.98	599	70.86	19.11** (8.45)	81.91** (39.80)
Actively searched for job in past 4 weeks	1,661	0.454	1,406	0.443	0.011 (0.018)	0.070 (0.127)
B. With inverse propensity weights for survey non-response						
Employed	2,078	0.466	1,793	0.492	-0.026** (0.024)	-0.189 (0.211)
Not working, but would like to work	2,078	0.153	1,793	0.214	-0.061* (0.019)	-0.440*** (0.170)
Hourly wage at main job ($; among the employed)	999	9.95	782	11.06	-1.11 (0.396)	-5.11 (3.15)
Weekly work hours (N)	1,980	16.48	1,707	16.36	0.113** (1.03)	0.818 (8.81)
Total pretax monthly earnings ($)	1,920	584.0	1,635	553.8	30.29** (51.32)	203.6 (386.3)
Satisfied with main job overall (among the employed)	1,083	0.347	867	0.431	-0.083 (0.037)	-0.417** (0.205)
Primary commute mode to main job last week (among the employed)						
Bus	997	0.435	792	0.538	-0.103 (0.037)	-0.501** (0.217)
Personal car	997	0.102	792	0.085	0.016 (0.024)	0.079 (0.099)
Round-trip commute time on typical day (minutes; among the employed)	781	68.78	599	66.14	2.64 (16.55)	11.32 (60.65)
Actively searched for job in past 4 weeks	1,661	0.379	1,406	0.431	-0.052 (0.027)	-0.337 (0.214)

Notes: This table compares respondents' answers to certain post-endline (15 month) survey questions between the high ($20) and low ($10) incentive groups across all three study arms. The majority of questions in the survey did not force a response. Participants were thus able to complete the survey without answering all questions. Following the methods shown in Appendix A of Coffman et al. (2019), we calculate the mean response value for the 'marginal' responder as $y_{marg} = \frac{r_{20}}{r_{20}-r_{10}} \cdot y_{20} - \frac{r_{10}}{r_{20}-r_{10}} \cdot y_{10}$, where r_{20} is the item response rate among the $20 incentive group, r_{10} is the item response rate among the $10 incentive group, and y_{20} and y_{10} are the mean response values among the respective incentive groups. Robust standard errors are in parentheses. The standard errors for the mean difference in responses between the marginal responders and always-responders are calculated using bootstrapping. ***p <0.01, **p <0.05, *p <0.1

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