The Role of the Fare in Welfare: Public Transportation Subsidies and their Effects on Low-Income Households*

Seth Chizeck & Oluchi Mbonu

April 2025

Abstract

Can reducing public transit fares improve mobility and socioeconomic outcomes for low-income individuals? We conduct a randomized experiment that offers fare discounts to 9,544 low-income households in one large U.S. county. Households are randomly assigned to receive no discount, a 50% discount, or a 100% discount on all public transit trips for 16 to 19 months. We measure participants' mode-specific travel behavior using a combination of smartphone GPS data, high-frequency surveys, and farecard transactions. GPS data indicates that free fares increase transit ridership by 43% relative to status quo prices, accompanied by a shift away from private vehicle use along several margins. Half-price fares yield no change in transit ridership. Both discount levels improve self-reported measures of travel capabilities, but neither one increases the overall frequency or spatial breadth of travel itself. Exploratory sub-group analyses reveal positive labor market impacts among those who were unemployed at baseline: free fares cause a 3.5 pp increase in the likelihood of being employed and a $2,845 increase in total earnings during the first six quarters for this sub-group. The social welfare impact of free fares exceeds the fiscal cost of the policy during the first two years. Fare-free transit shows promise as a means of helping disadvantaged job seekers and as a tool for mitigating the environmental externalities of car travel.

JEL Classification Codes: H4, H7, I3, R4, R5
Keywords: Public transportation, transit subsidies, randomized controlled trial

* **Chizeck:** Carnegie Mellon University (email: schizeck@andrew.cmu.edu). **Mbonu:** Harvard University (email: ombonu@g.harvard.edu). We are grateful to our partners who implemented the experiment: the Allegheny County (PA) Department of Human Services (especially Alex Jutca, Melanie Sanfilippo, and Jonathan Rainey), and Pittsburgh Regional Transit (especially Kelsey Shannon and Steven Angelo). We thank Emily Breza, Ed Glaeser, Felix Koenig, Gabriel Kreindler, David Phillips, Ben Sprung-Keyser, as well as audiences at APPAM, RECS, University of Michigan, MIT Policy Impacts, UEA, and SEA for helpful comments. We gratefully acknowledge funding from the Allegheny County Department of Human Services, J-PAL North America Social Policy Research Initiative, and Policy Impacts. This study was pre-registered with the AEA RCT registry (AEARCTR-0011001) and was approved under Carnegie Mellon IRB (2022_00000322) and Harvard IRB (22-0327). The views expressed here are solely those of the authors and do not necessarily reflect the views of Allegheny County.

1 Introduction

Public transportation riders typically must pay a fare upon boarding. This method of financing transit services may be sub-optimal if fares constrain riders' mobility and economic productivity. Uniform fare prices also have the potential to exacerbate inequalities, as lower-income riders rely disproportionately on public transit (Santos et al., 2014; Clark, 2017) and devote a larger share of their budget to transportation than any other major spending category besides housing.[1] To what extent do public transit fares hinder spatial movement and economic activity? In the labor market, travel costs have long been theorized to impede job search and the ability to access job opportunities, particularly 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). More broadly, it is unclear how strongly fare prices bind on the travel capabilities of urban residents relative to the frequency and accessibility of transit service.

Answers to these questions would inform cities' efforts to design more efficient and equitable transportation systems. Several cities around the U.S. have enacted means-tested reduced fares in recent years (Boyanton, 2023; Darling et al., 2021; George, 2023), while others are currently exploring such policies (Fitzgerald, 2023; Perdomo-Hernandez, 2023). Free fares became temporarily widespread during the Covid-19 pandemic, when many agencies waived the price of boarding, and debate continues on whether transit should be permanently free (Barry, 2020).

This paper uses a randomized controlled trial to study the effects of free and reduced-price public transportation fares on travel behavior, employment, health care utilization, and other socioeconomic outcomes among low-income households. Our study enrolled a sample of 9,544 households that receive Supplemental Nutrition Assistance (SNAP) benefits in Allegheny County, Pennsylvania, which includes the city of Pittsburgh. One adult (aged 18 - 64) per household was permitted to participate, with the option to include their children (aged 6 - 17). The total sample size of 9,544 adults and 4,928 children 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

[1] According to the 2022 Consumer Expenditure Survey, consumer units in the lowest income quintile spent 41.0% of their budget on housing and 15.1% on transportation.

16 to 19 months, depending on when the individual enrolled in the study.

We first examine the effects of the fare discounts on mobility and travel behavior. Our preferred estimates of the effect of fare discounts on public transit ridership come from Google Maps location history ("GPS") data that was collected from the smartphones of a subset of consenting participants throughout the study period. According to this rich geospatial data, free fares increased ridership by a statistically significant 1.48 (SE = 0.716) trips per week, a 43% increase relative to no discount. Half-price fares yielded no detectable change in transit ridership, with the 95% interval ranging from 1.45 fewer trips to 1.05 more trips per week. The nonlinearity in demand supports the idea that consumers value free products over and above the monetary cost (Shampanier et al., 2007). It also suggests that the half fare group faced mental transaction costs and other hassles, such as still needing to load money onto their fare cards, which disappear when fares become free.

The positive effect of free fares on transit ridership resulted mainly from substitution away from other modes of travel. Free fares caused a 5.6 percentage point reduction in the likelihood of taking a car trip on a given day, and reduced total weekly car travel by an estimated 1.67 trips. Free fares also increased the weekly distance (+6.8 miles) and duration (+39 minutes) of travel by public transit, with corresponding decreases in the distance (-10.15 miles) and duration (-75.6 minutes) of weekly travel by car. These patterns of substitution also appear in participants' responses to travel diary surveys that were administered at frequent intervals throughout the study. The free fares group was 2.9 percentage points (8.4%) less likely than the control group to report taking at least one car trip on a given day, with a corresponding 2.6 percentage point (4.5%) increase in the likelihood of reporting taking at least one public transit trip. Free fares recipients were also 4.6 percentage points (9.8%) less likely to report taking a walking or biking trip on a given day, suggesting some degree of substitution away from self-powered modes of travel as well. According to the GPS data, fare discounts had no effect on the number of trips taken per week when looking across all travel modes. The discounts also did not alter the frequency with which participants visited certain types of places, with no detectable effects on the number of weekly visits to grocery stores, convenience stores, restaurants, or schools. Together, these results suggest that fare discounts led participants to make greater use of public transportation for their travel needs, but did not necessarily lead them to take new trips that they would not otherwise have taken.

Moreover, the fare discounts did not lead to greater total mobility and may have even *reduced* the frequency and spatial breadth of travel by certain measures. Free fares recipients spent 76 fewer minutes traveling and traveled 8.8 fewer miles than the control group on a weekly basis when looking across all modes of travel. The free fares group also left their home 18.9% fewer times than the control group. Similarly, travel diary survey responses indicate that the free fares group visited 17.6% fewer places than the control group and was 18.7% more likely to not leave their house at all on a given day. We interpret these results as consistent with a shift away from car-based travel, as car trips tend to involve more raw spatial movement than walking or riding the bus. At the same time, fare discounts yielded large improvements in self-reported transportation security according to a validated questionnaire. Transportation security refers to the experience of being able to move from place to place in a safe and timely manner. Fare prices thus appear to constrain residents' *capacity* to travel rather than their level of raw spatial movement.

With these first-stage effects on travel in mind, we next examine treatment effects on downstream outcomes by linking the study participants to a variety of administrative data sets related to employment, public assistance, criminal justice, and health care. We also collect self-reported information on health, finances, and well-being from three waves of follow-up surveys that took place at six, 11, and 15 months after study enrollment.

Using state wage records, we find no detectable effect on the average sample member's cumulative likelihood of being employed in the first six complete calendar quarters after joining the study. However, this average effect is dampened by the fact that 30% of the adults in our sample reported being out of the labor force at baseline. Positive effects emerge when focusing on the adults who are closer to the margin of paid work. Among those who reported being out of work with a status of "unemployed" at baseline, free fares caused a 3.5 percentage point (6%) increase in the cumulative likelihood of having any paid employment in the first six quarters, as well as a \$2,845 (27.9%) increase in cumulative earnings over this time period. These improvements in labor market outcomes remain statistically significant and relatively stable across model specifications, although the earnings effect decreases to \$1,692 when winsorizing earnings at the 99th percentile. The gain in earnings appears to be driven mostly by movement into employment rather than by greater earnings when employed. Unlike the rest of the sample, the baseline-unemployed sub-group *increased* its total mobility along several dimensions in response to free fares, though it is unclear whether this increased spatial movement is a cause or a consequence of their employment gains.

We estimate a precise null effect on adult participants' overall likelihood of receiving health care, as measured from Medicaid claims data. The 95% confidence interval for the effect of free fares excludes effects larger than +/- 1 pp on the likelihood of having at least one Medicaid claim in the first 18 months (540 days) of study participation. Effects are similarly small for the use of specific categories of health care along the extensive and intensive margin, including no effect on the volume of routine preventive care among adults or their children. There is a suggestive 25% increase in the amount of behavioral health care that children received in response to free fares. The minimal changes in health care consumption are accompanied by similarly small effects on adults' self-reported health status according to follow-up surveys. The treatment did not affect ratings of overall life satisfaction or social connectedness. Nor did the treatment affect monthly savings, debt balances, or financial well-being as measured by the Consumer Financial Protection Bureau Financial Well-Being Scale.

Contributions and takeaways. Our study contributes to several bodies of literature in urban and labor economics. First, we provide improved experimental estimates of the price elasticity of demand for public transportation. Recent fare pricing RCT's in Boston (Rosenblum, 2020), Seattle (Brough, Freedman, & Phillips, 2022; Brough et al., 2024), and Washington, D.C. (Huberts et al., forthcoming) have all found evidence that riders use their assigned public transit farecards more frequently in response to discounted fares. This method of measuring trip-taking has reliability concerns, however, as riders may take trips using other payment methods or share their farecards with others. Our measurement of ridership using GPS data and high-frequency diaries results in much smaller and arguably more credible estimates of price elasticity than have been found in prior experiments. Our enhanced mobility measurements also establish the first robust evidence in this literature of mode substitution in response to fare subsidies.

We further build upon the existing RCT's by providing longer-term subsidies that last for a full 16 to 19 months – compared to previous studies' maximum of nine months – allowing participants to potentially make higher fixed-cost behavioral changes in response to sustained fare reductions. Additionally, the inclusion of children in our sample offers the opportunity to explore the relationship between transit prices and youth-specific outcomes such as school attendance and health care consumption. These features of our study build out a more complete picture of the impacts of transit subsidies on low-income households.

Second, we contribute to the literature on spatial mismatch, which considers the extent to which differential access to jobs across neighborhoods is responsible for disparities in labor market outcomes (Kain, 1968, 1992; Holzer et al., 1994; Ihlanfeldt & Sjoquist, 1998). Much of the research on transportation barriers to employment has focused on the effects of expanding public transit infrastructure (Gobillon et al., 2007; Tyndall, 2021; Holzer et al., 2003) or having access to a personal car (Blumenberg & Pierce, 2017; Raphael & Rice, 2002). Several RCT's have documented positive impacts of public transit subsidies on job search behavior (Phillips (2014), Franklin (2018), and Abebe et al. (2021)), suggesting that fare prices constrain lower-wage workers. Brough et al. (2024), however, find no effect of fare subsidies on employment and earnings when averaging across a broad cross-section of poor residents. We instead focus on a subset of people who are closer to the margin of paid work: those who self-report being unemployed at baseline. This group is most relevant for testing theoretical predictions of the effect of commute costs on labor supply. Our finding of large earnings gains among the unemployed provides novel evidence of spatial frictions in labor markets. In fact, the per capita cost-effectiveness of eliminating transit fares likely exceeds that of several other active labor market policies, including many vocational training programs.

Third, we add to research that explores ways of reducing car travel. Private vehicle trips account for a substantial share of greenhouse gas emissions worldwide, and reducing car-based travel is a key goal for addressing climate change. The first-best policy solutions, Pigouvian taxes and other price instruments, are often politically infeasible and can have a regressive distributional impact. There is also little credible evidence to date on the effectiveness of expenditure-based approaches to reducing car travel such as financial incentives or improving public transit service (Okraszewska et al., 2024). Our low-income sample relied heavily on automobiles at baseline, but they responded to free fares by re-optimizing their travel patterns and shifting away from cars along several margins. Importantly, their substitution away from car travel came with no decrease in labor output, and earned income even increased among the baseline-unemployed. Our study offers the strongest evidence to date that fare-free transit mitigates the negative externalities of car travel in the short-run, with no apparent loss of economic productivity in the process.

Fourth, we inform the longstanding debate on the extent to which transit should be subsidized by the government. The three main arguments in favor of subsidies are that: 1) Increased ridership provides scale economy benefits for transit operating costs per passenger mile (Mohring, 1972; Jansson, 1979) 2) Lower fares reduce the negative externalities of car travel if first-best car taxes are infeasible, and 3) Lower fares improve equity because poorer people rely disproportionately on transit. The main argument against subsidies is that expanding transit use has a negligible effect on traffic congestion in the long-run equilibrium (P. R. Stopher, 2004; Winston & Maheshri, 2007; Litman, 2004). Accordingly, the quantitative modeling literature on optimal urban transport pricing has delivered mixed results.[2] We analyze the net social welfare effect of free fares using the marginal value of public funds (MVPF) framework. While our analysis assumes only a partial equilibrium, we find free fares to have a positive social return on investment at least in the short run. This lends support to the idea that current fare prices are inefficiently high.

[2]Proost and Dender (2008), Parry and Small (2009), and Almagro et al. (2024) all find that optimal subsidies would extend far beyond current levels and may be near zero, while Winston and Shirley (2010) find that it would be more efficient to raise fares.

Our study has several policy takeaways. For labor policy, targeted fare subsidies appear to be a cost-effective means of helping unemployed workers move back into employment. For environmental policy, free fares are a promising tool for incentivizing more sustainable modes of travel while avoiding concerns about regressivity or reduced economic output. Finally, for transportation policymakers, we establish that fare prices strongly influence low-income individuals' travel mode choices. The increased ridership in response to free fares, while arguably moderate in magnitude, demonstrates that fare prices do still bind on riders. Even amid concerns about rampant fare evasion in U.S. cities (Leonhardt, 2024), riders are not able to dodge the fare every time they board. More broadly, eliminating transit fares yields social welfare returns in the first two years that likely exceed the fiscal cost of the policy. Policymakers should consider these findings when deciding whether to invest more heavily in public transportation.

2 Experimental design

2.1 Study setting

Our 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 transit 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.[3] 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.[4]

Allegheny County has significant income disparities across neighborhoods, as illustrated by the census tract-level poverty rates in Figure 1 panel B. At the same time, residents who rely on public transportation may have trouble reaching employment opportunities. The map in Figure 1 panel C presents the percentage of all jobs in Allegheny County that are

[3]Calculations based on data from Federal Transit Administration National Transit Database.
[4]Calculations based on data from American Community Survey Table S0802 2022 5-year estimates.

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 areas, such as the Hill District and Homewood 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, social services, and other urban amenities that are otherwise easy to reach by public transit.

Our study was designed and implemented in collaboration with the Allegheny County Department of Human Services (ACDHS) and 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. The study was publicly branded by ACDHS as the "Discounted Fares Pilot", a limited-time human services program that offered public transportation discounts to low-income residents.

2.2 Eligibility and recruitment

Eligibility criteria. Study enrollment began on November 17, 2022. The study was open to all individuals who lived in Allegheny County, 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.[5] 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. Enrollment for the study closed 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

[5] 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.

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]

2.3 Enrollment and random assignment

Study enrollment was done on a rolling basis through an online portal. Applicants first signed a consent form, then completed a short screening application followed by a baseline survey [7] The 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 by automatically cross-referencing the application with administrative SNAP records held by ACDHS. The baseline survey was mandatory; people could not enroll in the study without completing it. Before starting the baseline survey, applicants were shown a message emphasizing that their answers to the survey will not affect their random assignment outcome.

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. The random assignment was essentially conducted at the SNAP household level because each adult participant came from a different SNAP household. Participants were immediately informed about their eligibility for the study and their assigned fare discount level. All participants were thus randomized on the same date that they enrolled in the study. We use the terms 'randomization date' and 'enrollment date' interchangeably throughout this paper.

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

[6]The recruitment flier is shown in Appendix Figure D1.

[7]Appendix Figures D2 through D5 provide screenshots of the consent form and screening application.

the card within approximately one week of enrollment. These participants therefore 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.

Participants also indicated in their application whether they wished to receive ConnectCards for the 6-to-17 year-old children in their SNAP household. Participants who chose this option received additional ConnectCards for each child age 6 to 17 in their SNAP household.[8] These additional cards contained the same fare discount that the adult was assigned to.

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.

Provision of fare discount. Each participant received a ConnectCard that was programmed with the appropriate fare discount level. ConnectCards for participants in the control group and 50% discount 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 50% 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 50% discount 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.[9] The ConnectCards for the 100% discount 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 them a replacement card, so that each participant had only one active assigned card at a time.

[8] Children under age 6 already ride for free on all PRT vehicles.

[9] 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.

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.[10] 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.[11] 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 pilot 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 simultaneously deactivated on June 30, 2024. The study-issued ConnectCards for the half fare group and control group remained active indefinitely. However, ACDHS stopped providing replacement ConnectCards for these two groups on June 3, 2024, and began directing study participants with lost, stolen, or damaged farecards to join the permanent AlleghenyGo program instead.

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 status quo control group was in effect for a total of 18 months.

Analytic sample. The study enrolled a total of 9,574 adults (age 18 to 64, each from a separate SNAP beneficiary household) and 4,949 children ages 6 to 17. Twenty-three of these individuals were duplicate enrollees and are excluded from the study sample along with all participating members of their SNAP households. Another nine enrollees provided a combination of name, date of birth, and social security number that made it impossible to discern their true identity. These nine enrollees are also excluded from the sample. The resulting analytic sample contains a total of 14,472 individuals, including 9,544 adults.

3 Data and sample description

Public transportation fare discounts could impact many aspects of a person's life. We measure a variety of participant outcomes in order to capture the breadth of the program's effects. We use a combination of administrative and survey data to measure outcomes

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

[11]ACDHS decided to extend the fare discounts beyond 12 months because it was in the process of planning the follow-on permanent version of the pilot program, and did not want to cut off the study participants from their discounted fares before the new permanent program was in place.

related to transportation, travel, employment, health care, and criminal justice, as well as self-reported measures of financial stability, health, and well-being.

3.1 Administrative data

We draw upon several administrative datasets from ACDHS, PRT, and other agencies to measure participants' transportation patterns and their downstream socioeconomic outcomes. First, we link the study-issued ConnectCards to PRT records that capture the use of the card. These records provide information on the date and time of each card tap, as well as the PRT route on which the card was tapped. For the control group and half-fare cards, which required users to load fare value onto the card, we receive PRT data on the type of fare product that was used to pay for each card tap, and the remaining cash balance on the card at the time of each tap.

Second, we link participants to Pennsylvania unemployment insurance (UI) records. This dataset covers all UI-eligible employment in Pennsylvania, which excludes jobs such as independent contracting and informal work. The data reports whether an individual had UI-eligible employment in each calendar quarter, and how much money the person earned from each of his or her 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 is matched with the study sample based on social security number, meaning that the data is not available for the 90 adult sample members who do not have a social security number on file with ACDHS. The data is available for nearly all other participants starting in the fourth quarter prior to random assignment, and is available for a subset of participants going back to 12 quarters prior to random assignment.

Third, participants are linked with the universe of Medicaid health care claims for Allegheny County. Medicaid provides health insurance to individuals and families with low incomes. Over 97% of the study sample was enrolled in Medicaid at baseline, making this dataset a comprehensive source of information on participants' health care utilization. We are able to measure participants' use of health care at the claim level, including diagnosis codes and procedure billing codes for all types of physical health care, mental health care, and prescription drug fills. The mental health care data also includes the cost that was billed to the managed care organization for each claim. These costs do not represent the direct cost of care to Medicaid or taxpayers, as the managed care organization receives a fixed reimbursement from Medicaid on a per-patient basis. Nonetheless, these billed amounts provide a monetary measure of the intensity of care utilization.

Fourth, we measure involvement with the criminal justice system using records from the Allegheny County Jail and the county court system. The court data allows us to observe arrests and citations for all crimes committed within Allegheny County. The data is categorized by type of filing (summary, misdemeanor, or felony) and by type of crime (e.g. domestic violence, drugs, motor vehicle). We also observe bookings in the County Jail and the number of days spent in jail, as well as failures to appear for a criminal court hearing.

Fifth, we use ACDHS administrative records to observe participants' involvement in a variety of social services, including SNAP, Temporary Assistance for Needy Families (TANF), Supplemental Security Income (SSI), Medicaid, Section 8 rental housing subsidies, homeless shelters, child protective services, and the Pennsylvania Child Care Works subsidized child care program. Our data-sharing partnership with ACDHS also includes academic records for the 6-to-17 year-old study participants who attend Pittsburgh Public Schools. All of these social services and education records are linked using a common individual-level identifier within the ACDHS database.

3.2 Surveys and active data collection

Baseline survey. Each study applicant completed a mandatory baseline survey immediately before random assignment. Participants were told up front that their responses to the survey would have no influence on 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. Regarding transportation use, the survey asked how many one-way PRT trips the person took in the past week, how much money they spent last week on PRT, and which mode of payment they use most often to pay for PRT trips.

We gathered information on a variety of post-enrollment outcomes using three forms of data collection that required active engagement from the adult study participants (child participants were excluded from all active data collection activities).

Travel diaries. We administered text message-based travel diary surveys that asked participants the following five questions about their travels and whereabouts from 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

Participants were invited to opt into the travel diary surveys three days after they joined the study. Those who opted in received a survey every three days for the first two months, then one survey per month for the next 10 months, then one survey per week for the next two months. Those who did not opt in received further invitations in each subsequent month until they either opted in or opted out. Respondents were randomly assigned at the beginning of the study to receive either \$1 or \$2 for each diary that they completed throughout the study.[12]

Follow-up surveys. We fielded three rounds of web-based 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. The surveys asked questions related to transportation and travel behavior, employment, financial stability, health, and subjective well-being. Respondents were randomly assigned at the beginning of the study to receive either \$10 or \$20 for completing each survey. They received payment immediately after completing the survey.

GPS data. We invited all study participants to share their Google Maps location history data from their smartphone. This data contains detailed information on the phone's spatial mobility, including timestamped locations, travel patterns, and inferred modes of travel for each movement spell. This information allows us to estimate treatment effects separately by travel mode and explore substitution across modes.

Study participants were invited via text message and email to opt into the Google Maps data-sharing task. Those who opted in were provided with instructions for enabling the necessary settings in their Google Maps app to record their location history. Each month, a randomly selected subset of participants were prompted to export their Google Maps location history file and share it with the research team. Participants received \$1 for each day that their location history covered in the requested month. This monthly process continued until April 2024. In a final attempt to expand data collection, we invited all study participants to opt into the task in April 2024 and prompted all participants to share their data in early May 2024. Those who shared their data in this final month received \$10 if

[12]We use this randomization to test for non-response bias in Appendix C, following the procedure outlined in Dutz et al. (2022).

their location history covered at least 10 days in April 2024, and \$0 otherwise.

3.3 Sample description

Table 2 presents the baseline characteristics of the 9,544 adult study participants. The majority of participants are Black and female, and over half reported having no more than a high school education. Participants reported taking an average of 10 PRT trips and spending an average of \$30 on public transportation in the past week. More than 80% of the sample reported not having access to a car. Less than half of the sample reported being employed. Those who were employed reported working around 30 hours per week and earning \$13 to \$14 per hour. The administrative UI data echoes the low earnings of the sample, as only 51% of adult participants had paid employment in the quarter before enrollment, and those who were employed in this quarter earned an average of around \$4,400. The relatively low education and earnings of the sample are to be expected, given that all participants were receiving means-tested SNAP benefits in the months prior to enrollment. Table 2 also demonstrates that the random assignment worked as intended and yielded groups that were balanced on key characteristics. The small differences between the groups are not statistically significant at rates higher than what would be expected by random chance.

Table 2 also presents some characteristics of the entire study-eligible population, meaning all 89,024 Allegheny County residents ages 18 to 64 who received SNAP benefits in September 2022. Compared with the full eligible population, our study participants were more likely to be female, Black, employed, and living close to high-frequency transit service.

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.

4 Empirical strategy

We estimate the effects of the fare discounts using 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 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 Y_i 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 intent-to-treat effects, or the average effects of being assigned to the 50% and 100% discounts respectively. Standard errors are heteroskedasticity-robust and clustered at the individual level.

Our pre-analysis plan did not specify the exact covariates to be included. 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 or not the person lives inside the PRT seven-day frequent service walkshed.[13] These baseline covariates have non-missing data for all adult participants. We also adjust for the outcome variable measured prior to random assignment when such data is available.

Many of our focal study outcomes are measured at multiple time points. We use regression (1) to estimate treatment effects at various 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 use cross-sectional regressions with outcomes that are pooled over the entire post-enrollment study period and weighted by the total number of possible observations, such as when estimating effects on the likelihood of taking a transit trip on a given day from the travel diary data. Where appropriate, we test the robustness of the pooled cross-sectional results by using panel data models that include fixed effects for relative time and calendar time (individual fixed effects cannot be included because the treatment indicator is time-invariant).

Our pre-analysis plan listed two primary outcomes for the full sample: 1) Total earnings in the third full calendar quarter after random assignment, and 2) The number of primary health care visits in the first nine months after random assignment. The effects on these two outcomes are presented in Figures A2 and A4, respectively. Any statistically significant effects beyond our two pre-specified outcomes 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.,

[13] PRT defines a walkshed as the 1/4-mile area around a transit stop or the 1/2-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.

2006; M. L. Anderson, 2008) when presenting average effects for the full sample of adults or children. The q-values are based on the number of hypothesis tests within each document table.

5 Results

5.1 Treatment take-up

We begin by examining the use of the study-issued ConnectCards through which participants accessed their fare subsidies. The vast majority of treated participants successfully gained access to the intervention and made use of their fare subsidy for at least one trip.[14] Figure 2 shows the percentage of adults in each study group that ever tapped their assigned ConnectCard on a PRT vehicle.[15] 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 the average treatment effects on 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 6 to 9 times per month and the free fares group tapped their cards an additional 14 to 25 times per month.

Study-issued farecard taps do not provide a reliable measure of a person's actual volume of transit ridership for two reasons. First, this data does not capture boardings that were paid for using other farecards or other payment methods, or boardings where the person evaded the fare. Second, some participants shared their cards with other people, in which

[14] 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.

[15] 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.

case the farecard taps reflect some trips taken by people besides the intended participant.[16] In light of these measurement concerns, we do not consider the impacts on ConnectCard taps to be a reliable estimate of the effect of treatment on total transit ridership.

5.2 Public transportation ridership

Effects of free fares. Free fares increased public transit ridership relative to status quo prices. Table 3 presents effects on the number of public transportation trips taken per week, using various measures of ridership.[17] The bottom row contains our preferred estimates, which come from the smartphone Google Maps location history (GPS) data that was collected from a subset of adult participants. According to this data, free fares increased the weekly number of public transit trips by 1.48 from a base of 3.47 trips per week. On the extensive margin of daily ridership, free fares increased the likelihood of taking at least one public transportation trip on a given day by 5.2 percentage points from a base of 20.5% among the control group. (A similar effect appears in the travel diary responses, shown in Table 5 panel A). On the intensive margin, free fares increased the number of daily trips taken on days with at least one transit trip by 0.29 from a base of 2.09 trips (Appendix Table A13). These GPS-based effects remain relatively stable when adjusting for different sets of covariates, weighting each individual by the number of days covered by their GPS data, and using day-level panel regressions instead of pooled cross-sectional regressions (Appendix Table A13).

The positive effects grew in magnitude over the first five months of study participation, then plateaued and declined in months six through 12 (Appendix Figure A5). The increases in ridership were larger on weekdays than weekends and were concentrated only on trips taken by bus; trips taken by light rail did not change in response to fare discounts (Appendix Figure A7). Most of the increase in public transportation ridership took place during off-peak periods, although the difference between peak versus off-peak treatment effects is not statistically significant.[18] The participants who rode public transit least often at baseline had a larger ridership response to free fares than the participants who rode most often,

[16] Four percent of post-endline survey respondents in the free fares group reported sharing their card with other people. Card sharing may partly explain why participants in the free fares group reported spending a non-zero amount of money on transit despite having access to unlimited free trips (see Appendix Table A1 for these results). Card sharing also poses the threat of treatment spillovers if a higher-discount participant gave their card to a lower-discount participant. Appendix Table A19 provides some evidence that such spillovers were minimal.

[17] The terms "trip" and "boarding" are synonymous throughout this paper when discussing public transit ridership. A "trip" is defined as a single ride on a transit vehicle, which could be one part of a multi-stage journey with transfer boardings.

[18] Guzman and Hessel (2022) and Brough, Freedman, and Phillips (2022) similarly find suggestive evidence that ridership effects load on off-peak trips.

at least as measured using travel diary data that is better-powered to identify sub-group effects (Appendix Figure A6 panels A and B).[19] We estimate a local average treatment effect (LATE) of 1.51 additional transit trips per week according to GPS data, where compliers are defined as the 92% of free fares group members that used their assigned ConnectCard at least once during the study (Appendix Table A20).

An increase of 1.48 transit trips per week is a moderately large effect size relative to the control group; 1.48 additional trips is 43% of the control mean and 0.29 of the standard deviation of weekly rides among the control group. This treatment effect also has a nontrivial cash value: 1.48 trips per week for 12 months under status quo prices costs around $212. This represents 2.3% of the mean sample member's annualized earnings in the quarter before study enrollment. It also represents 14% of the sample's mean annualized spending on public transit as reported in the baseline survey.

These treatment effects on ridership may be attenuated by fare evasion; riders will be less sensitive to the price of a transit trip if they are able to simply evade the fare. While we have no data from PRT on systemwide rates of fare evasion, our post-endline survey included a question that allows us to estimate aggregate rates of fare evasion while masking individual answers.[20] The responses indicate that 11.5% of sample adults evaded the fare in the past two weeks. The fact that transit ridership increased at all in response to free fares shows that fare prices do eventually bind; riders cannot commit unlimited fare evasion whenever they do not have enough money to board. Regardless, any reduction in effect sizes due to fare evasion reflects real-world factors that would be present in any larger-scale implementation of transit subsidies.

Effects of half fares. The half fare treatment, unlike free fares, did not yield detectable effects on public transportation ridership according to GPS data, with point estimates of -0.012 for the effect on the likelihood of taking at least one transit trip on a given day and -0.203 for the number of trips taken per week. At the 5% level, we can reject half fare effects on the weekly number of transit trips greater than 1.045 and less then -1.45 trips. The small sample size of our GPS data (N = 472 adult participants) limits our power

[19]Participants who rode public transit least often at baseline are on the margin in the sense that they presumably joined the study because they wanted to ride public transit more frequently but could not afford to under regular prices. We return to this point in Section 6 when considering participants' private welfare gains from the subsidy.

[20]The survey question was "Please answer these two questions jointly: 1) Is your mother's birthday in January, February or March? 2) In the past two weeks, have you evaded paying the bus or T fare? That is, have you ridden the bus or T without paying in cash and without using a Connect Card with sufficient funds or a suitable pass on it?" The two answer choices were a) Yes to both or no both b) Yes to one and no to the other. The structure of this question follows the cross-wise technique in Yu et al. (2008).

to detect significant effects (an increase of 1.045 trips per week is over 30% of the control mean).[21] Nonetheless, the GPS data does not rule out the possibility that reducing fares from full to half price had no effect on public transit ridership for the average participant.

Demand elasticities. Table 4 translates the treatment effects on public transit ridership into demand elasticities and compares them with the elasticities from other fare discount experiments. Our preferred estimates from GPS data imply a price elasticity of -0.12 when going from full price to half price and 0.52 when going from half price to free.

There are at least two possible reasons for the nonlinearity in demand as fare prices fall from $2.75 to $1.35 to free. First, research across product domains has found that consumers respond disproportionately to free prices relative to low-cost prices (Shampanier et al., 2007; Baumbach, 2016). Second, the half fare participants still needed to load money onto their ConnectCards in order to access the discount, whereas the free fare group simply tapped their cards to ride for free. The half fare treatment thus involved hassles and mental transaction costs that did not exist for the free fares treatment.

Improved measurement of public transportation ridership. The use of smartphone GPS data to measure transit ridership represents a key methodological contribution of our study. Other randomized fare discount studies measure ridership primarily using the tap data from study-assigned farecards. However, as mentioned above, tap data has reliability issues due to individuals sharing their cards and taking trips using other payment modes or not paying at all. Studies in this literature have also asked participants to self-report how many transit trips they take. Our surveys included several questions along these lines. The results are shown in Table 3. The control group reported a mean weekly number of transit trips in the post-endline survey (11.95) that is more than double the weekly number of farecard taps among the free fares group (5.06). The point-estimated effects of discounts are in fact mostly negative according to survey responses, in some cases reaching levels of statistical significance.

These self-reported trip counts have several measurement concerns: they may be inflated by researcher demand effects and distorted by memory error or ambiguity in the wording

[21] The 472/9,544 = 4.9% participation rate in the GPS data-sharing task also raises concerns about selection bias. We explore the extent of selection into the GPS task in Appendix section C. The free fares group was 1.5 percentage points more likely to share GPS data than the control group. Participants who opted to share their data were 5.5 percentage points more likely to be male and 21.8 percentage points more likely to be White.

of the question.[22] Smartphone GPS data, in contrast, passively records a person's trips using a device that stays in close proximity to the person being studied. At the same time, high-frequency text message travel diaries provide a method of data collection that is more accessible and user-friendly than GPS data-sharing, with no apparent loss of measurement fidelity compared with GPS data. Our finding that travel diaries do no worse than GPS data, at least when measuring the daily extensive margin of transit ridership, constitutes a new finding in the fare subsidy literature. See Appendix B for an extended analysis of the levels of agreement between our three sources of data that measure transit ridership.

Overall, we find the elasticity of demand for public transit to be much smaller than previously estimated when using a measure of trip-taking (GPS data) that is arguably more reliable than farecard usage or the self-reported number of trips taken per week (Table 4).

Income effects. Free transit fares had an average annual cash value of $359.32, based on the average number of payable (i.e. would not have been deemed a free transfer under regular prices) trips taken by the free fares group per year. Our price intervention therefore served as an implicit income transfer that changes the recipient's budget constraint. It is possible that a portion of the observed increase in public transit trips resulted from participants having more money freed up to spend on travel. For at least two reasons, we find it unlikely that a $359 cash transfer would produce a similar effect as our treatment. First, the increase in transit ridership resulted mostly from mode substitution rather than from new trips, as we describe in the next section below. Second, a recent cash transfer study with low-income participants found that only 6.5% of the total consumption response to the transfer went towards non-durable transportation expenditures (Bartik et al., 2024). If individuals allocated 6.5% of a $359 transfer to public transit, it would only cover the cost of 8.5 additional payable trips per year. This is a small fraction of the 45 additional payable trips per year that we observe in response to free fares.

[22] The relatively low follow-up survey response rates (34.5% for the midline, 38.2% for the endline, and 37.9% for the post-endline) raise the possibility that survey-based outcome measures such as these are biased by selection into (non)response. We explore the extent of nonresponse bias for the post-endline survey and the travel diaries in Appendix C. Although the three study arms had significantly different rates of overall post-endline survey completion and item-level completion, we find suggestive evidence that the likelihood of completing the survey was independent of potential outcomes after conditioning on the same set of covariates that is used in our benchmark treatment effect-estimating model. Nonresponse-weighted treatment effects are shown in Appendix Table A11 for travel-related follow-up survey outcomes and in Appendix Table A12 for the travel diary outcomes.

5.3 Other mobility outcomes

Mode substitution. The positive effect of free fares on transit ridership consisted mostly of travel mode substitution. Table 5 presents strong evidence of mode substitution from both the surveys and the GPS data. Travel diary respondents in the free fares group were 2.6 percentage points (4.5%) more likely than the control group to report taking at least one public transit trip on a given day, with a corresponding 2.9 percentage point (8.4%) reduction in rates of taking a car trip and a 4.6 percentage point (9.8%) reduction in rates of taking a walking or biking trip.

The GPS data further indicates travel mode switching. Free fares subjects were 5.2 pp more likely than the control group to take a public transit trip on a given day, and 5.6 pp less likely to take a car trip. They also took 1.67 fewer car trips per week than the control group, although the 95% confidence interval includes zero.[23] Furthermore, free fares reduced the likelihood by 9.6 percentage points (16.4%) that a person used a car for some segment of their most common journey, defined as the origin-destination pair that appeared most often in the person's GPS data prior to joining the study. Participants thus reduced their use of cars even when holding their travel path constant. Half fares produced a weaker pattern of mode substitution in the travel diary data and no detectable pattern in the GPS data.

The degree of substitution away from from car travel may seem disproportionate given that only 18% of participants reported having any access to a car in the baseline survey. However, the participants who reported no car access at baseline still had an average of 11.7 car trips per week in their GPS data prior to joining the study. Furthermore, the average control group member took 13.4 GPS car trips per week during the study, compared with only 3.5 public transit trips and 4.9 self-powered trips. Cars are by far the most common mode of travel among our study sample despite the sample's low self-reported rates of vehicle access and ownership. This leaves substantial room for substitution away from car travel towards cheaper options.

Effects on travel capabilities. We used the six-item Transportation Security Index (TSI-6) instrument developed by Murphy et al. (2024) to estimate the effect of fare discounts on recipients' perceived ability to meet their travel needs. This questionnaire was

[23]GPS car trips cover all types of automobile travel, including ridehailing trips, carpooling, and rides in another person's car.

part of the post-endline survey at 15 months after random assignment.[24] The TSI-6 defines "transportation security" as the experience of being able to move from place to place in a safe and timely manner. The free fares group experienced an 11.9 percentage-point reduction in rates of moderate-to-high transportation *insecurity*, compared with a 4.7 percentage-point reduction among the half fares group (Appendix Table A1).

It is noteworthy that 42% of respondents in the free fares group reported moderate-to-high levels of transportation insecurity despite having access to unlimited free public transit. Transportation issues persisted for many sample members even when fares were free, perhaps because of inadequacies in public transit services or other non-financial barriers to accessing transit. For comparison, the rate of moderate-to-high insecurity was only 17% among the free fares group members who reported having access to a car at baseline.

Effects on total mobility. We find little evidence that fare subsidies cause recipients to travel more extensively overall. Relative to regular fares, the subsidized fares did not increase the number of unique points of interest (i.e. places in Google Maps) that participants visited per week or the total number of trips they took per week, according to GPS data (Table 6). The confidence intervals allow us to reject free-fare increases of more than 14% of the control mean for the number of trips taken per week. We reject similarly small increases of more than 0.01 additional hours (1%) spent traveling per day and 1.4 additional miles (12%) traveled per day. In fact, the GPS-based point estimates are negative for nearly all treatment effects shown in Table 6. While some of these estimates are unstable across specifications (see Appendix Table A13), they nonetheless suggest the possibility that fare subsidies *reduced* spatial movement.

The travel diaries offer more precisely-estimated evidence of reductions in some dimensions of spatial mobility (Panel A in Table 6). The free fares group reported visiting 0.551 (14.9%) fewer places and was 2.1 percentage points (15.7%) more likely to report not leaving their house at all on a given day relative to the control group. The half fares treatment produced equally large negative effects on these measures. These effects remain statistically significant after adjusting for multiple testing and are robust to alternative specifications, including models that use nonresponse weights to adjust for selection into diary completion

[24]The six questions in this instrument are: In the past 30 days, how often...1) Did you have to reschedule an appointment because of a problem with transportation? 2) Did you skip going somewhere because of a problem with transportation? 3) Were you not able to leave the house when you wanted to because of a problem with transportation? 4) Did you feel bad because you did not have the transportation you needed? 5) Did you worry about inconveniencing your friends, family, or neighbors because you needed help with transportation? 6) Did problems with transportation affect your relationships with others?

(Appendix Table A12).

There is at least one marginal sub-group, those who were unemployed at baseline, that stands out as having greater total mobility in response to free fares. Members of this sub-group who received free fares increased their total distance traveled and the number of unique places visited per day (Appendix Table A16). We discuss this in more detail in Section 5.4.

Reasons for lack of increase in total mobility. It may be counterintuitive that reducing transit fares to zero produces no increase in the breadth or frequency of a person's travels and may even reduce some dimensions of travel. We now discuss the margins of adjustment behind this result.

The absence of an increase in total mobility is consistent with individuals re-optimizing towards less car travel. Free fares led to less car usage along several margins. Treatment group members took fewer car trips per week and were less likely than the control group to take at least one car trip on a given day (Appendix Table A13). They were even four percentage points (27%) less likely to report owning a car in the 15-month survey (Appendix Table A1), suggesting that some people no longer find it optimal to pay the fixed costs of car maintenance once transit fares become free.[25] Car trips tend to take more time and cover more distance than bus trips in absolute terms; the control group traveled twice as far by car than by bus and spent 1.9 times more time traveling by car than by bus per journey from home (Appendix Table A13). Shifting towards less car-based travel therefore leads to less total movement.

A deeper look into the GPS data reveals signs of other changes in travel behavior beneath the null effects on total mobility. Free fares led to increased trip chaining, as recipients took 15% more trips per journey from home, driven mainly by more transit trips, while also increasing the distance traveled per journey from home by 4%.[26] At the same time, free fares recipients were 5.5% less likely to travel at all on a given day but took 3.6% more trips on the days they did travel (Appendix Table A13). These patterns, while only suggestive due to statistical imprecision, signal a shift towards longer, less frequent journeys from home. The GPS data does not directly flag carpool trips, but the findings of less frequent trips from home and less widespread travel are both consistent with participants

[25]Several study participants expressed in qualitative interviews that cars were a necessary evil in their lives, providing important mobility security while also requiring costly fuel and upkeep that can be unaffordable.

[26]We define a person's home location in the GPS data as the place where they stayed most often between 2 am and 4 am in a given week. For the mobility outcomes that depend on the person's home location, our treatment effect estimates are generally robust in sign to alternative definitions of home location, though the magnitudes and levels of precision vary.

becoming less reliant on friends or family for car travel, instead taking less superfluous trips and more geographically-direct trips to their destination on their own.

More broadly, fare prices alone do not appear to constrain the types of places that the average participant visits. According to GPS data, free fares produced no detectable change in the number of visits per week to restaurants, grocery stores, shopping centers, schools, health care facilities, or "new" places that the participant never visited before joining the study (Appendix Table A13).

Mobility takeaway. Fare discounts, especially free fares, alter travel behavior along several margins. Recipients of the discounts substituted away from cars and, more suggestively, from self-powered modes of travel, while making greater use of public transportation. The increased transit ridership shows that fare evasion is not pervasive enough to make demand completely inelastic to fare prices, as some observers have posited. The decrease in car travel serves to reduce negative externalities such as carbon emissions, traffic congestion, and accidents, which contributes to the intervention's overall positive societal return on investment (see Section 6).

Fare discounts did not lead to more widespread travel overall. Free fares caused recipients to divest from car travel, which in turn may have actually reduced their total mobility. Recipients also shifted their travel patterns towards leaving home less often and taking more chained trips per journey from home.

5.4 Labor market outcomes

Full sample effects. Half fares and free fares both produced small and insignificant effects on labor market outcomes when averaging across the full sample of working-age adults. Two-thirds of the control group had paid employment at some point during the first six complete calendar quarters after the quarter in which they joined the study, according to UI wage records. Six quarters corresponds roughly to the length of time that the fare subsidies were in effect. The fare discounts did not significantly affect the likelihood of having employment over this time period. For free fares, the 95% confidence interval rules out an effect of more than +/- two percentage points (Table 7 Panel A).

The impact of fare discounts on cumulative earnings over the first six quarters was also indistinguishable from zero, with the 95% confidence interval for free fares spanning from -$588 to $977. The upper bound of this interval represents 5.7% of the control group's mean earnings over the first six quarters. The earnings effects include individuals who had no earnings during this time period. These estimates are mostly robust to alternative covariates and to winsorizing earnings at the 99th percentile (Appendix Table A14 panel A).

Effects by baseline employment status. It is not necessarily surprising that the treatment had negligible effects for the average sample member, because the adults in our study represent a broad cross-section of low-income residents with varying levels of engagement with the labor market. At baseline, only 43% reported being currently employed at least part-time. 27% reported being unemployed, and another 15% said they were unable to work due to health conditions. The remaining share consisted of students, retirees, people on a temporary leave of absence from work, and people who were not able to work due to caregiving responsibilities.

Panels B through D in Table 7 disaggregate the full-sample effects by self-reported baseline employment status. We cannot rule out null effects on cumulative Q1-Q6 employment and earnings for those who were employed at baseline or for those who were not working for reasons other than being "unemployed".

A more positive picture emerges, however, when focusing on the adults who reported being unemployed at baseline (panel D). This subset of participants provides perhaps the most relevant test of spatial mismatch theory (i.e. the effect of commute costs on labor outcomes), as they are closer to the margin of employment. Relative to the control group, free fares increased the cumulative likelihood of having any employment in Q1 - Q6 for this group by 3.5 percentage points (6% of the control mean). Free fares also increased this group's cumulative Q1 - Q6 earnings by $2,845 (27.9%). Both of these effects reach conventional levels of statistical significance, and their respective t-statistics are 1.67 and 2.61. Half fares had no effects on these outcomes.

The positive free-fares earnings effect among the unemployed sub-group remains relatively stable across covariate adjustments but decreases to $1,692 when winsorizing earnings at the 99th percentile (Appendix Table A14 panel B) or removing outlier observations that exceed rule-of-thumb thresholds. The effect is robust to randomly dropping 10% of non-zero earnings observations in the data, with estimates ranging from $1,519 (SE = $1,041) to $4,045 (SE = $1,272) across 10,000 iterations.[27] A Poisson quasi-maximum likelihood regression with covariates yields an estimated mean earnings effect of 10.1%.[28] Further, the large difference in the earnings impacts between the baseline employed and the baseline unemployed is significant at the $p < 0.05$ level (Appendix Table A18 panel C).

For the baseline unemployed sub-group, the employment and earnings gains in response

[27]This check is similar in spirit to Young (2019).

[28]Per the guidance in Chen and Roth (2024), this specification delivers a percentage change in average earnings that handles values of zero and does not vary with arbitrary rescalings of the outcome units.

to free fares materialized relatively quickly after the start of treatment (Appendix Figure A2). The cumulative likelihood of employment reached a plateau by Q3 (panel A), leading to detectable increases in earnings within each specific calendar quarter between Q2 and Q6 (Panel B).[29] Cumulative earnings effects grew linearly over the six quarters (Panel C).

The above pattern of employment and earnings gains in response to free fares does not appear when using an alternative indicator of baseline unemployment: receipt of UI benefits in the quarter before joining the study. Among those who received such benefits, free fares did not cause detectable increases in cumulative employment or earnings in the first six quarters, and both the sign and magnitude of these estimates are unstable across specifications (not reported). This discrepancy 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 in the quarter prior to enrollment and only 5.7% received UI in the 4 quarters before enrollment. This contrasts with a take-up rate of around 30% among all eligible U.S. workers (FRED Economic Data, 2023) and is in keeping with research showing lower rates of UI benefit eligibility and take-up among poorer workers.[30] More strikingly, the self-reported unemployed who *did* receive UI at baseline had mean earnings of $21,287 in the year prior to enrollment, compared with earnings of only $4,829 among the self-reported unemployed who did not receive UI. Unemployed SNAP adults who receive UI are thus highly positively selected in ways that appear to make them less responsive to the work-promoting effects of free fares.

Theoretical predictions. To help interpret the above employment impacts, it is useful to consider how fare discounts theoretically affect the time and monetary costs of commuting to work.[31] Free fares led to some degree of substitution in modes of commuting, with a 13.1 percentage-point increase in self-reported rates of primarily commuting by bus and corresponding decreases in rates of commuting primarily by car (-6.7 pp) and by walking or biking (-6.2 pp) (Appendix Table A2). Regarding the cost effects of these mode shifts, our surveys did not ask participants how much money they spent on commuting. However, the reductions in self-reported weekly PRT spending (Appendix Table A1),

[29]The Q3 full-sample effect in Appendix Figure A2 panel B is a registered primary outcome in our pre-analysis plan. It shows a positive effect of $183 (SE = 81.6). Q3 is in fact the only quarter in the first six quarters in which there was a significant positive effect on earnings for the full sample.

[30]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).

[31]This follows a literature dating to Oi (1976) and Cogan (1981) that models labor supply decisions with fixed costs of traveling to work.

together with the fact that 54% of employed control group members reported using public transit to get to work (Appendix Table A2), suggest that the treatment likely reduced the monetary cost of commuting on average. Free fares did not significantly affect self-reported round-trip commute times on a typical day, although the confidence intervals are wide (Appendix Table A2).

A standard static labor supply model helps to predict a person's response to changes in commute costs along the extensive margin. First consider an unemployed worker who would only ever take the bus to work regardless of fare prices. The free-fares treatment reduces their (potential) commute costs but does not change their (potential) commute time. In this case, the model unambiguously predicts an increase in employment (Appendix Figure A8 panel A). The same holds true for a reduction in commute *time* (panel B), as would occur if the person switches from walking to taking the bus. It is also possible that the free fares treatment simultaneously *reduces* the commute costs and *increases* the commute time that an unemployed worker 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 the bus when it becomes free. In this scenario, the net effect on employment is ambiguous and depends on 1) the person's potential hourly wage 2) the slowness of the bus relative to a car, and 3) the shape of the person's preferences over consumption and leisure (panels C and D).[32]

When looking instead at the *intensive* margin of labor supply, the predicted effects of changes in commuting costs are not as clear-cut for at least three reasons. First, the interior effects of any shifts in a worker's time or money budget will depend on the shape of their preferences for work versus 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. Third, a worker can adjust their labor supply over several different margins of time in response to a change in the daily costs of commuting. They can adjust their hours worked per day, days worked per week, weeks worked per year, et cetera. These various margins make it more difficult to predict the net effect on total labor supply.[33]

[32]Our data suggests 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 A2).

[33]In particular, the predicted effects on total labor supply depend on assumptions regarding whether choices are made over continuous or discrete units of time. For example, Gutierrez-i-Puigarnau and van Ommeren (2009) predict that an increase in daily commute time will lead a worker to work fewer days but more hours per day. However, this assumes that there are no binding constraints on a person's time within a given day, such that very long daily commutes do not mechanically reduce the total amount of time that a person has available for work.

The standard labor supply model thus predicts that free fares will increase labor supply along the extensive margin in at least most scenarios, with more ambiguous predictions for the intensive margin.

Mechanisms behind earnings gains. The earnings gains among the baseline-unemployed sub-group appear to be driven mainly by increased employment (i.e. the extensive margin) and perhaps by less frequent transitions into and out of the labor force, rather than by increased income when employed.

For this sub-group, we cannot rule out zero effects of free fares on self-reported hourly wages (among the employed), weekly work hours, and the number of jobs currently held (Appendix Table A14 panel B). The confidence intervals on these effects are fairly wide, however, and do not preclude substantial positive effects. The point estimate of the effect of free fares on cumulative Q1-Q6 earnings for this group becomes much smaller ($977, s.e. $1,265) 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 intensive-margin effects.[34] Moreover, quantile regressions show no systematic differences in effects on earnings across the distribution of positive earnings values (Appendix Figure A1).

The 3.5 percentage point increase in employment also manifests in self-reported data from the 15-month survey, although it is less precisely-estimated than in the UI data (Appendix Table A2). This increase in self-reported employment was accompanied by a reduced rate of reporting being "unemployed and seeking work", further supporting the idea that the treatment led to movement from being unemployed to being employed. We also find statistically significant evidence that free fares led to more *stable* employment among the baseline-unemployed; the free fares group had employment in 0.217 (9.6%) more quarters than the control group during the first six quarters (Appendix Table A14 panel B). Together, the above results suggest that the increased earnings among the baseline-unemployed are primarily a result of increased labor supply along the extensive margin.

The employment gains among the baseline-unemployed do not appear to stem from increased job search effort. Our follow-up surveys asked several questions about job search.

[34]We attempt to bound the intensive margin causal effect on earnings 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 [-$3,094 (s.e $1,907), $1,916 (s.e $1,464)] in levels and [-0.12 (s.e 0.12), 0.21 (s.e 0.146)] in logs. Our data is thus not very informative about the size of the intensive margin effect on earnings for the baseline unemployed, at least without additional assumptions about the characteristics of the always takers.

Appendix Table A2 shows no detectable effect of free fares on self-reported rates of actively searching for a job among the baseline-unemployed. Among the active job searchers in this sub-group, the free fares recipients did not apply to more jobs or spend more time searching for a job than the control group. This result contrasts with prior research showing that transportation subsidies increase job search intensity among unemployed adults in Washington, D.C. (Phillips, 2014) and among youth in developing countries (Franklin, 2018; Banerjee & Sequeira, 2023).

Finally, unlike the other participants, the baseline-unemployed sub-group *increased* its total mobility along several dimensions in response to free fares. According to GPS data, 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 (Appendix Table A16). This contrasts with negative point-estimated effects on these outcomes for the rest of the sample. Furthermore, according to the travel diaries, the baseline-unemployed had 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 transit trips per week, contrasting with only 0.139 additional trips among the baseline-employed (Appendix Table A16). These results hint at a relationship between increased total mobility and employment gains among job-seekers, although it is unclear whether this increased mobility is a cause (e.g. spatial job search) or a consequence (e.g. more days spent commuting) of their increased employment. Free fares appear to enable more reliable transportation to work via public transit. This alleviates mobility constraints for the baseline-unemployed and leads to employment gains.

Employment takeaways. The null average effects on employment and earnings among the entire adult sample reflect the fact that many participants are not near the margin of working for pay. Our sample-wide null effects reproduce the finding from Brough et al. (2024) that fare discounts do not improve labor market outcomes for the average participant when looking at a very broad cross-section of low-income people. However, we are able to uncover a more striking result when disaggregating these effects by the individual's self-reported baseline work status and focusing on those who are closer to the margin of work. Free fares have an economically large positive effect on the earnings of the baseline-unemployed. Although this result is exploratory and was not a pre-registered estimate, it strongly hints at the presence of spatial frictions in labor markets. Reducing the cost of commuting lowers the daily reservation wages of unemployed workers, thus increasing employment at the margin.

5.5 Health care use

Full sample average effects. Public transit subsidies had limited effects on the consumption of health care.[35] Table 8 presents average treatment effects on the adult sample's use of Medicaid-funded health care within the first 540 days after enrolling in the study. This time period corresponds roughly to the 18 months when the fare discounts were in effect. Over 91% of the control group received some health care during this time period, and the discounts had a precisely-estimated zero effect (i.e. no extensive margin effects). The effect shows no time trend when disaggregating by month (Appendix Figure A4 panel A). Effects are similarly small when looking specifically at physical health-related care and behavioral health-related care. The control group received physical health care on 33.6 days, and fare discounts did not detectably affect this outcome.[36]

Effects by type of care. We further unpack the effects of free fares for various types of health care (Appendix Table A15). Free fares had a negligible effect on the use of specific categories of physical health care along the extensive or intensive margin, although the point estimates and intervals tend to vary across specifications (Appendix Table A15 Panel A).[37] Of note is the null effect on the number of days with non-ER outpatient care. This type of care includes well-visits, checkups, and other preventive health services that signal investments in one's basic health. Follow-up survey responses echo these claims-based results, showing no effect on the self-reported number of ER visits in the past six months or

[35] Our administrative data on health care usage comes solely from Medicaid claims. The estimated effects on care usage therefore reflect small differences in rates of Medicaid enrollment between the three study arms. The share of Medicaid enrollees among the study sample decreased from 97% to 84% over the first 18 months of study participation. This decrease was mostly uniform across study arms, but the control group became slightly more likely to attrit from Medicaid starting in month 13 and was two percentage points less likely than the free fares group to be on Medicaid by month 18 (Appendix Table A6 Panel C). Our follow-up surveys asked some questions about health care usage. The responses, which include participants who are not on Medicaid, align reassuringly with the null effects found in the Medicaid claims-based analysis.

[36] We measure the intensive margin of care utilization in terms of the number of days with at least one claim because it is difficult to parse out distinct visits to a health care provider in the claims data. This way of measuring care deviates from our pre-registered health care outcome, which proposed to measure the "total number of primary care visits taken in the first nine months after random assignment." We further deviate from this pre-registered outcome by only categorizing claims as ER or non-ER and inpatient or outpatient. We categorize care this way because it is not straightforward to define "primary care" and reliably identify such care in claims data.

[37] The distribution of the number of days with care is heavily right-skewed for all categories of care. Correspondingly, quantile treatment effects are mostly zero in the bottom half of the outcome distribution and are limited to the far upper tail for the less common types of care such as non-ER inpatient (Appendix Table A3).

the number of months since the person's last doctor visit (Appendix Table A3). The null effect on emergency room care usage does not appear to result from behavioral responses that took more than 18 months to materialize, as shown by the stable cumulative effects over time (Appendix Figure A4 panel C). The cumulative effect on non-ER outpatient care usage, however, does exhibit an upward trend starting midway through the subsidy period (panel B), perhaps suggesting a delayed reaction to free fares that would eventually lead to detectable increases in care usage if the discount lasted longer than 18 months.

Among sub-categories of *behavioral* health care (Panel B in Appendix Table A15), we again observe limited effects on the intensive or extensive margins of care utilization over the first 540 days.[38] Free fares may have decreased the number of days with substance use treatment and the total cost of behavioral health care that was billed to the Medicaid managed care organization in Allegheny County, although these effects are not stable across specifications.

Sub-group heterogeneity. The effect of free fares on the number of days with an ER outpatient claim in the first 18 months does not systematically differ by the participant's sex, race, or baseline employment status. Across types of care, the intensive margin effects do not differ by whether the person received the given type of care in the year prior to enrollment or by their quartile rank of the number of days with care in this period.

An exploratory machine learning-based treatment targeting analysis, following the methods in Yadlowsky et al. (2021), gives no indication that the null average effect on the number of days with non-ER outpatient care masks heterogeneity across sub-groups (results not reported). We are additionally unable to reject the "sharp null" hypothesis that free fares had no effect for every single participant on the number of days with non-ER outpatient care. This is based on tests with randomization inference and exact p-values using a variety of test statistics. Free fares may not have influenced the consumption of preventive health care (either positively or negatively) for *any* of the individuals in our sample.

Interpretation of results. Several factors make it reasonable to expect a minimal average effect of fare discounts on the overall use of health care. First, the expected

[38] The sample has a notably high base rate of behavioral health care usage, with a 36% control group rate of receiving crisis care in the first 18 months and a 61% rate for non-crisis care (Appendix Table A15). Crisis-oriented behavioral health care includes psychiatric hospitalizations, calls to a 24-hour mental emergency hotline, and ER visits with behavioral health-related diagnoses. Non-crisis care includes routine counseling and therapy appointments. Medicaid patients are known to have higher rates of mental health disorders than the general population (Saunders, Heather, 2025), and they comprise a disproportionate share of all mental health-related emergency room visits (Santo et al., 2021).

direction of such effects is theoretically ambiguous. Reduced fares could make it easier for low-income individuals to visit the doctor and address their health needs.[39] At the same time, lower fares could provide financial benefits that lead to fewer adverse health experiences, thus lessening a person's need for health care. Any effects on care consumption involve a combination of changes in health needs and changes in access. On the health needs front, we find mixed evidence of changes in self-reported health at 15 months after enrollment, as discussed further below. On the access front, we do not detect effects on self-reported rates of having no health insurance or rates of delaying medical care for cost reasons (Appendix Table A3; the surveys did not ask about delaying or skipping medical care for transportation reasons).

Second, Medicaid patients in Pennsylvania are already entitled to unlimited free trips to and from medical appointments through the state's Medical Assistance Transportation Program (MATP). Appendix Table A7 presents the impact of the fare discounts on the use of MATP services. The free fares group took 20% fewer MATP-funded trips than the control group per month after joining the study (a 0.122-trip reduction from a baseline of 0.617 trips per month), suggesting that participants partially substituted one form of subsidized transit for another when taking health care-related trips. Third, virtual health care appointments have become more common in recent years since the COVID-19 pandemic.[40] Our claims data does not identify virtual visits, but telemedicine serves to reduce transportation barriers to care.

Third, recent studies have not established a clear link between means-tested transfers and health care utilization. For example, Miller et al. (2024) find no effect of unconditional cash transfers on the likelihood of having a primary care visit, while Agarwal et al. (2024) find that recipients of a cash transfer had fewer ER visits.[41] For interventions that are not directly related to health care, the effects on recipients' consumption patterns may be too diffuse to register changes in health care usage.

Overall, our estimates do not indicate a strong relationship between public transportation costs and health care utilization. Given the opacity of the mechanisms and the varying directions of effects for specific types of care, we take away that fare prices only modestly

[39] Syed et al. (2013) and Wolfe et al. (2020) discuss transportation as a potential barrier to health care access.

[40] Among Medicaid patients in urban areas, telemedicine increased from 0.2% of all services in 2019 to 6.4% of services in 2021 (Warrier et al., 2024).

[41] Our finding of no effect on overall care usage differs from the Seattle fare discount experiment. In that study, Brough et al. (2024) find that reducing fares from half price to free causes a 5.6 percentage point (16.1%) decrease in the cumulative likelihood of receiving any Medicaid-funded care. This effect materializes within 3 months and persists for up to 24 months. The difference between our estimates and theirs could be explained by sample composition and data coverage: Only 59% of their sample was on Medicaid at baseline (and thus could be observed in health care data), compared with 97% of our sample.

influence the consumption of health care, while noting that certain suggestive effects are worthy of future confirmatory analysis.

5.6 Other socioeconomic outcomes

Self-reported finances, health, and well-being. We collected data on many dimensions of financial stability, physical and mental health, and subjective well-being over the three waves of follow-up surveys. Table A4 presents average treatment effects on self-reported financial outcomes for post-endline (15-month) survey respondents. Neither discount level affected participants' amount of monthly savings or their likelihood of being able to afford an unexpected $400 expense. Nor did either discount affect participants' self-reported amount of liquid assets, debt balance, or financial well-being score according to the Consumer Financial Protection Bureau Financial Well-Being Scale. Free fares may have reduced rates of certain financial hardships, such as using a credit card to help pay bills (25.4% reduction) and not paying one's full phone or internet bill (13.2% reduction).

The treatment had minimal effects on most survey-based measures of health and subjective well-being at 15 months post-enrollment (Appendix Table A3). Neither subsidy level affected participants' overall life satisfaction. Free fares caused an estimated 4.2 percentage point (7.6%) reduction in the likelihood of rating one's health as good or better, although the significance of this effect does not survive correction for multiple testing. There is further evidence of travel mode substitution in how free fares (but not half fares) respondents reported getting to the doctor. Our surveys included a battery of questions about mental health symptoms, self-efficacy, and feelings of social connectedness. Fare discounts produced small, statistically insignificant effects on nearly all of these measures (Appendix Table A3).

Receipt of public assistance. Reduced transit fares could improve participants' ability to enroll in or maintain access to public assistance programs. On the other hand, it could ease financial burdens such that participation in these programs is no longer necessary. We find no effects on rates of receiving SNAP, TANF, SSI, child care subsidies, or Section 8 rental subsidies as of the 18th month after enrollment (Appendix Table A6 Panel C). There is also no trend over time in the likelihood of receiving these benefits over the first 18 months. Free fares increased the likelihood of receiving Medicaid in month 18 by an estimated two percentage points.

Neither discount level affected the use of homeless shelters along the extensive or intensive margin in the first 18 months (Appendix Table A6 Panel A). Free fares may have slightly increased the likelihood of being involved in a child protective services referral (the process that initiates an investigation for child maltreatment), although the significance of this effect is not robust to multiple testing.

Contact with criminal justice system. Treatment effects on criminal activity are reported in Appendix Table A5. Nearly 8% of adults in the control group had a criminal charge filed against them in Allegheny County in the first year after joining the study, and 4.3% spent time in the Allegheny County Jail. The relatively high base rate of contact with the criminal justice system among our sample raises the possibility that transportation subsidies could facilitate additional crime.[42] The subsidies could also lessen financial hardship in a way that reduces the motive to engage in criminal activity. Half fares led to a marginally significant 1.2 percentage-point (15.2%) increase in the likelihood of having a criminal charge relative to the control group, although the significance does not survive the false discovery rate correction. This estimated increase is driven primarily by misdemeanor charges. Free fares did not affect rates of having a criminal charge. Neither discount affected the amount of time spent in jail. Fare discounts also did not affect the overall likelihood of failing to appear at a pretrial criminal court hearing, a result that was also found in (Brough, Freedman, Ho, et al., 2022).

The time-limited nature of the subsidy. All of the above impacts on mobility and socioeconomic outcomes inherently reflect the time-limited nature of the treatment. Participants were told throughout the study that their fare discount was temporary. Even after ACDHS announced that the discounts would last more than 12 months, the participants who inquired for more details were generally told by staff that the program would end at some point in 2024. Although the discounts lasted for up to 19 months, participants may have held off on making the sorts of larger life changes or personal investments that a person might make if they were assured of permanent access to free transit. The treatment, for example, did not lead to higher rates of moving to a new home (not reported).

We can partially explore the role of shorter versus longer subsidy duration using the fact that study enrollment took place over a three-month period, but the extension of the fare discounts beyond 12 months was announced to all participants on the same day (October 17, 2023). The latest cohort of study enrollees was therefore aware of the extended length

[42] Existing work has not found a positive relationship between public transit accessibility and crime rates (Billings et al., 2011; Ridgeway & Macdonald, 2016), including no detectable effects found in the Seattle fare discount experiment (Brough et al., 2024). Khanna et al. (2025) find that expanding cable car service in Medellín, Colombia leads to reduced overall criminal activity in the city.

of the subsidies for a three-month larger portion of their total time in the study than the earliest cohort of enrollees. The participants who anticipated shorter versus longer subsidy durations did not generally differ in their average treatment effects on downstream outcomes (not reported). Our results nonetheless do not rule out the possibility that fare discounts could generate larger socioeconomic ripple effects under a more permanent, larger-scale implementation.

5.7 Effects on child outcomes

Our study included 4,928 children ages six to 17. These children received their own ConnectCards that were programmed with the same fare discount level to which their parent or guardian was assigned. The child fare discounts in this study were primarily meant to make the intervention more beneficial for the adults, recognizing that parents often ride public transportation with their children and must pay the fare for each child over age five. Nonetheless, children may derive their own benefits from fare discounts apart from the benefits for adults. Teenagers often take public transit trips by themselves to visit friends, attend after-school activities, or work at a job. The cost of fares may pose a particularly acute barrier for older youth who have little income of their own.

Although children were not included in our surveys, we leverage administrative data to measure an array of outcomes for the child sample. We focus here on four domains: travel behavior, health care use, academic outcomes, and labor market outcomes (for older teenagers).

Travel behavior. Most children tapped their study-issued farecard at least once: 80.9% in the control group, 79.0% for half fares, and 87.7% for free fares. Our only measure of the children's volume of transit ridership comes from farecard boarding data. The control group tapped their study-issued card 0.14 times per week. Half fares led to 0.69 (SE = 0.05) additional taps per week and free fares led to another 3.36 (SE = 0.11) taps per week.

Among the study adults that had children, the control group reported taking an average of 1.46 trips together with their children on a given day. The estimated effects of fare discounts on this outcome are slightly negative but not statistically significant (Appendix Table A1). Any reductions on this measure might imply that the fare discounts enabled children to take more transit trips independently of their parents. Parents in the free fares group were also 18.8 percentage points (54.5%) more likely than the control group to report that their children used their study-issued ConnectCards to accompany them on trips. According to the parents, children in both treatment groups were also more likely than the control group to use their assigned farecards to go to stores and visit friends. The treatment thus provided more affordable transit trips for children for a variety of travel purposes.

Health care use. As with the adult sample, fare subsidies did not affect children's overall likelihood of receiving health care in the first 18 months (540 days) after enrollment (Appendix Table A8). The subsidies had negligible effects on children's physical health care consumption along the extensive or intensive margin for almost all types of care, including no detectable effect on non-ER outpatient claims that include routine check-ups and well-visits.

In contrast to the adult sample, however, free fares increased children's likelihood of receiving behavioral health care, with an estimated 3.6 percentage point (10.4%) increase in the likelihood of having at least one behavioral health claim and a 2.22-day increase (25.1%) in the number of days with such care. This increase was driven by non-crisis care, which includes routine counseling and therapy appointments. These increases, which do not survive the multiple testing correction, would likely indicate improved access to care in light of the high prevalence of unmet mental health needs among economically vulnerable youth (Hodgkinson et al., 2017).

Academic outcomes. We observe academic outcomes for the 37% of child participants who were attending Pittsburgh Public Schools during the study. The results are shown in Appendix Table A9. Fare discounts produced no detectable effect on the number of days that students were absent from school in either the 2022-2023 school year (only looking at days after the student entered the study) or the 2023-2024 school year.[43] There is some evidence of improvement in standardized test scores for students in elementary and middle school. Free fares caused an estimated 0.135 standard deviation unit increase in test scores across all subject tests, and half fares caused a marginally significant 0.101 standard deviation-unit increase. Many Pittsburgh Public Schools students already receive unlimited free public transit trips through the district. This weakens the experimental contrast between the treatment and control children and makes it less likely that any observed academic gains are driven by improved mobility.

Labor market outcomes. Finally, we examine the effects on the labor market outcomes of youth study participants who were 16 or 17 years old at baseline. We limit the

[43] In a prior quasi-experimental study, Munoz and Sandoval (2022) find that free bus passes for high school students in Florida lead to increased absenteeism.

analysis to this age range because teenagers under 16 are less likely to be working in paid UI-covered jobs. Appendix Table A10 presents the results. The 16 and 17 year-olds in the control group had a rate of employment in the first six quarters that was slightly *higher* than the employment rate among the adult control group members (72.9% versus 66.6%). Teenage SNAP recipients are thus less negatively-selected on their ability to work than their adult counterparts.

Fare discounts did not have a detectable impact on cumulative employment or earnings among the 16 and 17 year-olds in the first six quarters after enrollment. The 95% confidence interval for the effect of free fares on cumulative Q1-Q6 earnings rules out increases of more than $1,003 and decreases of more than $2,016 (which is 30% of the control mean).

6 Cost effectiveness of free fares

In this section, we put the above causal estimates into context by evaluating the cost-effectiveness of free transit fares for SNAP recipients. We focus only on the free fares treatment because that is where we see the strongest effects. We also calculate the marginal value of public funds (MVPF). Further details on these calculations are in Appendix D.

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. Free fares cost PRT an estimated $297.44 per person per year in foregone revenue. The program cost $3.41 to administer per person per year. We assume that there is no marginal operating expense to PRT for an additional passenger boarding. The program thus had a direct annual cost of $300.85 per person.

Cost effectiveness at reducing car travel. Our preferred estimate from GPS data shows that free fares reduce car travel by 10.15 miles per person per week (Column (3) in Appendix Table A13 panel B), or 527.8 miles per year. This amounts to a cost of $300.85 / 527.8 = $0.57 per vehicle mile eliminated.

How does this compare with other approaches to reducing car travel? Policies such as fuel taxes, road tolls, and congestion pricing are not comparable with our treatment because they raise revenue rather than spend public funds.[44] There are two approaches, besides fare subsidies, to reducing car travel through government expenditures: transportation demand management (TDM) and expanding public transit service. TDM refers to behavioral in-

[44]Few RCT's have studied the impact of price instruments on car usage. Hintermann et al. (2024) cite extant studies and present experimental results showing that a Pigouvian pricing scheme in Switzerland leads to a mode shift away from driving.

terventions and financial incentives that promote sustainable alternatives to car travel. In perhaps the largest TDM experiment to date, Rosenfield et al. (2020) find that monetary rewards do not reduce car usage among employee commuters at an urban U.S. university. We know of no other TDM studies that provide a credible causal estimate of cost-effectiveness with which to compare our results.[45]

Regarding expansions or improvements to public transit service, studies have used transit worker strikes and infrastructure investments to estimate the effect of public transit supply on car travel.[46] These studies conclude that the effect depends on the time horizon, with short-term reductions in car travel giving way to longer-run increases as less-congested roadways induce new car trips. These studies generally compare observed congestion levels with the counterfactual absence of *any* transit services rather than with a marginal change in service levels. More comparable to our results are the estimates in Beaudoin and Lawell (2018), which show that a 10% increase in transit capacity leads to a 0.7% reduction in car travel in the short run. Translating this to the Allegheny County context yields a government cost of $0.1219 per vehicle mile eliminated. It may therefore be more cost-effective to reduce car travel in the short-term by increasing transit service than by making fares free.

Cost effectiveness at promoting employment among the unemployed. The direct annual cost of free fares to the government is $286.55 per person when focusing on the baseline-unemployed sub-group. Free fares increased the earned income of baseline-unemployed participants by an average of $2,845 over six quarters (Table 7 panel C), for a return on investment (ROI) of ($2,845 × (2/3)) / $286.55 = 6.62 per year.

This metric can be compared with other recent policies and programs that show causal evidence of increasing the earnings of unemployed workers. For example, eligibility for wage insurance through the U.S. Trade Adjustment Assistance program increased workers' earnings by an average of $4,565 per year over the first four years following displacement from work (Hyman et al., 2024). The program has an estimated total cost of $2,970 per eligible worker, for an ROI of 1.54 per year during the first four years. An individualized social service intervention in Texas increased the earnings of baseline-unemployed participants by $421 per month as measured after 24 months (Evans et al., 2025). This came at a program cost of $22,950 per person, for an implied ROI of 2.27 during the first two years. The Per

[45] See Semenescu et al. (2020) and Whillans et al. (2021) for reviews of the TDM literature. Studies to date have been limited by small sample sizes, a lack of causal identification, and a reliance on self-reported data.

[46] For the studies that leverage strikes, see M. L. Anderson (2014), Bauernschuster et al. (2017), and Adler and van Ommeren (2016). Notable studies looking at the expansion of transit infrastructure include P. R. Stopher (2004), Baum-Snow et al. (2005), and Winston and Maheshri (2007).

Scholas sectoral-focused job training program increased trainees' cumulative earnings by \$28,661 after 63 months at a cost of \$4,459 per person, for an ROI of 6.43 over this time period (Schaberg & Greenberg, 2020). Free transit fares thus compare favorably with the earnings ROI of other active labor market programs, at least when amortizing the other programs' fixed costs over a relatively short time span.

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 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.

Appendix Table D1 presents the results. The MVPF ranges from 1.59 to 2.00 when providing free fares to all working-age SNAP recipients. The MVPF is larger for providing free fares to *unemployed* SNAP recipients; it may be as high as 10.57 for this group depending on how their willingness to pay for the policy is valuated. For reference, a simple non-distortionary transfer from the government to an individual has an MVPF of one.

The MVPF of free fares can be compared with that of other policies. In the environmental realm, our full-sample MVPF is on par with subsidies for home weatherization, home appliance rebates, and electric vehicles, but is smaller than subsidies for renewable energy production (Hahn et al., 2024). As a workforce development policy, free fares for the unemployed have an MVPF that is larger than many vocational training programs and larger than enhanced UI benefits. Among SNAP-related policies, our full-sample MVPF is smaller than reducing eligibility renewal burdens but larger than removing work requirements or providing application assistance to the elderly.[47] In general, the upper-bound MVPF of 10.57 for the unemployed sub-group ranks highly among both environmental policies and labor market policies, reflecting the dual social benefit of free transit fares for this group.

7 Conclusion

Poor urban residents rely heavily on public transportation, and there are concerns that fare prices constrain mobility and economic activity for this population. A better understanding of the role of fare prices in the lives of lower-income riders would help governments design more equitable and efficient transportation services. With this motivation, our paper

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

studies the effect of transit fare discounts on the travel behavior and socioeconomic outcomes of a large sample of SNAP households. We conduct a randomized trial that assigns each household to receive either free fares, half-price fares, or regular-price fares for 16 to 19 months. We measure outcomes using an array of administrative data linkages combined with follow-up surveys, daily travel diaries, and GPS logs from the phones of consenting participants.

We find that reducing fares to zero leads to approximately 1.5 additional transit trips per week, while half-price fares do not increase ridership. Free fares cause riders to substitute strongly away from car travel, with no increase in aggregate spatial mobility combined across travel modes. Among the adults who were unemployed at baseline, free fares substantially increase their likelihood of employment and their total earned income in the first 18 months. This result implies that at least some members of our study population are not able to achieve economically-optimal use of public transportation under status quo prices.

Our results demonstrate that there is economic merit to the wave of interest in fare-free transit that has swept many U.S. cities since the COVID-19 pandemic. Free fares show promise both as a tool for supporting disadvantaged job seekers and as a method of incentivizing more environmentally sustainable forms of travel. Policymakers should account for these twin benefits as they weigh the case for greater investment in public transportation.

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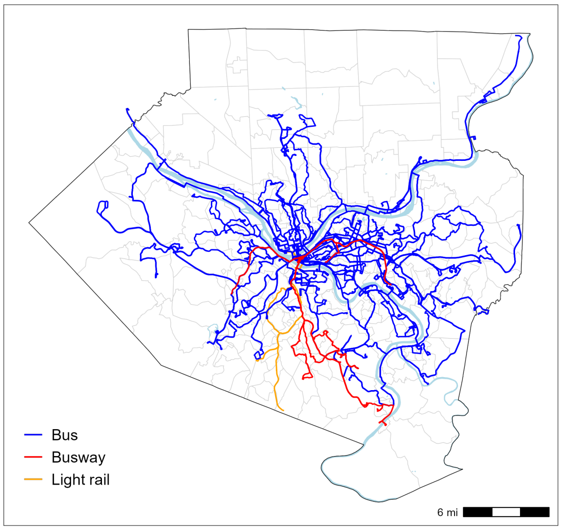
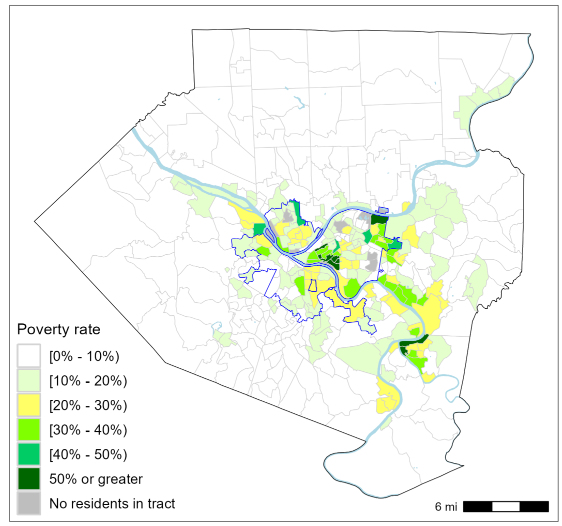
Figures

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

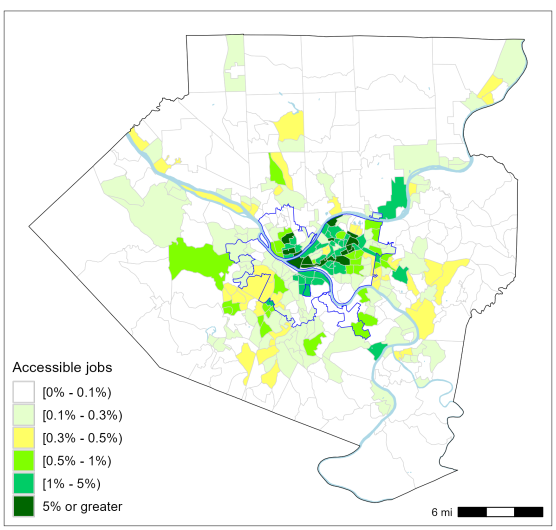
(a) Pittsburgh Regional Transit (PRT) service routes



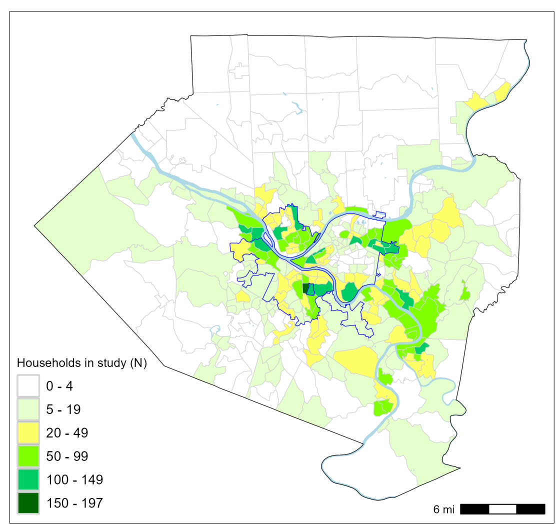
(b) Share of residents below poverty level, by census tract



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

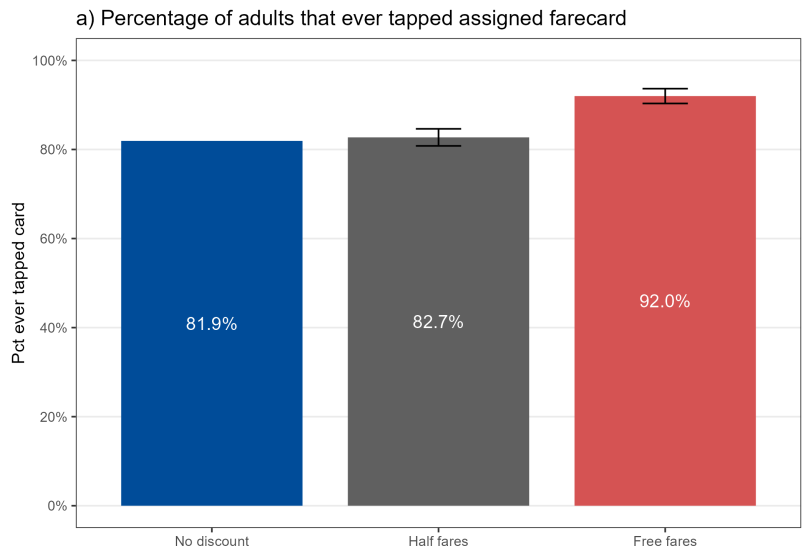


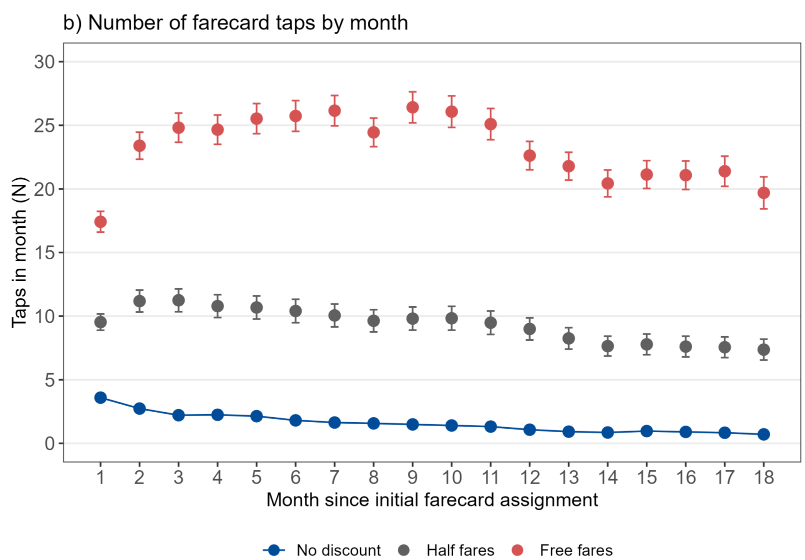
(d) Number of participating households by census tract



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 among adult participants





Notes: Figure presents rates of treatment take-up by way of using the study-issued farecards. Panel A presents the percentage of adult 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 adults 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 adult participants who were not assigned a ConnectCard. It also excludes 21 participants (14 adults and 7 children) 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).

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 for adults

	Entire study-eligible population	No discount	Half fares	Free fares	Half fares vs. no discount diff.	Free fares vs. no discount diff.
A. Demographics						
Female	0.606	0.717	0.726	0.721	0.008 (0.011)	0.004 (0.011)
Age (years)	40.80	39.64	39.56	39.42	-0.079 (0.310)	-0.214 (0.312)
Black	0.438	0.588	0.591	0.588	0.003 (0.012)	$<$0.001 (0.012)
Hispanic	0.012	0.032	0.033	0.035	0.001 (0.004)	0.003 (0.005)
More than high school degree	0.181	0.364	0.358	0.375	-0.006 (0.012)	0.011 (0.012)
B. Transportation						
Access to car						
Owns a car	-	0.057	0.057	0.058	$<$0.001 (0.006)	0.001 (0.006)
Borrows a car from friend	-	0.079	0.076	0.077	-0.003 (0.007)	-0.002 (0.007)
Shares a car with others in household	-	0.029	0.025	0.031	-0.005 (0.004)	0.002 (0.004)
None	-	0.819	0.829	0.818	0.010 (0.010)	-0.002 (0.010)
PRT trips last week (N)	-	10.12	9.99	10.00	-0.134 (0.323)	-0.118 (0.332)
PRT spending last week ($)	-	30.36	30.02	29.32	-0.343 (0.807)	-1.04 (0.803)
Lives in PRT 7-day frequent service walkshed	0.250	0.357	0.360	0.359	0.003 (0.012)	0.003 (0.012)
C. Employment (from baseline survey)						
Currently employed	-	0.432	0.424	0.425	-0.009 (0.012)	-0.007 (0.012)
Hours worked per week at main job (N)	-	30.41	30.91	30.96	0.501 (0.421)	0.556 (0.424)
Hourly wage at main job ($)	-	13.59	13.39	13.46	-0.194 (0.139)	-0.128 (0.141)
D. Employment in quarter prior to enrollment (from UI records)						
Had any paid employment	0.402	0.514	0.521	0.511	0.007 (0.013)	-0.003 (0.013)
Total earnings among those employed ($)	5,076	4,420	4,353	4,469	-67.05 (116.3)	49.19 (119.3)
Test for joint orthogonality						
F-stat					1.125	0.785
p-value					0.309	0.695
Total sample size		**3,149**	**3,241**	**3,154**		

Notes: Table presents mean baseline characteristics for the adult study sample. The demographics and transportation characteristics come from the baseline survey that all participants were required to complete immediately before enrolling in the study. The 'hours worked per week at main job' and 'hourly wage at main job' numbers only include the participants who reported being currently employed in the baseline survey. The employment characteristics in Panel Dcome from Pennsylvania unemployment insurance (UI) records. In Panel C, baseline survey items that permitted unbounded continuous-valued responses are winsorized at the 99th percentile. The significance of the differences in group means is estimated using a regression with no covariate adjustment. 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: Impacts on number of public transportation trips per week

Outcome	N	Control mean	Treatment effect: Half fares	Treatment effect: Free fares	Free vs. half fares
Study-issued farecard taps per week (from PRT admin data)	9,174	0.298	1.52***††† (0.067)	4.76***††† (0.098)	3.24***††† (0.116)
"In the past week, how many trips have you taken on a PRT bus or the T in Allegheny County? Count a one-way ride as one trip."					
From midline survey (6 months)	3,819	9.87	-0.471 (0.451)	0.581 (0.453)	1.05***† (0.401)
From endline survey (11 months)	4,046	12.90	-2.69** (1.20)	-1.60 (1.18)	1.09* (0.626)
From post-endline survey (15 months)	4,048	11.95	-2.58 (2.00)	-0.696 (2.11)	1.88** (0.919)
Response value × 7: "How many bus or light rail trips did you take yesterday? Count a one-way journey as one trip." (from post-endline survey)	3,922	12.95	-0.480 (1.53)	-0.659 (1.36)	-0.179 (1.15)
Public transit trips per week (from GPS data)	472	3.47	-0.203 (0.637)	1.48** (0.716)	1.69***†† (0.502)

Notes: Table presents estimates of the effect of being assigned to each treatment status (50% discount or 100% discount) on the number of public transportation trips taken per week by the adult sample. Column N indicates the number of participants across the three study arms that have non-missing data for the given outcome. 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), and lives within the PRT 7-day frequent service walkshed (y/n). The GPS data estimates additionally adjust for the outcome measured in the 365 days before the person enrolled in the study. 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: Elasticities of demand for public transportation

	Present study, using farecard data (Pittsburgh)	Present study, using GPS data (Pittsburgh)	Rosenblum (2020) (Boston)	Brough et al. (2022) (Seattle)	Huberts et al. (forthcoming) (D.C.)
Full price to half price					
Point estimate	**10.00*** **	**-0.12**	0.58**	N/A	2.49
95% CI	**[9.1, 10.9]**	**[-0.84, 0.60]**	[0.21, 0.95]		[1.33, 3.64]
Half price to free					
Point estimate	**1.75*** **	**0.52*** **	N/A	3.42***	2.17***
95% CI	**[1.63, 1.88]**	**[0.22, 0.82]**		[2.95, 3.88]	[1.78, 2.56]

Notes: Table presents the price elasticities of demand for public transportation, comparing our results with the results of other recent fare discount experiments with low-income samples. Huberts et al. measure ridership in terms of "trips" instead of boardings, where one trip is defined as all linked transit stages that take place within a two hour window. ***p < 0.01, **p < 0.05, *p < 0.1

Table 5: Travel mode substitution in response to fare discounts

Outcome	N	Control mean	Treatment effect: Half fares	Treatment effect: Free fares	Free vs. half fares
A. From travel diaries					
Likelihood of taking at least one trip on given day					
Car trip	7,041	0.346	-0.025**† (0.011)	-0.029***†† (0.011)	-0.005 (0.010)
Public transportation trip	7,030	0.576	-0.015 (0.013)	0.026**† (0.012)	0.040***††† (0.011)
Walk or bike trip	7,022	0.469	-0.033**†† (0.013)	-0.046***††† (0.013)	-0.013 (0.012)
B. From post-endline survey					
Response value × 7: "How many trips did you take yesterday? Count a one-way journey as one trip."					
Car trips	3,960	0.929	-0.105 (0.079)	-0.188**†† (0.073)	-0.083 (0.060)
Public transportation trips	3,922	1.85	-0.069 (0.218)	-0.094 (0.194)	-0.026 (0.164)
Walk or bike trips	3,915	1.12	-0.127 (0.130)	-0.008 (0.148)	0.118 (0.137)
"What mode of transportation did you use most often in the past seven days?"					
Car	4,062	0.197	-0.005 (0.015)	-0.060***††† (0.014)	-0.055***††† (0.013)
Public transportation	4,062	0.629	0.030 (0.019)	0.124***††† (0.018)	0.094***††† (0.016)
Walk or bike	4,064	0.099	-0.018 (0.012)	-0.041***††† (0.011)	-0.023**†† (0.010)
Other	4,064	0.076	-0.007 (0.011)	-0.022**† (0.010)	-0.016* (0.009)
C. From smartphone GPS data					
Number of trips per week					
Car trips	472	13.39	0.441 (1.40)	-1.67 (1.44)	-2.11* (1.14)
Public transportation trips	472	3.47	-0.203 (0.637)	1.48**† (0.716)	1.69***††† (0.502)
Walk or bike trips	472	4.94	-0.204 (0.508)	0.385 (0.513)	0.589 (0.492)
Likelihood of taking at least one trip on given day					
Car trip	472	0.520	-0.014 (0.032)	-0.056* (0.032)	-0.042 (0.027)
Public transportation trip	472	0.205	-0.012 (0.025)	0.052**† (0.026)	0.064***†† (0.022)
Walk or bike trip	472	0.298	-0.027 (0.026)	0.022 (0.025)	0.048**† (0.024)
Mode of travel for person's most common journey					
Car	286	0.586	-0.080* (0.048)	-0.090**†† (0.036)	-0.009 (0.045)
Public transportation	286	0.087	0.007 (0.039)	0.005 (0.030)	-0.002 (0.028)
Walk or bike	286	0.317	0.073 (0.056)	0.080 (0.053)	0.007 (0.043)

Notes: Table presents estimates of the effect of being assigned to each treatment status (50% discount or 100% discount) on travel mode choices for the adult sample. Column N indicates the number of participants across the three study arms that have non-missing data for the given outcome. 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), and lives within the PRT 7-day frequent service walkshed (y/n). The GPS data estimates in Panel C additionally adjust for the outcome measured in the 365 days before the person enrolled in the study. The estimates in Panel A include normalized weights for the number of travel diaries that the person completed. 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 6: Effect of fare discounts on breadth and frequency of travel

Outcome	N	Control mean	Treatment effect: Half fares	Treatment effect: Free fares	Free vs. half fares
A. From travel diaries					
Number of places visited yesterday (N)	6,966	3.69	-0.535***††† (0.160)	-0.551***††† (0.148)	-0.016 (0.126)
Did not leave house yesterday	7,001	0.134	0.034***††† (0.008)	0.021***†† (0.007)	-0.012* (0.007)
B. From smartphone GPS data					
Unique POI's visited per week (N)	472	10.43	-0.005 (0.791)	0.141 (0.881)	0.146 (0.719)
Number of trips per week in total (N)	472	21.86	-0.065 (1.47)	-0.108 (1.65)	-0.043 (1.30)
Time spent traveling per day (hours)	472	1.30	-0.048 (0.119)	-0.182* (0.101)	-0.133 (0.110)
Total distance traveled per day (miles)	472	12.03	-0.004 (1.44)	-1.26 (1.36)	-1.25 (1.14)
Mean daily maximum distance from home (miles)	449	5.47	-1.87** (0.858)	-1.28* (0.753)	0.590 (0.711)
Staying at home					
Likelihood of leaving house on a given day	449	0.493	-0.013 (0.038)	-0.057 (0.037)	-0.044 (0.034)
Number of times left house per day (N)	449	0.739	0.009 (0.074)	-0.125* (0.066)	-0.134** (0.062)
Time spent at home per day (hours)	449	12.87	0.684 (0.938)	0.157 (0.910)	-0.528 (0.672)

Notes: Table presents estimates of the effect of being assigned to each treatment status (50% discount or 100% discount) on various measures of the breadth and frequency of travel for the adult sample. Column N indicates the number of participants across the three study arms that have non-missing data for the given outcome. 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), and lives within the PRT 7-day frequent service walkshed (y/n). The GPS data estimates in Panel B additionally adjust for the outcome measured in the 365 days before the person enrolled in the study. The estimates in Panel A include normalized weights for the number of travel diaries that the person completed. 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 7: Effect of fare discounts on adults' cumulative employment outcomes over the first six quarters after enrollment

Outcome	Control mean	Treatment effect: Half fares	Treatment effect: Free fares	Free vs. half fares
A. Full sample (N = 9,458)				
Had any paid employment	0.666	-0.010 (0.009)	<0.001 (0.009)	0.010 (0.009)
Number of quarters with employment (N)	3.04	0.008 (0.045)	0.042 (0.045)	0.035 (0.044)
Cumulative earnings ($)	17,289	-65.11 (401.0)	194.2 (399.2)	259.3 (397.1)
B. Employed at baseline (N = 4,074)				
Had any paid employment	0.931	-0.014 (0.022)	-0.016 (0.021)	-0.001 (0.022)
Number of quarters with employment (N)	4.70	0.006 (0.114)	0.041 (0.112)	0.035 (0.115)
Cumulative earnings ($)	29,581	-762.3 (821.8)	-1,076 (821.2)	-313.3 (838.5)
C. Not working at baseline - Unemployed (N = 2,605)				
Had any paid employment	0.578	-0.005 (0.021)	0.035* (0.021)	0.039** (0.020)
Number of quarters with employment (N)	2.25	-0.020 (0.111)	0.217** (0.109)	0.237** (0.106)
Cumulative earnings ($)	10,212	-101.0 (1,106)	2,845*** (1,088)	2,946*** (1,005)
D. Not working at baseline - Other reason (N = 2,865)				
Had any paid employment	0.360	-0.009 (0.021)	-0.010 (0.021)	<0.001 (0.020)
Number of quarters with employment (N)	1.33	0.002 (0.119)	0.036 (0.122)	0.034 (0.117)
Cumulative earnings ($)	5,784	1,639 (1,113)	164.1 (1,289)	-1,475 (1,225)

Notes: Table presents estimates of the effect of being assigned to each treatment status (50% discount or 100% discount) on employment outcomes for the adult participants. The data comes from Pennsylvania unemployment insurance (UI) administrative records. The outcomes are measured cumulatively over the first six complete calendar quarters after the quarter in which the person enrolled in the study. 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 (only applies to panel A in this table)

Table 8: Effect of fare discounts on health care utilization among the adult sample within the first 540 days after enrollment

		Treatment effect		
Outcome (N = 9,544)	Control mean	Half fares	Free fares	Free vs. half fares
Received any health care	0.914	0.006 (0.007)	0.002 (0.007)	-0.004 (0.007)
Physical health care				
Received any care	0.900	0.001 (0.007)	<0.001 (0.007)	-0.001 (0.007)
Days with at least one claim (N)	33.63	0.246 (0.834)	1.25 (0.850)	1.01 (0.868)
Behavioral health care				
Received any care	0.665	-0.005 (0.011)	-0.004 (0.011)	<0.001 (0.011)
Days with at least one claim (N)	23.50	-1.05 (0.852)	-1.14 (0.851)	-0.096 (0.892)

Notes: Table presents estimates of the effect of being assigned to each treatment status (50% discount or 100% discount) on health care utilization for the adult sample, as measured in the first 540 days after enrollment. Data comes from Medicaid claims. 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 365 days before the person enrolled in the study. Robust standard errors are in parentheses. ***p <0.01, **p <0.05, *p <0.1; † refers to comparable thresholds for sharpened FDR q-values

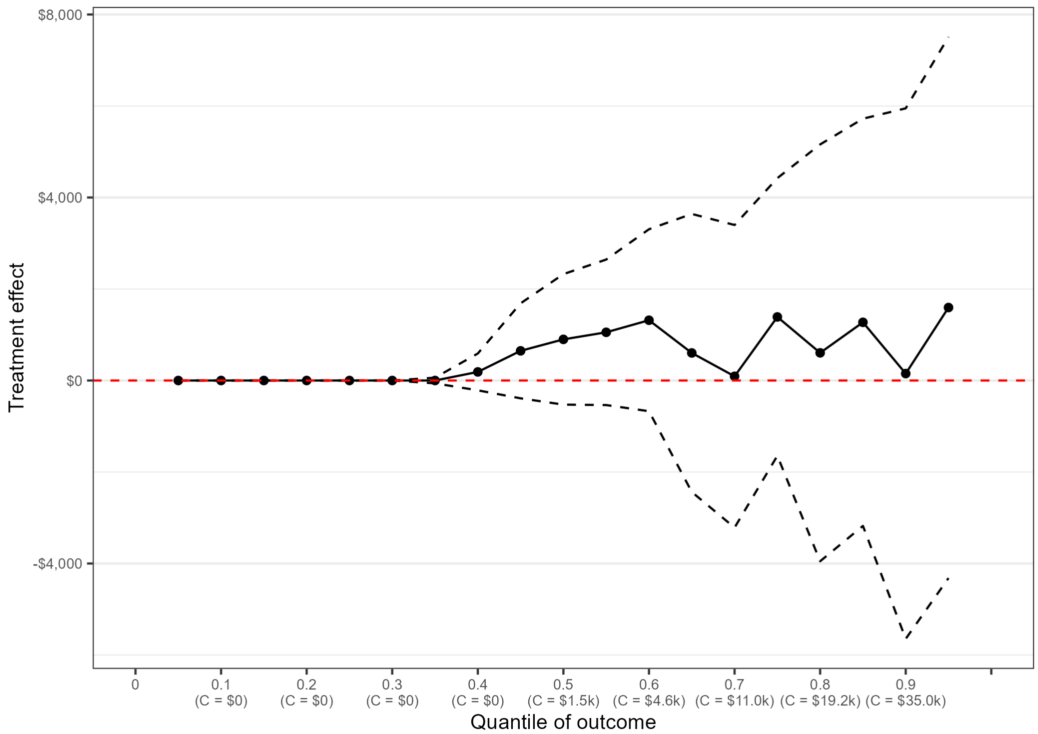
The Role of the Fare in Welfare: Public Transportation Subsidies and their Effects on Low-Income Households

Online Appendix

Seth Chizeck and Oluchi Mbonu

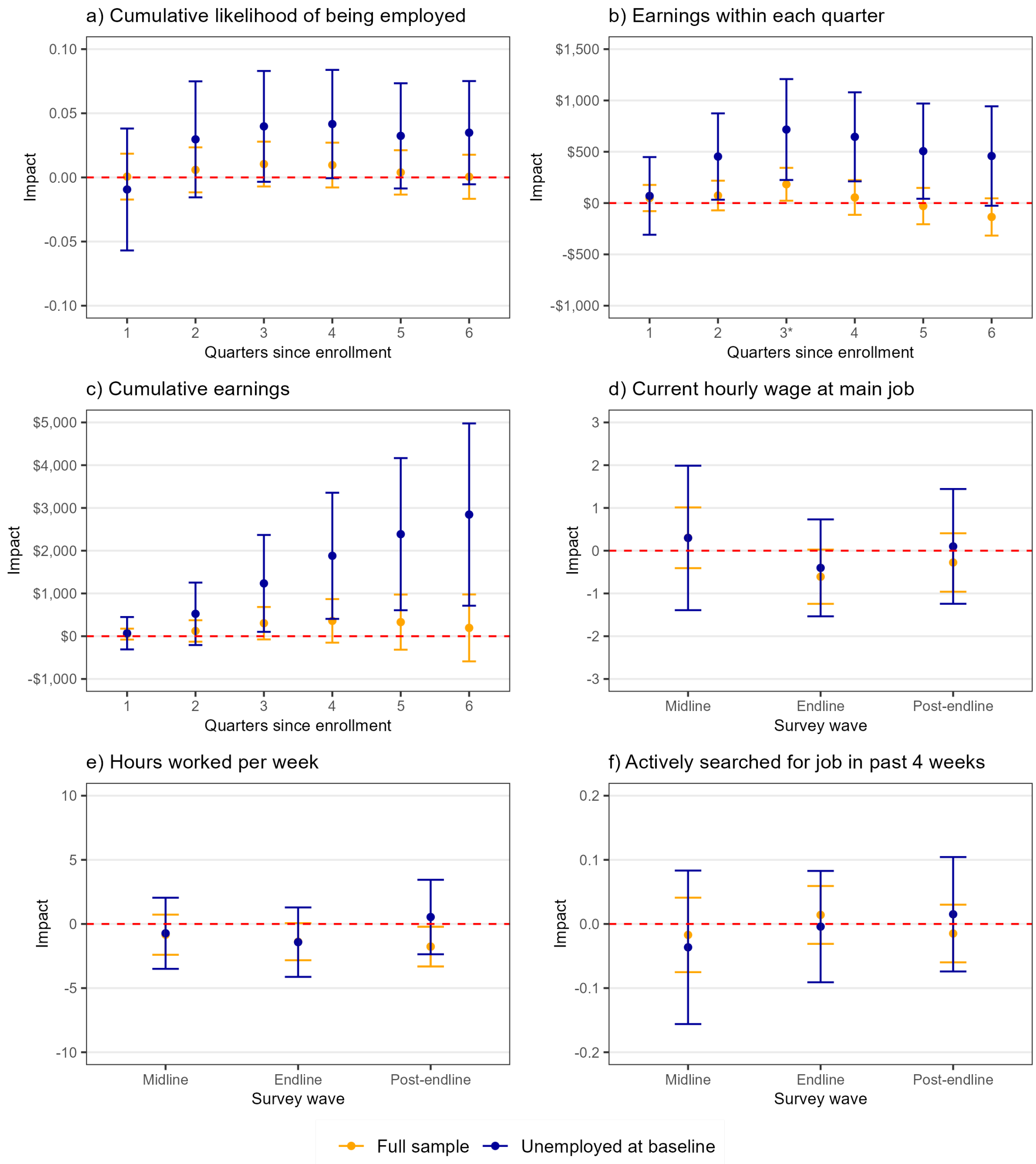
A Additional figures and tables

Figure A1: Effect of free fares relative to no discount on quantiles of the distribution of cumulative earnings in first 6 quarters after enrollment, among those unemployed at baseline



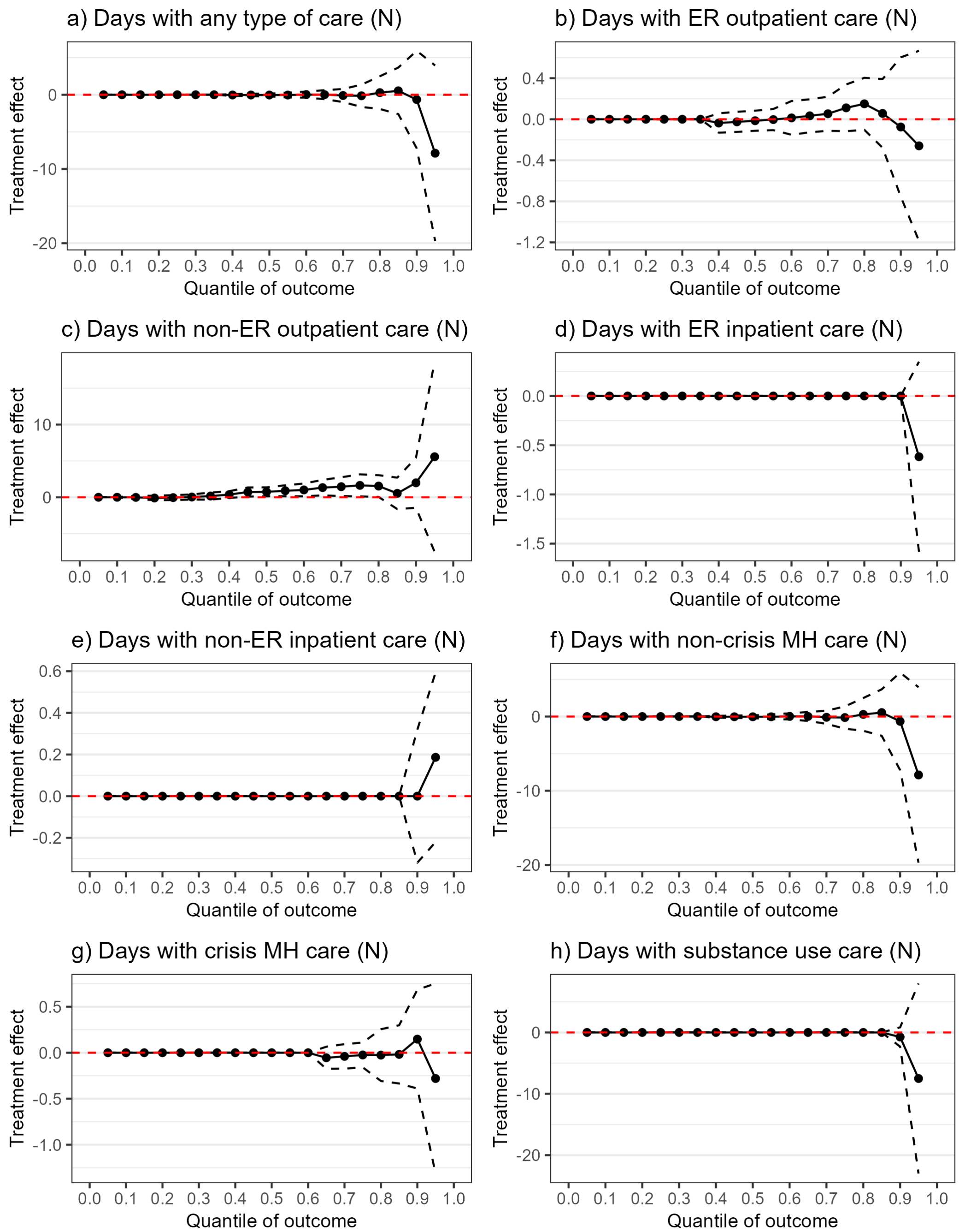
Notes: Figure presents estimates of the effect of being assigned to free fares relative to no discount on quantiles of cumulative earnings over the first six complete calendar quarters since the person enrolled in the study. The analysis is limited to participants who self-reported being unemployed in the baseline survey. Data comes from Pennsylvania unemployment insurance (UI) records. Estimates come from a quantile regression of the outcome on an indicator for being assigned to free fares relative to no discount, adjusting for the following baseline covariates: Age (years), female (y/n), Black (y/n), more than high school education (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 the person enrolled in the study. X-axis labels report the quantile value for the control group. Dashed lines represent 95% confidence intervals using bootstrapped standard errors.

Figure A2: Effect of free fares relative to no discount on employment outcomes over time



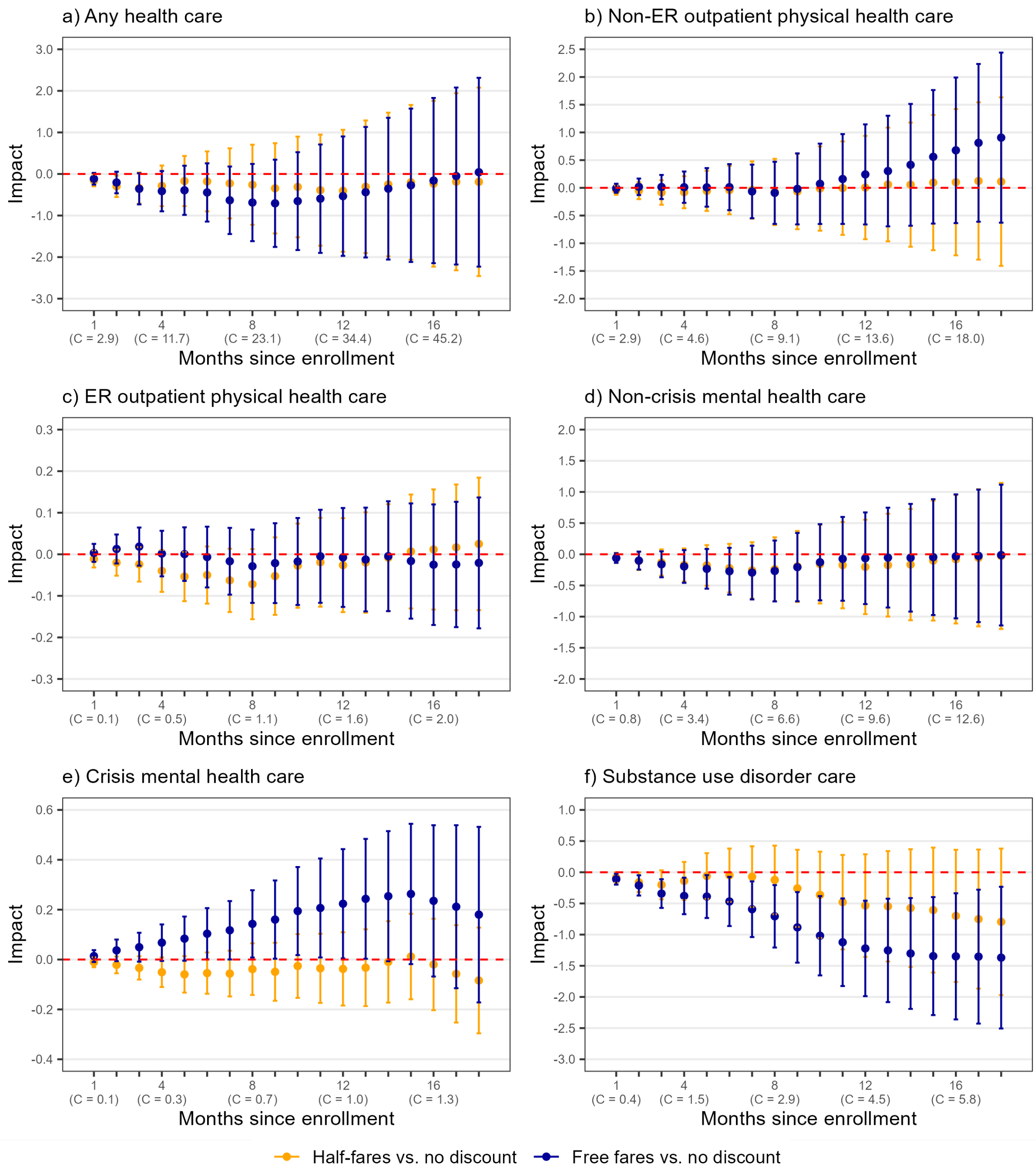
Notes: Figure presents estimates of the effect of being assigned to free fares relative to no discount on employment outcomes over time for the adult sample. The effects in panels A through C come from Pennsylvania unemployment insurance (UI) records. These effects adjust for the following baseline covariates: 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 effects in panels D through F come from follow-up surveys. These effects adjust for the same covariates but without the lagged outcome. The full-sample effect in Q3 in Panel B is a pre-registered primary study outcome. Error bars represent 95% confidence intervals using robust standard errors.

Figure A3: Impacts on quantiles of the distribution of number of days with a health care claim in the first 540 days after enrollment, for free fares versus no discount



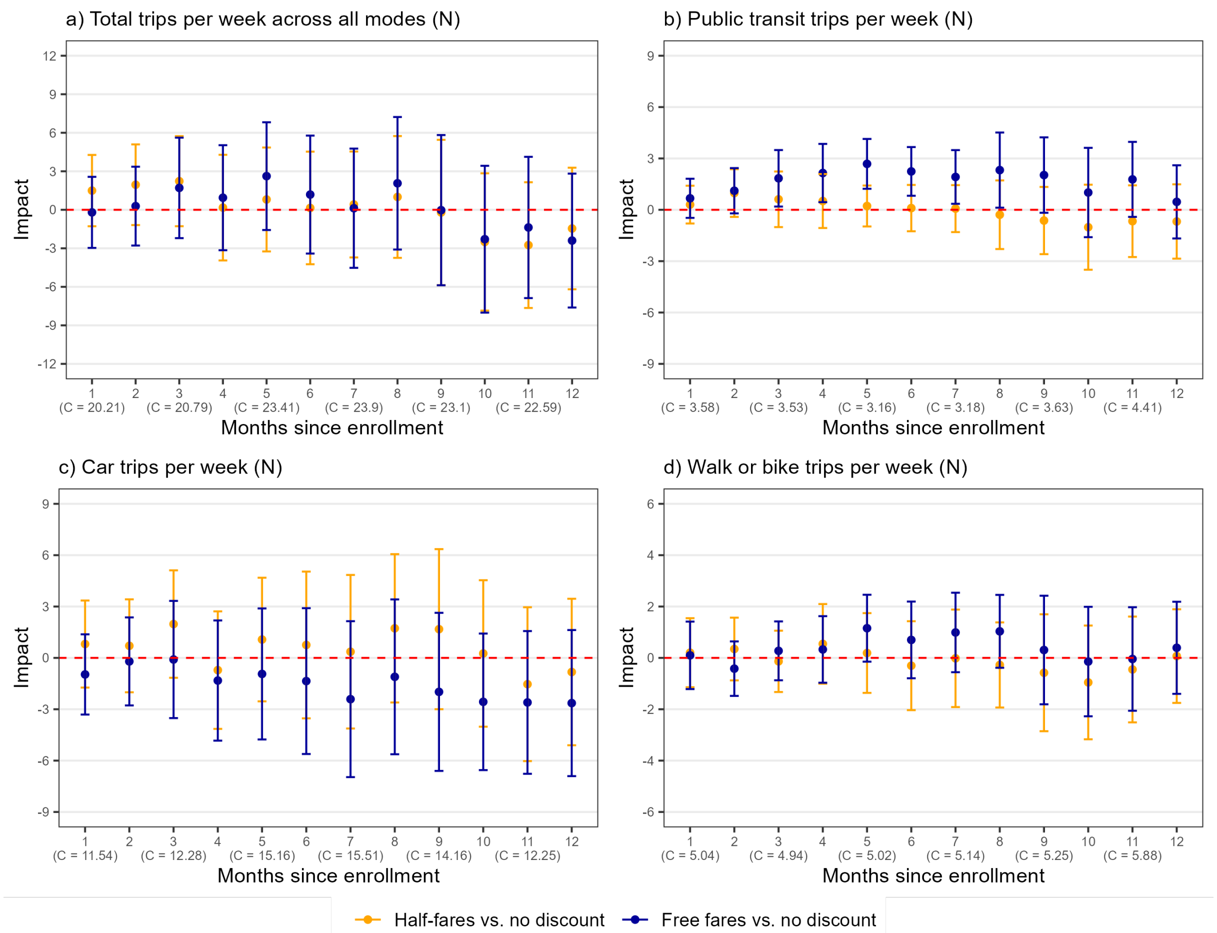
Notes: Figure presents estimates of the effect of being assigned to free fares relative to no discount on quantiles of the number of days that a person received health care in the first 540 days after enrolling in the study. Data comes from Medicaid claims records. Estimates come from a quantile regression of the outcome on an indicator for being assigned to free fares relative to no discount, 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. Dashed lines represent 95% confidence intervals using bootstrapped standard errors.

Figure A4: Impacts on the cumulative number of days with a health care claim over first 18 months



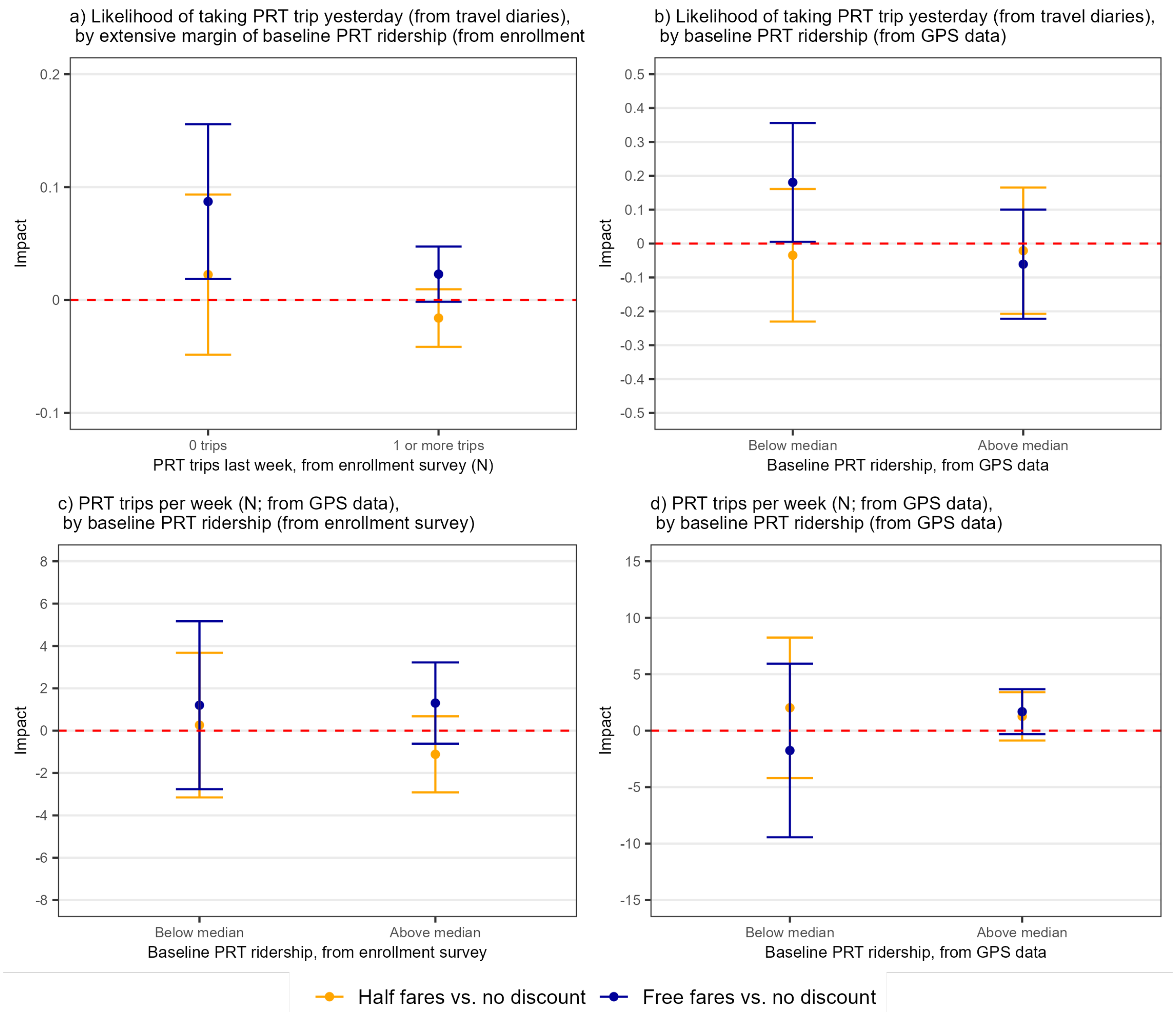
Notes: Figure presents estimates of the effect of being assigned to each discount on the cumulative number of distinct days with at least one Medicaid-funded health care claim in each of the first 18 months after enrollment. Data comes from Medicaid claims records. The outcome is the number of days on which the person had at least one claim, measured cumulatively between the person's study enrollment date and the end of the given month. The treatment effect in Panel B month 9 is a pre-specified confirmatory study outcome. Estimates come from a regression of the outcome on indicators for 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.

Figure A5: Effect of fare discounts on number of trips per week over time



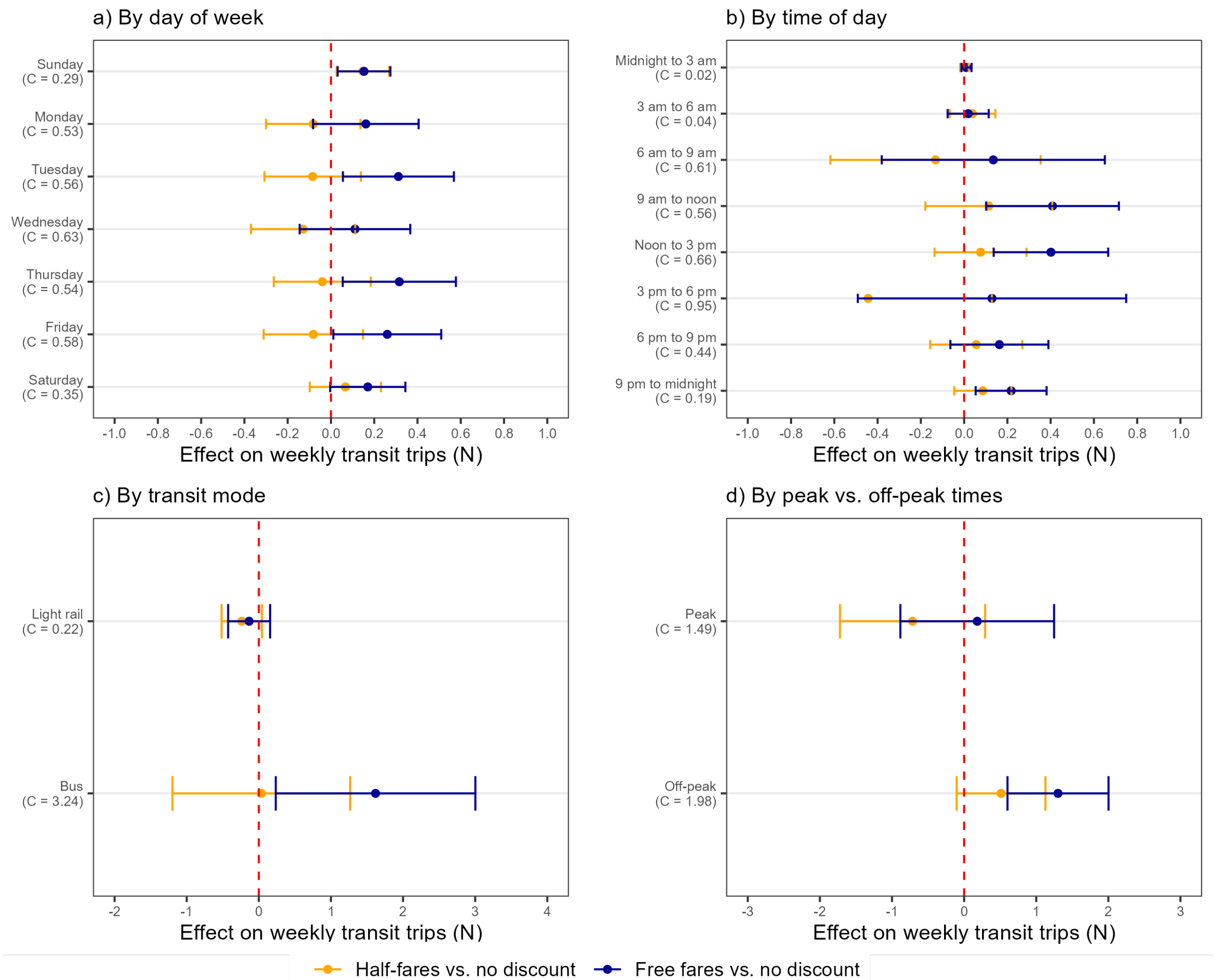
Notes: Figure presents estimates of the effect of fare discounts on the number of trips taken per week over time. Data comes from Google Maps location history (GPS) data. Treatment effects are estimated by running repeated cross-sectional regressions by month. The regressions adjust for the following 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.

Figure A6: Effect of fare discounts on public transit ridership, by baseline level of ridership



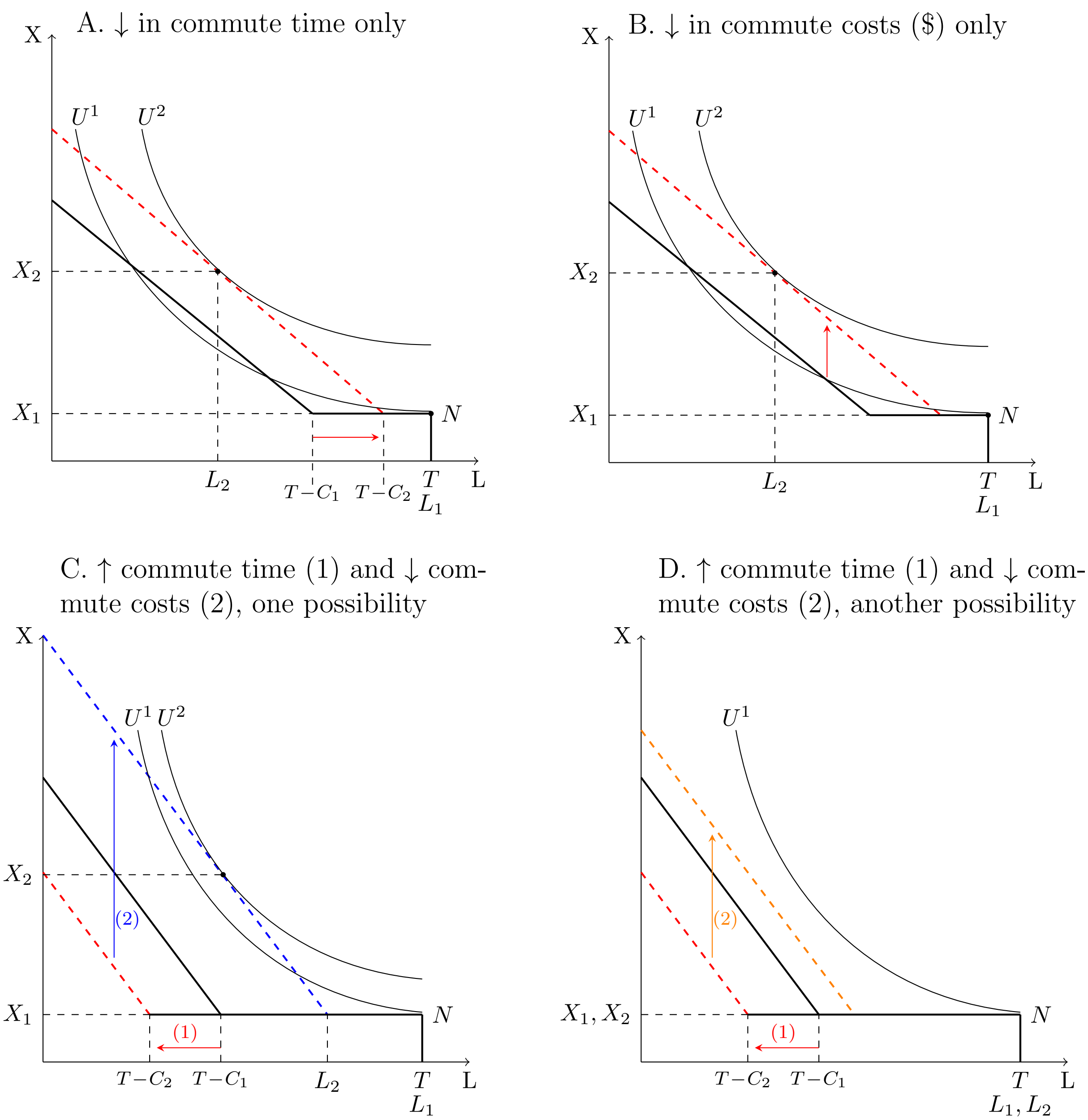
Notes: Figure presents estimates of each fare discount level on various measures of public transit ridership among the adult sample. The effects are disaggregated by the person's level of public transit ridership before enrolling in the study. The outcomes in panels A and B are measured from the travel diary surveys. Estimates in panels A and B are from a regression of the outcome on indicators for treatment status, with normalized weights for the number of travel diaries each person completed. The regression also adjusts 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). The estimates in Panels C and D come from a regression of the outcome on indicators for 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 in the 365 days prior to enrollment. Error bars show 95% confidence intervals using robust standard errors.

Figure A7: Impacts on number of public transit trips per week according to smartphone GPS data, grouped by mode and timing of trip



Notes: Figure presents estimates of the effect of being assigned to each treatment status (50% discount or 100% discount) on the number of public transit trips per week among the adult sample. Data comes from smartphone Google Maps location history records. Peak hours are defined as 6 am to 9 am and 3 pm to 6 pm on weekdays. 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 number of public transit trips per week in the 365 days before the person enrolled in the study. Error bars show the 95% confidence intervals using robust standard errors.

Figure A8: 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.

Table A1: Effects of fare discounts on self-reported transportation and travel outcomes at 15 months after enrollment

Outcome	N	Control mean	Treatment effect: Half fares	Treatment effect: Free fares	Free vs. half fares
PRT spending last week ($)	3,474	33.53	-5.64**†† (2.39)	-17.09***††† (2.80)	-11.45***††† (2.17)
Method of payment used most often for PRT trips					
ConnectCard	3,521	0.367	0.242***††† (0.021)	0.434***††† (0.019)	0.192***††† (0.018)
Cash	3,521	0.334	-0.117***††† (0.020)	-0.217***††† (0.018)	-0.100***††† (0.015)
Other	4,064	0.247	-0.099***††† (0.016)	-0.180***††† (0.014)	-0.080***††† (0.012)
None	4,059	0.644	-0.004 (0.019)	0.011 (0.018)	0.014 (0.017)
Access to a car					
I own a car	4,059	0.147	-0.013 (0.013)	-0.040***††† (0.012)	-0.028**†† (0.011)
I sometimes borrow a car from a friend	4,059	0.091	0.008 (0.012)	0.013 (0.011)	0.005 (0.011)
I share a car with others	4,059	0.072	-0.004 (0.010)	-0.008 (0.009)	-0.004 (0.009)
I sometimes rent a car	4,059	0.019	0.007 (0.006)	0.005 (0.005)	-0.002 (0.006)
Have shared study ConnectCard with someone else	2,796	0.042	0.004 (0.014)	0.009 (0.013)	0.005 (0.009)
Still have study ConnectCard in possession	2,677	0.693	0.165***††† (0.030)	0.242***††† (0.028)	0.077***††† (0.015)
Trips taken with children yesterday (N)	2,439	1.46	-0.045 (0.116)	-0.136 (0.124)	-0.091 (0.105)
How have your children used their ConnectCards?					
To go to school	1,261	0.262	-0.028 (0.045)	0.206***††† (0.052)	0.234***††† (0.044)
To go to stores	1,261	0.214	0.104**† (0.049)	0.252***††† (0.051)	0.147***††† (0.051)
To visit friends	1,261	0.128	0.076**†† (0.033)	0.284***††† (0.044)	0.208***††† (0.043)
To go to extracurricular activities	1,261	0.192	0.020 (0.048)	0.165***††† (0.057)	0.145***††† (0.050)
To accompany me on trips	1,261	0.345	0.093 (0.058)	0.188***††† (0.057)	0.095* (0.055)
6-item Transportation Security Index (TSI) score category					
No insecurity/secure	3,919	0.182	0.061***††† (0.017)	0.092***††† (0.016)	0.031* (0.017)
Marginal/low insecurity	3,919	0.288	-0.013 (0.019)	0.027 (0.019)	0.040**†† (0.017)
Moderate/high insecurity	3,919	0.531	-0.047**†† (0.021)	-0.119***††† (0.020)	-0.072***††† (0.019)

Notes: Table presents estimates of the effect of being assigned to each treatment status (50% discount or 100% discount) on self-reported transportation and travel outcomes for the adult sample. Data comes from the post-endline survey, which took place 15 months after the participant enrolled in the study. 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), and lives within the PRT 7-day frequent service walkshed (y/n). Column N indicates the number of individuals across the three study arms that have non-missing data for the given outcome. Sample sizes vary across outcomes due to differing midline 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 A2: Effects of fare discounts on self-reported employment outcomes at 15 months after enrollment, among adults who were unemployed at baseline

			Treatment effect		
Outcome	N	Control mean	Half fares	Free fares	Free vs. half fares
Employment situation					
Employed	944	0.404	-0.065 (0.041)	0.035 (0.039)	0.100*** (0.038)
Unemployed and seeking work	944	0.309	0.059 (0.040)	-0.028 (0.037)	-0.086** (0.037)
In school or training program	944	0.029	<0.001 (0.016)	0.007 (0.015)	0.006 (0.014)
Unable to work due to illness/injury	944	0.175	0.017 (0.032)	<0.001 (0.030)	-0.016 (0.030)
Homemaker	944	0.062	0.008 (0.022)	-0.013 (0.019)	-0.021 (0.019)
Retired	944	0.011	-0.005 (0.010)	-0.002 (0.010)	0.003 (0.008)
Hourly wage at main job ($; among the employed)	328	14.38	-0.067 (0.779)	0.112 (0.675)	0.179 (0.692)
Weekly work hours (N)					
Including zeroes	944	13.01	-2.52 (1.67)	0.306 (1.65)	2.83* (1.45)
Excluding zeroes	335	33.76	0.207 (2.76)	1.73 (3.08)	1.53 (2.43)
Total jobs held (N)	944	0.414	-0.109** (0.048)	-0.021 (0.048)	0.088** (0.043)
Rating of aspects of main job (1-10)					
Fit with your experience and skills	371	6.71	0.703* (0.391)	-0.058 (0.344)	-0.761** (0.373)
Opportunities for promotion over next 3 yrs	369	5.26	-0.230 (0.478)	-0.406 (0.396)	-0.176 (0.462)
Satisfied with aspects of main job					
Pay	371	0.319	0.016 (0.066)	0.038 (0.061)	0.022 (0.065)
Other aspects of main job besides pay	370	0.328	0.038 (0.071)	0.037 (0.063)	-0.001 (0.069)
All aspects of job overall	372	0.445	0.044 (0.075)	-0.004 (0.067)	-0.049 (0.072)
Do you work from home for main job?					
No	371	0.798	0.082 (0.060)	0.031 (0.055)	-0.051 (0.054)
Yes	371	0.101	-0.011 (0.049)	-0.039 (0.041)	-0.028 (0.043)
Sometimes	371	0.101	-0.071* (0.040)	0.008 (0.043)	0.079** (0.037)
Primary commute mode to main job last week					
Bus	329	0.543	0.070 (0.078)	0.131* (0.070)	0.062 (0.070)
Light rail	329	0.019	0.019 (0.021)	0.012 (0.019)	-0.007 (0.025)
Personal car	329	0.181	-0.102** (0.046)	-0.067 (0.045)	0.034 (0.039)
Carpool	329	0.029	0.028 (0.028)	0.012 (0.024)	-0.015 (0.030)
Walk or bike	329	0.124	-0.041 (0.053)	-0.062 (0.046)	-0.021 (0.039)
Ridesharing app (e.g. Uber or Lyft)	329	0.057	0.012 (0.034)	0.007 (0.031)	-0.005 (0.034)
Round-trip commute time on typical day (minutes)	260	87.66	35.83 (54.44)	9.18 (32.68)	-26.65 (52.61)
Actively searched for job in past 4 weeks	768	0.543	-0.018 (0.048)	0.015 (0.046)	0.033 (0.044)
Job search activities among active searchers					
Jobs applied to in past 4 weeks (N)	399	11.83	-3.97*** (1.49)	-2.15 (1.72)	1.82 (1.23)

Table A2: Effects of fare discounts on self-reported employment outcomes at 15 months after enrollment, among adults who were unemployed at baseline *(continued)*

Outcome	N	Control mean	Treatment effect: Half fares	Treatment effect: Free fares	Free vs. half fares
Time spent searching for a job last week (hours)	398	12.58	-0.321 (1.80)	-0.519 (1.41)	-0.198 (1.67)
Applied to a job posting	403	0.750	-0.065 (0.062)	-0.041 (0.059)	0.024 (0.059)
Looked at job postings	403	0.707	0.105* (0.058)	-0.059 (0.061)	-0.164*** (0.055)
Traveled around to search in person	403	0.250	-0.073 (0.051)	-0.016 (0.052)	0.056 (0.047)
Posted or updated resume or other info	403	0.388	-0.024 (0.067)	0.068 (0.064)	0.092 (0.061)
Contacted an employer in person	403	0.336	-0.097* (0.055)	-0.081 (0.054)	0.016 (0.049)
Contacted an employer online	403	0.328	-0.020 (0.063)	-0.006 (0.060)	0.014 (0.057)

Notes: Table presents estimates of the effect of being assigned to each treatment status (50% discount or 100% discount) on self-reported employment outcomes for the adult sample members who reported being unemployed in the baseline survey. The outcome data comes from the post-endline survey, which took place 15 months after the participant enrolled in the study. 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), 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 three study arms that have non-missing data for the given outcome. Sample sizes vary across outcomes due to differing midline 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 A3: Effects of fare discounts on self-reported health outcomes at 15 months after enrollment

			Treatment effect		
Outcome	N	Control mean	Half fares	Free fares	Free vs. half fares
Life satisfaction rating (0-10)	3,797	5.78	-0.014	0.034	0.048
			(0.121)	(0.116)	(0.112)
Current health good or better	3,807	0.552	-0.015	-0.042**	-0.027
			(0.021)	(0.020)	(0.019)
How has your health changed in past 6 months?					
Gotten better	3,771	0.113	0.010	0.004	-0.006
			(0.015)	(0.014)	(0.013)
Gotten worse	3,771	0.204	-0.030*	0.006	0.036**
			(0.016)	(0.016)	(0.015)
Stayed the same	3,771	0.683	0.021	-0.010	-0.030*
			(0.020)	(0.019)	(0.018)
Has no health insurance	3,734	0.045	0.017	0.015	-0.002
			(0.010)	(0.010)	(0.010)
Time since last doctor visit (months)	2,914	7.12	0.943	0.030	-0.914
			(0.953)	(0.878)	(0.888)
ER visits in past 6 months (N)	3,571	0.935	0.002	0.021	0.019
			(0.071)	(0.066)	(0.065)
Cost-saving measures taken in past 6 months					
Delayed medical care in past 6 months b/c of cost	3,689	0.214	-0.008	-0.016	-0.008
			(0.017)	(0.017)	(0.016)
Skipped doses	738	0.443	0.021	-0.019	-0.040
			(0.053)	(0.052)	(0.048)
Took less medication	738	0.434	-0.032	-0.020	0.012
			(0.051)	(0.050)	(0.047)
Delayed filling a prescription	738	0.605	0.043	0.048	0.006
			(0.052)	(0.051)	(0.048)
Primary mode of travel to last doctor's appt					
Bus or light rail	3,697	0.546	0.006	0.087***†††	0.081***†††
			(0.021)	(0.020)	(0.019)
Walk or bike	3,697	0.082	-0.001	-0.023**	-0.022**
			(0.012)	(0.011)	(0.010)
Personal car	3,697	0.169	-0.017	-0.035**	-0.018
			(0.015)	(0.014)	(0.013)
Ridesharing app	3,697	0.096	0.016	-0.025**	-0.042***†††
			(0.013)	(0.012)	(0.012)
Bothered by the following at least half of the days in past 2 weeks					
Little interest or pleasure in doing things	3,649	0.226	-0.012	0.004	0.016
			(0.018)	(0.017)	(0.016)
Feeling down, depressed, or hopeless	3,648	0.253	-0.017	-0.017	<0.001
			(0.018)	(0.018)	(0.017)
Feeling tired or having little energy	3,657	0.324	-0.003	0.007	0.010
			(0.020)	(0.019)	(0.018)
Feeling bad about yourself, or that you are a failure or have let people down	3,646	0.250	-0.037**	-0.018	0.019
			(0.018)	(0.018)	(0.016)

Table A3: Effects of fare discounts on self-reported health outcomes at 15 months after enrollment *(continued)*

Outcome	N	Control mean	Treatment effect: Half fares	Treatment effect: Free fares	Free vs. half fares
Thoughts that you would be better off dead or of hurting yourself in some way	3,649	0.092	-0.004 (0.012)	-0.012 (0.012)	-0.008 (0.011)
Feeling nervous, anxious, or on edge	3,647	0.312	-0.031 (0.019)	-0.019 (0.019)	0.012 (0.018)
Social and emotional well-being					
I have a sense of direction and purpose in life	4,064	0.591	-0.033 (0.020)	-0.010 (0.020)	0.023 (0.019)
I can count on friends or relatives to help me if I am in trouble	4,064	0.470	-0.008 (0.021)	0.014 (0.020)	0.023 (0.019)
I will be able to achieve most of my goals	4,064	0.506	-0.015 (0.020)	-0.019 (0.020)	-0.004 (0.019)
I often feel that I have little influence over things that happen to me	4,064	0.300	-0.002 (0.019)	-0.011 (0.018)	-0.009 (0.017)
How often do you feel lonely? (0-10 scale where 0 is never and 10 is always)	3,706	4.37	-0.146 (0.140)	-0.137 (0.135)	0.009 (0.130)
Strong or very strong sense of belonging to local community	4,064	0.215	-0.002 (0.017)	0.017 (0.017)	0.019 (0.016)

Notes: Table presents estimates of the effect of being assigned to each treatment status (50% discount or 100% discount) on self-reported health outcomes for the adult sample. Data comes from the post-endline survey, which took place 15 months after the participant enrolled in the study. All 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), and lives within the PRT 7-day frequent service walkshed (y/n). Column N indicates the number of individuals across the three study arms that have non-missing data for the given outcome. 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 A4: Effects of fare discounts on self-reported financial outcomes at 15 months after enrollment

			Treatment effect		
Outcome	N	Control mean	Half fares	Free fares	Free vs. half fares
Has a bank account	3,643	0.652	-0.049** (0.021)	-0.053*** (0.020)	-0.005 (0.019)
Number of credit cards (N)	3,507	1.24	0.065 (0.060)	-0.032 (0.054)	-0.097* (0.055)
Could not afford $400 expense	3,615	0.506	-0.001 (0.022)	0.017 (0.021)	0.018 (0.020)
Money left over per month ($)	3,462	73.25	-0.816 (6.45)	-1.08 (6.61)	-0.264 (6.13)
Cash + checking/savings acct balance ($)	3,420	477.4	-14.62 (26.24)	-29.96 (25.46)	-15.33 (23.44)
Current debt balance ($)	1,587	333.9	-77.97 (81.83)	-68.52 (76.39)	9.45 (64.04)
Remaining credit on credit cards ($)	497	98.97	-2.19 (22.50)	-17.68 (20.51)	-15.49 (18.21)
Which debts do you currently have?					
Credit cards	2,306	0.620	<0.001 (0.030)	-0.028 (0.028)	-0.028 (0.027)
Student loans	2,306	0.471	0.055** (0.028)	0.048* (0.026)	-0.006 (0.025)
Auto loans	2,306	0.212	<0.001 (0.023)	-0.016 (0.021)	-0.017 (0.020)
Other personal loans	2,306	0.233	-0.015 (0.026)	0.004 (0.025)	0.019 (0.024)
Self or partner has retirement plan	3,306	0.116	-0.014 (0.013)	-0.002 (0.012)	0.012 (0.012)
CFPB financial well-being score (sd)	3,413	0.030	-0.031 (0.044)	-0.049 (0.043)	-0.017 (0.041)
Hardships experienced in past 30 days					
Did not pay full amt of rent or mortgage	2,461	0.344	-0.025 (0.026)	-0.039 (0.025)	-0.013 (0.023)
Did not pay full amt of utility bill	2,461	0.471	0.011 (0.027)	-0.004 (0.026)	-0.015 (0.025)
Did not pay full amt of phone or internet bill	2,461	0.303	-0.028 (0.025)	-0.040* (0.023)	-0.011 (0.022)
Borrowed money to help pay bills	2,461	0.406	-0.016 (0.027)	0.012 (0.026)	0.027 (0.024)
Took out a loan to help pay bills	2,461	0.029	0.005 (0.011)	-0.007 (0.009)	-0.012 (0.009)
Used credit card to help pay bills	2,461	0.122	0.002 (0.017)	-0.031** (0.015)	-0.033** (0.014)
Worried that food would run out	2,461	0.416	-0.009 (0.027)	-0.003 (0.025)	0.005 (0.024)
Unstable housing b/c of financial problems	2,461	0.067	-0.007 (0.014)	-0.017 (0.014)	-0.010 (0.013)

Notes: Table presents estimates of the effect of being assigned to each treatment status (50% discount or 100% discount) on self-reported financial outcomes for the adult sample. Data comes from the post-endline survey, which took place 15 months after the participant enrolled in the study. The 'CFPB financial well-being score' outcome comes from a Consumer Financial Protection Bureau questionnaire that is available at https://www.consumerfinance.gov/consumer-tools/educator-tools/financial-well-being-resources/measure-and-score/. All 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), and lives within the PRT 7-day frequent service walkshed (y/n). Column N indicates the number of individuals across the three study arms that have non-missing data for the given outcome. Sample sizes vary across outcomes due to differing midline 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 A5: Effects of fare discounts on criminal justice outcomes in first 365 days after enrollment

		Treatment effect		
Outcome (N = 9,544)	Control mean	Half fares	Free fares	Free vs. half fares
A. Likelihood of having a criminal charge in Allegheny County				
Any criminal charge	0.079	0.012*	0.006	-0.005
		(0.007)	(0.006)	(0.007)
By type of charge				
Summary	<0.001	<0.001	<0.001	<0.001
		(<0.001)	(<0.001)	(0.001)
Misdemeanor	0.056	0.013**	0.006	-0.007
		(0.006)	(0.006)	(0.006)
Felony	0.033	-0.002	0.001	0.004
		(0.004)	(0.004)	(0.004)
By type of crime				
Person	0.017	0.009**	0.006*	-0.002
		(0.004)	(0.004)	(0.004)
Property	0.028	0.004	<0.001	-0.004
		(0.004)	(0.004)	(0.004)
Public Order	0.015	-0.003	-0.003	<0.001
		(0.003)	(0.003)	(0.003)
Domestic violence	0.020	-0.002	-0.005	-0.003
		(0.003)	(0.003)	(0.003)
Drugs	0.015	-0.002	<0.001	0.001
		(0.003)	(0.003)	(0.003)
Other crime type	0.005	<0.001	<0.001	<0.001
		(0.002)	(0.002)	(0.002)
B. Likelihood of failing to appear for an Allegheny County criminal court hearing				
First pretrial hearing	0.071	-0.026	0.006	0.032
		(0.021)	(0.027)	(0.023)
Any pretrial hearing	0.042	-0.001	0.003	0.004
		(0.014)	(0.014)	(0.014)
C. Incarcerations in Allegheny County Jail				
Spent any time in jail	0.043	0.002	<0.001	-0.002
		(0.005)	(0.005)	(0.005)
Days spent in jail (N)	2.51	-0.355	-0.110	0.245
		(0.412)	(0.457)	(0.423)

Notes: Table presents estimates of the effect of being assigned to each treatment status (50% discount or 100% discount) on various criminal justice outcomes for the adult study sample. Outcomes are measured cumulatively over the first 365 days after the person enrolled in the study. Panel A presents impacts on the likelihood that the participant had at least one criminal charge in Allegheny County in this time period. Data for Panel A and B outcomes comes from administrative records for criminal cases in the Court of Common Pleas and the Magisterial District Court for Allegheny County, Pennsylvania. In Panel A, the data is limited to "original" filings, meaning the initial criminal charge that was applied when the case first originated. Definitions for the charge types and crime categories are shown on page 20 here: https://www.courtstatistics.org/__data/assets/pdf_file/0031/88735/State-Court-Guide-to-Statistical-Reporting.pdf. Panel B presents impacts on the likelihood that an adult study participant failed to appear at a criminal court hearing for which they are the defendant. In Panel B, the data only captures failures to appear in court that result in a bench warrant, which comprise the vast majority of all failures to appear at a criminal hearing. The failure-to-appear outcome for each participant is measured as the percentage of their criminal court hearings at which they failed to appear. The denominator of this outcome excludes hearings during which the person was incarcerated in the Allegheny County Jail, because jail inmates cannot fail to appear in court. Data for Panel C comes from Allegheny County Jail administrative records. All estimates in the table 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), and lives within the PRT 7-day frequent service walkshed (y/n). The estimates in Panels A and C additionally adjust for the outcome measured in the 365 days before the person enrolled in the study. 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 fare discounts on social services involvement and public benefits receipt

		Treatment effect		
Outcome (N = 9,544)	Control mean	Half fares	Free fares	Free vs. half fares
A. Involvement with homelessness services in first 18 months after enrollment				
Stayed at homeless shelter	0.021	0.002 (0.004)	-0.001 (0.003)	-0.003 (0.004)
Days spent in homeless shelter (N)	1.63	-0.363 (0.377)	-0.553 (0.356)	-0.190 (0.303)
B. Involvement with child welfare services in first 18 months after enrollment				
Had a child welfare referral	0.183	0.006 (0.009)	0.019** (0.009)	0.012 (0.009)
Child welfare referrals (N)	0.914	0.058 (0.063)	0.028 (0.060)	-0.030 (0.059)
C. Likelihood of receiving public benefits in 18th month after enrollment				
SNAP	0.780	0.007 (0.010)	0.003 (0.010)	-0.005 (0.010)
TANF	0.050	-0.001 (0.005)	<0.001 (0.005)	0.001 (0.005)
Medicaid	0.827	0.013 (0.009)	0.020** (0.009)	0.007 (0.009)
SSI	0.138	0.001 (0.005)	0.004 (0.005)	0.003 (0.005)
Section 8 rental subsidy	0.181	-0.004 (0.007)	0.003 (0.007)	0.006 (0.006)
Child care subsidy	0.076	-0.002 (0.005)	<0.001 (0.005)	0.002 (0.005)

Notes: Table presents estimates of the effect of being assigned to each treatment status (50% discount or 100% discount) on the receipt of various social services and public benefits. Data comes from Allegheny County Department of Human Services (ACDHS) and Pennsylvania Department of Human Services (PADHS) administrative records. The estimates in panels A through C come 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 365 days before the person enrolled in the study. 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: Effects of fare discounts on number of Medical Assistance Transportation Program (MATP) trips taken per month

		Treatment effect		
MATP trips per month (N = 9,544)	Control mean	Half fares	Free fares	Free vs. half fares
All modes	0.617	-0.056 (0.055)	-0.122**† (0.055)	-0.066 (0.048)
Public transit	0.373	-0.040 (0.041)	-0.123***††† (0.036)	-0.084***†† (0.029)
Drive self	0.061	-0.228 (0.191)	-0.088 (0.190)	0.140 (0.117)
Ridehailing	0.004	0.137 (0.174)	-0.315***†† (0.105)	-0.452***†† (0.143)
ACCESS paratransit	0.178	0.094 (0.118)	0.111 (0.121)	0.017 (0.114)

Notes: Table presents estimates of the effect of being assigned to each treatment status (50% discount or 100% discount) on the adult sample's use of the Pennsylvania Medical Assistance Transportation Program (MATP). This program provides unlimited free trips to and from medical appointments for individuals with Medicaid health insurance. A single MATP trip is defined as a one-way trip, either from home to the doctor or vice versa. The mode of the trip depends on MATP policies related to the mobility needs of the rider and the feasibility of taking public transit to the appointment. Data comes from MATP administrative records that are complete going back to January 1, 2015. 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 total number of MATP trips of the given mode that the participant took prior to their study enrollment (N). 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 A8: Effects of fare discounts on health care utilization among the child sample within the first 540 days after enrollment

Outcome (N = 4,928)	Control mean	Treatment effect: Half fares	Treatment effect: Free fares	Free vs. half fares
Received any health care	0.886	0.005 (0.011)	0.016 (0.011)	0.011 (0.011)
A. Physical health care				
Has at least one claim				
Any physical health care	0.875	0.003 (0.012)	0.013 (0.011)	0.010 (0.011)
Non-ER outpatient	0.854	-0.004 (0.012)	0.016 (0.012)	0.019 (0.012)
ER outpatient	0.377	0.005 (0.017)	$<$0.001 (0.017)	-0.005 (0.017)
Non-ER inpatient	0.015	-0.007* (0.004)	-0.005 (0.004)	0.002 (0.003)
ER inpatient	0.020	-0.006 (0.005)	-0.006 (0.005)	$<$0.001 (0.004)
Days with at least one claim (N)				
Any physical health care	8.35	0.281 (0.542)	0.230 (0.479)	-0.051 (0.524)
Non-ER outpatient	4.79	0.293 (0.383)	0.174 (0.276)	-0.119 (0.372)
ER outpatient	0.735	0.014 (0.050)	0.067 (0.053)	0.053 (0.052)
Non-ER inpatient	0.068	-0.044** (0.022)	0.021 (0.041)	0.065* (0.036)
ER inpatient	0.110	-0.040 (0.034)	-0.025 (0.038)	0.015 (0.034)
Prescription fills (N)	4.99	-0.019 (0.340)	0.082 (0.341)	0.101 (0.321)
Days covered by a prescription (N)	82.16	0.092 (4.67)	4.98 (4.67)	4.88 (4.68)
B. Behavioral health care				
Has at least one claim				
Any behavioral health care	0.345	-0.001 (0.017)	0.036** (0.017)	0.037** (0.017)
Non-crisis	0.330	0.004 (0.017)	0.034** (0.017)	0.029* (0.016)
Crisis	0.093	0.004 (0.010)	0.011 (0.010)	0.007 (0.010)
Substance use treatment	0.004	0.006** (0.003)	0.008** (0.003)	0.002 (0.004)
Days with at least one claim (N)				
Any behavioral health care	8.84	0.575 (1.05)	2.22** (1.05)	1.65 (1.08)
Non-crisis	7.79	0.528 (0.987)	1.94** (0.986)	1.41 (1.02)
Crisis	0.301	-0.063 (0.052)	-0.006 (0.057)	0.057 (0.048)
Substance use treatment	0.027	0.083** (0.040)	0.098** (0.049)	0.015 (0.060)
Prescription fills (N)	1.22	0.027 (0.171)	0.283 (0.177)	0.256 (0.182)
Days covered by a prescription (N)	28.24	-0.660 (3.35)	4.82 (3.56)	5.48 (3.46)
Cost of care to managed care org. ($)	1,434	-60.24 (234.7)	310.6 (252.2)	370.9 (238.1)

Notes: Table presents estimates of the effect of being assigned to each treatment status (50% discount or 100% discount) on health care utilization for the child sample, as measured in the first 540 days after enrollment. Data comes from Medicaid claims. Estimates are from a regression of the outcome on indicators for each treatment status, with no covariate adjustment. 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 A9: Effects of fare discounts on Pittsburgh Public School student outcomes

Outcome	N	Control mean	Treatment effect: Half fares	Treatment effect: Free fares	Free vs. half fares
A. Absences and suspensions					
2022-2023 school year (after study enrollment)					
Absences - Any (N)	1,480	16.40	0.143	1.28	1.13
			(0.966)	(1.01)	(0.972)
Absences - Excused (N)	1,480	3.90	0.078	0.271	0.193
			(0.300)	(0.323)	(0.321)
Absences - Unexcused (N)	1,480	12.50	0.066	1.00	0.939
			(0.920)	(0.946)	(0.915)
Out-of-school suspensions (N)	1,480	0.680	0.034	0.088	0.054
			(0.134)	(0.121)	(0.138)
2023-2024 school year					
Absences - Any (N)	1,360	24.62	-0.233	1.48	1.71
			(1.54)	(1.58)	(1.51)
Absences - Excused (N)	1,360	5.78	-0.300	-0.178	0.122
			(0.453)	(0.437)	(0.442)
Absences - Unexcused (N)	1,360	18.84	0.067	1.66	1.59
			(1.47)	(1.50)	(1.43)
Out-of-school suspensions (N)	1,360	1.07	-0.043	-0.058	-0.016
			(0.205)	(0.181)	(0.194)
B. Pennsylvania System of School Assessment (PSSA) test scores					
2022-2023 school year					
English Language Arts score (SD)	631	-0.164	0.099*	0.075	-0.025
			(0.056)	(0.055)	(0.058)
Math score (SD)	635	-0.531	0.115**	0.058	-0.057
			(0.055)	(0.055)	(0.056)
Science score (SD)	203	1.78	0.006	0.083	0.077
			(0.175)	(0.184)	(0.189)
Mean score across all subjects (SD)	640	-0.120	0.111*	0.048	-0.063
			(0.062)	(0.061)	(0.064)
2023-2024 school year					
English Language Arts score (SD)	673	-0.238	0.118**	0.103*	-0.015
			(0.056)	(0.055)	(0.057)
Math score (SD)	674	-0.466	0.077	0.081	0.004
			(0.052)	(0.053)	(0.055)
Science score (SD)	206	1.79	0.119	0.231	0.113
			(0.176)	(0.170)	(0.175)
Mean score across all subjects (SD)	682	-0.145	0.101*	0.135**	0.035
			(0.058)	(0.061)	(0.063)

Notes: Table presents estimates of the effect of being assigned to each treatment status (50% discount or 100% discount) on the academic outcomes of children in the sample who attend Pittsburgh Public School District schools. Data comes from Pittsburgh Public Schools administrative records. Absences and suspensions in the 2022-2023 school year are limited to the portion of the school year after the student became enrolled in the study. The PSSA English Language Arts and Mathematics tests are taken by students in grades 3 to 8, and the Science test is taken by students in grades 4 to 8. The English Language Arts test for the 2022-2023 school year was administered in late April 2023, and the Math and Science tests were administered in early May 2023 (i.e. after all students had enrolled in the study). Test scores are expressed as standard deviation units. Estimates are from a regression of the outcome on indicators for each treatment status, with no covariate adjustment. Column N indicates the total number of participants across the three study arms that have non-missing data for the given outcome. 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 A10: Effects of fare discounts on cumulative employment outcomes for older youth in the first six full calendar quarters after enrollment

		Treatment effect		
Outcome (N = 697)	Control mean	Half fares	Free fares	Free vs. half fares
Had any paid employment	0.729	0.040 (0.041)	0.006 (0.041)	-0.034 (0.040)
Number of quarters with employment (N)	2.93	0.122 (0.216)	-0.027 (0.215)	-0.149 (0.215)
Earnings ($)	6,628	594.1 (799.0)	-506.9 (770.2)	-1,101 (792.0)
Number of employers worked for (N)	1.79	0.201 (0.175)	0.021 (0.170)	-0.180 (0.165)
Number of NAICS sectors worked in (N)	1.22	0.177* (0.104)	0.046 (0.099)	-0.131 (0.102)

Notes: Table presents estimates of the effect of being assigned to each treatment status (50% discount or 100% discount) on employment outcomes for the participants who were 16 or 17 years old when they joined the study. The outcomes are measured cumulatively in the first fix complete calendar quarters after the quarter in which the person enrolled in the study. Data comes from Pennsylvania unemployment insurance (UI) administrative records. Estimates are from a regression of the outcome on indicators for each treatment status, with no covariate adjustment. N indicates the number of individuals across the three study arms that have non-missing data for these outcomes. 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 A11: Robustness of effects of free fares relative to no discount on travel outcomes measured from post-endline survey

Outcome	N	Control mean	(1)	(2)	(3)	(4)
PRT trips last week (N)	4,048	11.95	-0.420 (2.00)	-0.696 (2.11)	-0.866 (2.01)	-0.618 (2.18)
PRT spending last week ($)	3,474	33.53	-17.13*** (2.59)	-17.09*** (2.80)	-19.43*** (2.89)	-17.45*** (2.69)
6-item Transportation Security Index (TSI) score category						
No insecurity/secure	3,919	0.182	0.084*** (0.016)	0.092*** (0.016)	0.094*** (0.019)	0.094*** (0.017)
Marginal/Low insecurity	3,919	0.288	0.033* (0.018)	0.027 (0.019)	0.048** (0.021)	0.028* (0.017)
Moderate/High insecurity	3,919	0.531	-0.117*** (0.020)	-0.119*** (0.020)	-0.142*** (0.023)	-0.122*** (0.020)
Still have study ConnectCard in possession	2,677	0.693	0.216*** (0.025)	0.242*** (0.028)	0.205** (0.094)	0.220*** (0.027)
Trips taken with children yesterday across all modes (N) (only among participants with children)	2,439	1.46	-0.111 (0.151)	-0.136 (0.124)	-0.102 (0.148)	-0.143 (0.126)
How have your children used their ConnectCards?						
To go to school	1,261	0.262	0.218*** (0.032)	0.206*** (0.052)	0.332*** (0.092)	0.195*** (0.061)
To go to stores	1,261	0.214	0.271*** (0.031)	0.252*** (0.051)	0.416*** (0.070)	0.270*** (0.054)
To go visit friends	1,261	0.128	0.261*** (0.028)	0.284*** (0.044)	0.319*** (0.070)	0.295*** (0.040)
To go to extracurricular activities	1,261	0.192	0.238*** (0.030)	0.165*** (0.057)	0.286*** (0.092)	0.188*** (0.060)
To accompany me on trips	1,261	0.345	0.216*** (0.033)	0.188*** (0.057)	0.026 (0.132)	0.222*** (0.053)
No covariates			X			X
Includes benchmark covariates				X		
Post-double LASSO covariate selection					X	
Includes nonresponse weights						X

Notes: Table presents the robustness of the effect of being assigned to the 100% discount relative to no discount on various travel-related outcomes measured from the post-endline survey, which took place 15 months after the participant enrolled in the study. The estimates in column (1) are from a regression of the outcome on an indicator for treatment status, with no covariate adjustment. The effects in column (2) adjust for the benchmark set of covariates used throughout the main text. Column (3) uses the post-double LASSO method to select the model covariates. Column (4) includes survey nonresponse weights that are generated using a logit model that includes the benchmark set of covariates on the right-hand side. 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. Sample sizes vary across outcomes due to differing survey item response rates. Robust standard errors are in parentheses. ***p <0.01, **p <0.05, *p <0.1

Table A12: Robustness of effects of free fares relative to no discount on travel diary outcomes

Outcome	Control mean	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Number of places visited yesterday (N)	3.69	-0.648*** (0.176)	-0.553*** (0.148)	-0.563*** (0.149)	-0.605*** (0.131)	-0.570*** (0.100)	-0.551*** (0.148)	-0.489*** (0.167)
Took at least one trip across all diaries								
Car trip	0.714	0.047*** (0.013)	0.032*** (0.012)	0.013 (0.009)	0.044*** (0.012)	0.015* (0.008)	0.013 (0.009)	0.003 (0.011)
Public transportation trip	0.847	0.035*** (0.010)	0.035*** (0.008)	0.027*** (0.007)	0.037*** (0.009)	0.032*** (0.009)	0.026*** (0.007)	0.024*** (0.009)
Walk or bike trip	0.800	-0.016 (0.012)	-0.003 (0.011)	-0.011 (0.010)	-0.016 (0.011)	-0.011 (0.010)	-0.011 (0.010)	-0.012 (0.013)
Likelihood of taking at least one trip yesterday								
Car trip	0.346	-0.005 (0.009)	-0.029*** (0.011)	-0.031*** (0.011)	-0.019** (0.008)	-0.033*** (0.008)	-0.029*** (0.011)	-0.031** (0.014)
Public transportation trip	0.576	0.006 (0.010)	0.025** (0.012)	0.026** (0.012)	0.011 (0.009)	0.028*** (0.008)	0.026** (0.012)	0.032** (0.016)
Walk or bike trip	0.469	-0.060*** (0.011)	-0.046*** (0.013)	-0.046*** (0.013)	-0.051*** (0.008)	-0.049*** (0.010)	-0.046*** (0.013)	-0.043** (0.017)
Likelihood of leaving house yesterday								
For work	0.406	-0.019** (0.010)	-0.025** (0.011)	-0.026** (0.011)	-0.023*** (0.008)	-0.026*** (0.008)	-0.024** (0.011)	-0.029** (0.014)
For school	0.131	-0.017** (0.007)	-0.012* (0.007)	-0.012* (0.007)	-0.018*** (0.006)	-0.012** (0.005)	-0.011 (0.007)	-0.010 (0.009)
For groceries	0.508	-0.045*** (0.010)	-0.029*** (0.011)	-0.030*** (0.011)	-0.040*** (0.009)	-0.028*** (0.007)	-0.028*** (0.011)	-0.024* (0.014)
For leisure	0.238	-0.016* (0.008)	-0.024** (0.010)	-0.025*** (0.010)	-0.016** (0.008)	-0.026*** (0.008)	-0.023** (0.010)	-0.029** (0.012)
For health care	0.170	-0.024*** (0.007)	-0.010 (0.007)	-0.011 (0.007)	-0.017*** (0.007)	-0.008* (0.005)	-0.009 (0.007)	-0.006 (0.009)
For social services	0.084	-0.030*** (0.005)	-0.019*** (0.005)	-0.020*** (0.005)	-0.027*** (0.005)	-0.019*** (0.004)	-0.018*** (0.005)	-0.019*** (0.006)
For other reason	0.281	-0.023*** (0.009)	-0.013 (0.010)	-0.011 (0.010)	-0.027*** (0.008)	-0.011 (0.008)	-0.013 (0.010)	-0.008 (0.012)
Did not leave house yesterday	0.134	0.025*** (0.007)	0.022*** (0.007)	0.023*** (0.007)	0.026*** (0.006)	0.021*** (0.006)	0.021*** (0.007)	0.018* (0.010)
Pooled mean outcome across all diaries		X			X		X	
Diary-level panel data			X	X		X		X
Includes day, month, and year fixed effects				X		X		
Includes nonresponse weights					X	X		
Includes weights for number of diaries completed							X	
Limited to those who completed at least 20 diaries								X

Notes: Table explores the robustness of the effect of being assigned to the 100% discount relative to no discount on outcomes collected from travel diaries. Columns (1), (4), and (6) use pooled cross-sectional data in which the outcome is the simple average of each participant's responses to the given diary question. Columns (2), (3), (5), and (7) use panel data with one observation per person per diary response. The survey nonresponse weights in columns (4) and (5) are generated using a logit model that includes the following baseline characteristics: 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). These same covariates are included in all treatment effect-estimating regressions in the table. Robust standard errors are in parentheses. ***p <0.01, **p <0.05, *p <0.1

Table A13: Robustness of effects of free fares relative to no discount on mobility outcomes from smartphone GPS data

Outcome	Control mean	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A. Trip-taking by mode								
Likelihood of taking at least one trip during entire study (%)								
By public transportation	0.788	0.074*	0.133***	0.056	0.223***	0.002	0.049	-
		(0.044)	(0.051)	(0.046)	(0.069)	(0.043)	(0.043)	
By private vehicle	0.962	0.010	0.016	-0.019	0.062	-0.007	-0.018	-
		(0.021)	(0.025)	(0.013)	(0.041)	(0.005)	(0.011)	
By walk or bike	0.909	0.030	0.037	-0.047**	0.160***	-0.038**	-0.045***	-
		(0.031)	(0.039)	(0.019)	(0.059)	(0.016)	(0.017)	
Likelihood of using car during study (%)								
For less than 5% of all trips	0.023	0.005	-0.021	0.027	-0.011	0.015	0.027	-
		(0.018)	(0.026)	(0.020)	(0.030)	(0.010)	(0.018)	
For less than 10% of all trips	0.078	-0.028	-0.059	0.014	-0.017	0.009	0.019	-
		(0.029)	(0.038)	(0.040)	(0.043)	(0.036)	(0.034)	
For less than 15% of all trips	0.141	-0.040	-0.054	-0.036	0.074	-0.048	-0.041	-
		(0.038)	(0.045)	(0.050)	(0.056)	(0.053)	(0.046)	
For less than 20% of all trips	0.195	-0.021	-0.014	-0.004	0.013	-0.011	<0.001	-
		(0.045)	(0.053)	(0.056)	(0.058)	(0.061)	(0.052)	
Likelihood of using public transportation during study (%)								
For less than 5% of all trips	0.391	-0.149***	-0.163***	-0.129**	-0.146**	-0.138**	-0.123**	-
		(0.054)	(0.060)	(0.061)	(0.072)	(0.059)	(0.058)	
For less than 10% of all trips	0.484	-0.136**	-0.132**	-0.120*	0.256	-0.146**	-0.127**	-
		(0.057)	(0.063)	(0.063)	(0.204)	(0.061)	(0.059)	
For less than 15% of all trips	0.594	-0.150***	-0.155**	-0.145**	-0.065	-0.208***	-0.146**	-
		(0.057)	(0.063)	(0.070)	(0.179)	(0.067)	(0.065)	
For less than 20% of all trips	0.641	-0.157***	-0.173***	-0.107	-0.358***	-0.125*	-0.120*	-
		(0.057)	(0.062)	(0.072)	(0.096)	(0.071)	(0.066)	
Likelihood of taking at least one trip per day (%)								
By public transportation	0.205	0.073***	0.069**	0.052**	0.088**	0.062**	0.059**	0.003
		(0.027)	(0.031)	(0.026)	(0.036)	(0.026)	(0.025)	(0.060)
By private vehicle	0.520	-0.050	-0.049	-0.056*	-0.053	-0.069**	-0.058*	0.025
		(0.032)	(0.034)	(0.032)	(0.044)	(0.029)	(0.030)	(0.064)
By walking or biking	0.298	0.022	0.019	0.022	0.060	0.028	0.021	0.028
		(0.029)	(0.031)	(0.025)	(0.041)	(0.028)	(0.025)	(0.060)
By other mode	0.009	-0.004**	-0.004**	-0.006***	-0.003	-0.005***	-0.005***	0.001
		(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.006)
All travel modes	0.702	-0.040	-0.041	-0.039	-0.014	-0.031	-0.038	-0.008
		(0.029)	(0.032)	(0.027)	(0.043)	(0.023)	(0.025)	(0.061)
Number of trips per week (N)								
By public transportation	3.47	1.56**	0.999	1.48**	2.01**	1.36*	1.52**	0.846
		(0.624)	(0.844)	(0.716)	(0.868)	(0.790)	(0.749)	(1.44)
By private vehicle	13.39	-2.18	-1.79	-1.67	-0.455	-1.99	-1.71	-1.22
		(1.35)	(1.42)	(1.44)	(1.54)	(1.36)	(1.27)	(2.52)
By walking or biking	4.94	0.017	-0.012	0.385	0.845	0.308	0.366	0.403

Table A13: Robustness of effects of free fares relative to no discount on mobility outcomes from smartphone GPS data *(continued)*

Outcome	Control mean	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		(0.621)	(0.637)	(0.513)	(0.891)	(0.548)	(0.489)	(1.38)
By other mode	0.064	-0.026**	-0.027**	-0.043***	-0.018	-0.038***	-0.039***	0.004
		(0.013)	(0.012)	(0.013)	(0.024)	(0.012)	(0.012)	(0.044)
All travel modes	21.86	-0.622	-0.832	-0.108	1.42	-0.671	-0.147	0.263
		(1.50)	(1.70)	(1.65)	(2.03)	(1.59)	(1.56)	(3.43)
Number of trips per day on days with at least one trip (N)								
By public transportation	2.09	0.160	0.058	0.290**	0.534**	0.279*	0.282**	-
		(0.101)	(0.143)	(0.133)	(0.221)	(0.145)	(0.132)	
By private vehicle	3.16	-0.222	-0.148	-0.099	0.047	-0.116	-0.107	-
		(0.172)	(0.189)	(0.200)	(0.200)	(0.188)	(0.179)	
By walking or biking	1.97	-0.019	-0.003	0.062	0.075	0.033	0.053	-
		(0.082)	(0.080)	(0.073)	(0.130)	(0.071)	(0.066)	
By other mode	1.07	-0.006	-0.020	-0.077	-0.007	-0.065	-0.094*	-
		(0.032)	(0.045)	(0.058)	(0.063)	(0.047)	(0.049)	
All travel modes	4.20	0.075	0.068	0.152	0.386	0.072	0.152	-
		(0.178)	(0.209)	(0.205)	(0.488)	(0.215)	(0.200)	
Mode of travel for person's most common journey								
Likelihood of using public transportation	0.087	-0.004	0.016	0.005	-0.043	-0.017	0.004	-
		(0.032)	(0.034)	(0.030)	(0.040)	(0.034)	(0.028)	
Likelihood of using private vehicle	0.586	0.048	0.011	-0.090**	-0.026	-0.092**	-0.104***	-
		(0.058)	(0.057)	(0.036)	(0.060)	(0.036)	(0.033)	
Likelihood of walking or biking	0.317	-0.044	-0.021	0.080	-0.260	0.098*	0.087*	-
		(0.057)	(0.057)	(0.053)	(0.158)	(0.057)	(0.048)	
B. Time and distance traveled								
Time spent traveling per day (hours)								
By public transportation	0.202	0.079**	0.038	0.093***	0.113**	0.102***	0.097***	0.084
		(0.038)	(0.049)	(0.035)	(0.056)	(0.032)	(0.035)	(0.080)
By private vehicle	0.830	-0.095	-0.100	-0.180**	0.020	-0.203**	-0.168**	0.136
		(0.087)	(0.106)	(0.088)	(0.119)	(0.089)	(0.079)	(0.182)
By walking or biking	0.185	0.016	0.019	-0.003	0.040	-0.015	-0.005	0.070
		(0.029)	(0.030)	(0.034)	(0.037)	(0.036)	(0.032)	(0.071)
By other mode	0.087	-0.051*	-0.060**	-0.058***	-0.071	-0.055***	-0.051***	-0.029
		(0.029)	(0.028)	(0.018)	(0.065)	(0.018)	(0.017)	(0.057)
All travel modes	1.30	-0.051	-0.103	-0.182*	0.109	-0.201**	-0.164*	0.231
		(0.101)	(0.120)	(0.101)	(0.137)	(0.093)	(0.091)	(0.212)
Total distance traveled per day (miles)								
By public transportation	1.57	0.628**	0.466	0.974***	0.542	1.03***	0.996***	0.825
		(0.306)	(0.413)	(0.259)	(0.470)	(0.243)	(0.249)	(0.634)
By private vehicle	8.65	-2.03*	-1.13	-1.45*	-2.31	-1.25	-1.48*	-0.687
		(1.15)	(1.19)	(0.874)	(2.03)	(0.884)	(0.789)	(2.01)
By walking or biking	0.310	-0.087*	-0.051	-0.020	-0.066	-0.038	-0.032	0.052

Table A13: Robustness of effects of free fares relative to no discount on mobility outcomes from smartphone GPS data *(continued)*

Outcome	Control mean	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		(0.051)	(0.039)	(0.036)	(0.074)	(0.033)	(0.031)	(0.142)
By other mode	1.50	-0.225	0.071	-0.911	0.628	-0.590	-0.740	-7.71*
		(0.729)	(0.775)	(0.871)	(0.623)	(0.747)	(0.708)	(4.18)
All travel modes	12.03	-1.72	-0.644	-1.26	-1.58	-1.04	-1.14	-6.84
		(1.46)	(1.50)	(1.36)	(2.28)	(1.20)	(1.18)	(4.83)
Mean daily maximum distance from home (miles)	5.47	-0.942	0.016	-1.28*	-0.887	-0.899	-1.23*	-2.03
		(0.848)	(0.857)	(0.753)	(1.16)	(0.767)	(0.702)	(3.64)
C. Staying at home								
Likelihood of leaving house on a given day (%)	0.493	-0.043	-0.036	-0.057	-0.036	-0.024	-0.046	-0.047
		(0.036)	(0.041)	(0.037)	(0.030)	(0.040)	(0.035)	(0.077)
Number of times left house per day (N)	0.739	-0.108*	-0.087	-0.125*	-0.047	-0.076	-0.111*	-0.102
		(0.064)	(0.068)	(0.066)	(0.082)	(0.070)	(0.058)	(0.132)
Time spent at home per day (hours)	12.87	0.376	0.306	0.157	0.269	0.772	0.329	-0.089
		(0.823)	(0.946)	(0.910)	(0.649)	(0.991)	(0.867)	(1.74)
D. Travels per journey from home								
Number of trips per journey away from home (N)								
By public transportation	2.02	0.317	0.340	0.584**	0.640**	0.651**	0.562**	-
		(0.238)	(0.281)	(0.260)	(0.324)	(0.252)	(0.232)	
By private vehicle	3.21	-0.022	0.142	0.094	0.151	0.004	0.096	-
		(0.300)	(0.373)	(0.267)	(0.424)	(0.293)	(0.250)	
By walking or biking	1.98	0.266	0.316	0.305	0.579***	0.370**	0.287	-
		(0.195)	(0.242)	(0.191)	(0.218)	(0.182)	(0.176)	
By other mode	0.584	-0.067	0.014	-0.060	0.199*	-0.032	-0.032	-
		(0.091)	(0.101)	(0.151)	(0.108)	(0.149)	(0.135)	
All travel modes	4.45	0.501	0.685	0.673	0.879	0.587	0.655	-
		(0.557)	(0.710)	(0.568)	(0.613)	(0.578)	(0.512)	
Distance traveled per journey away from home (miles)								
By public transportation	7.32	0.109	0.070	1.60	-0.697	1.62	1.62	-
		(1.35)	(1.99)	(1.58)	(2.65)	(1.45)	(1.41)	
By private vehicle	13.66	2.50	6.16	6.46	2.09	6.19	6.81	-
		(3.55)	(5.65)	(6.50)	(4.06)	(6.77)	(6.11)	
By walking or biking	0.891	-0.130	0.050	-0.025	-0.088	-0.042	-0.027	-
		(0.149)	(0.206)	(0.162)	(0.169)	(0.160)	(0.149)	
By other mode	170.2	-40.25	-16.33	-93.68	74.73	-74.21	-81.01	-
		(69.43)	(78.54)	(112.5)	(59.15)	(101.6)	(97.65)	
All travel modes	25.01	-7.19	-4.78	1.03	1.81	6.86	0.638	-
		(10.33)	(13.96)	(14.58)	(4.43)	(10.26)	(11.62)	
Time spent traveling per journey away from home (hours)								
By public transportation	0.888	0.065	0.016	-0.056	0.237	-0.098	-0.062	-
		(0.114)	(0.139)	(0.134)	(0.156)	(0.136)	(0.114)	

Table A13: Robustness of effects of free fares relative to no discount on mobility outcomes from smartphone GPS data *(continued)*

Outcome	Control mean	(1)	(2)	(3)	(4)	(5)	(6)	(7)
By private vehicle	1.82	0.169 (0.422)	0.309 (0.478)	-0.051 (0.550)	0.626* (0.331)	-0.635 (0.536)	-0.060 (0.514)	-
By walking or biking	0.762	-0.061 (0.192)	0.077 (0.215)	-0.101 (0.224)	0.443 (0.328)	-0.186 (0.185)	-0.105 (0.206)	-
By other mode	3.67	-0.417 (0.703)	-0.064 (0.842)	-0.308 (1.11)	0.650 (1.00)	-0.176 (1.20)	0.028 (0.929)	-
All travel modes	2.34	0.044 (0.532)	0.194 (0.617)	-0.790 (0.852)	0.717** (0.326)	-1.50* (0.839)	-0.603 (0.764)	-
E. Places visited								
Number of unique places visited per day (N)	1.49	-0.046 (0.112)	-0.060 (0.128)	0.020 (0.126)	0.108 (0.163)	-0.018 (0.125)	0.020 (0.122)	0.042 (0.259)
Number of visits per week (N)								
Places to eat or drink	1.70	-0.117 (0.228)	0.028 (0.222)	-0.104 (0.247)	-0.043 (0.294)	-0.215 (0.256)	-0.094 (0.211)	-0.174 (0.532)
Grocery stores	0.713	0.081 (0.101)	0.113 (0.125)	0.090 (0.106)	0.146 (0.138)	0.027 (0.107)	0.067 (0.098)	0.237 (0.223)
Health care	0.288	0.049 (0.070)	-0.048 (0.136)	0.044 (0.053)	0.131** (0.053)	0.056 (0.056)	0.042 (0.048)	0.071 (0.190)
School	0.510	-0.145 (0.095)	-0.137 (0.104)	-0.145 (0.122)	0.017 (0.126)	-0.185 (0.130)	-0.151 (0.115)	0.324 (0.251)
Shopping (non-food)	3.03	-0.066 (0.303)	0.009 (0.327)	0.051 (0.287)	0.504 (0.437)	0.083 (0.246)	0.088 (0.258)	-1.26* (0.704)
Gas stations and convenience stores	1.47	-0.371* (0.208)	-0.261 (0.170)	-0.176 (0.171)	-0.150 (0.284)	-0.169 (0.175)	-0.182 (0.153)	0.496 (0.505)
Transportation facilities	1.61	0.294 (0.287)	0.042 (0.418)	0.180 (0.346)	0.427 (0.454)	0.059 (0.430)	0.187 (0.380)	0.878 (0.771)
Private residences besides own home	<0.001	0.002 (0.002)	0.001 (<0.001)	0.002 (0.002)	0.001 (0.002)	0.002 (0.001)	0.002 (0.002)	-0.003 (0.002)
Other points of interest	1.80	-0.096 (0.216)	-0.261 (0.220)	0.101 (0.186)	-0.062 (0.329)	0.029 (0.201)	0.081 (0.187)	0.271 (0.511)
Places the person never visited before joining study	11.14	-0.369 (0.874)	-0.515 (0.984)	0.129 (1.01)	1.01 (1.23)	-0.306 (1.01)	0.064 (0.981)	0.616 (2.11)
Likelihood of visiting a user-rated location per day (%)	0.634	-0.042 (0.028)	-0.036 (0.030)	-0.029 (0.027)	-0.026 (0.042)	-0.027 (0.024)	-0.028 (0.024)	-0.015 (0.063)
Number of user ratings among locations visited per day (N)	744.8	-30.69 (73.33)	-67.36 (85.53)	-87.04 (63.05)	-20.90 (97.81)	-76.10 (60.22)	-78.00 (57.93)	22.89 (194.0)
Pooled mean outcome		X	X	X	X	X	X	
Day-level panel data with day, month, & year FE's								X
Includes benchmark covariates			X	X		X	X	X
Includes pre-enrollment outcome as covariate				X		X	X	X

Table A13: Robustness of effects of free fares relative to no discount on mobility outcomes from smartphone GPS data *(continued)*

Outcome	Control mean	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post-double LASSO covariate selection					X			
Includes weights for GPS day coverage						X		
Includes weights for GPS participation							X	

Notes: Table presents estimates of the effect of being assigned to free fares relative to no discount on mobility outcomes measured from participants' smartphone Google Maps location history data. The models in columns (1) through (6) use cross-sectional data in which the outcome is the pooled mean over the person's entire GPS data. The model in column (5) includes normalized weights for each participant that are based on the number of post-enrollment days covered by the person's GPS data. The model in column (6) includes weights for non-participation in the GPS data-sharing task; the weights are based on propensity scores from a logit model that includes the benchmark set of baseline characteristics as predictors of non-participation. The model in column (7) uses an unbalanced day-level panel data set and includes fixed effects for the day of the week, month, and year. Robust standard errors are in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table A14: Robustness of effects of free fares relative to no discount on employment outcomes

	N	Control mean	(1)	(2)	(3)	(4)	(5)	(6)
A. Among full sample								
Cumulative outcomes in first 6 quarters after enrollment, from UI records								
Had any paid employment	6,241	0.666	0.005	0.004	<0.001	0.007	-	-
			(0.012)	(0.010)	(0.009)	(0.010)		
Number of quarters with employment (N)	6,241	3.04	0.051	0.056	0.042	-	-	-
			(0.065)	(0.052)	(0.045)			
Earnings ($)	6,241	17,289	177.7	205.9	194.2	543.8	-	23.55
			(576.1)	(501.9)	(399.2)	(450.5)		(474.2)
Number of employers worked for (N)	6,241	1.65	0.097*	0.093**	0.042	-	-	-
			(0.050)	(0.045)	(0.039)			
Number of NAICS sectors worked in (N)	6,241	1.14	0.039	0.037	0.029	-	-	-
			(0.029)	(0.026)	(0.023)			
Received any UI benefits	6,241	0.087	0.003	0.004	0.003	-	-	-
			(0.007)	(0.007)	(0.007)			
Amount of UI benefits received ($)	6,241	394.1	8.43	10.94	3.54	-	-	8.16
			(43.57)	(43.01)	(42.97)			(37.72)
Self-reported outcomes from post-endline (15 month) survey								
Currently employed	2,579	0.523	-0.023	-0.020	-	-0.015	-0.019	-
			(0.020)	(0.018)		(0.019)	(0.018)	
Hourly wage at main job ($; among the employed)	1,199	15.01	-0.393	-0.157	-	-0.446	-0.036	-0.276
			(0.316)	(0.430)		(0.313)	(0.427)	(0.349)
Total jobs currently held (N)	2,579	0.960	-0.271	-0.329	-	-0.265	-0.323	-0.069***
			(0.382)	(0.449)		(0.377)	(0.441)	(0.025)
Weekly work hours (N)	2,579	17.13	-1.87**	-1.77**	-	-2.25***	-1.79**	-
			(0.835)	(0.792)		(0.806)	(0.795)	
Total monthly earnings ($)	2,576	892.4	-173.1	-147.1	-	-120.8	-136.6	-73.65*
			(131.6)	(118.4)		(126.5)	(114.6)	(38.14)
Actively searched for job in past 4 weeks	2,040	0.468	-0.024	-0.015	-	-0.021	-0.012	-
			(0.022)	(0.023)		(0.025)	(0.023)	
B. Among those unemployed at baseline								
Cumulative outcomes in first 6 quarters after enrollment, from UI records								
Had any paid employment	1,713	0.578	0.039	0.041*	0.035*	0.034	-	-
			(0.024)	(0.023)	(0.021)	(0.025)		
Number of quarters with employment (N)	1,713	2.25	0.195*	0.236**	0.217**	0.281**	-	-
			(0.114)	(0.114)	(0.109)	(0.121)		
Earnings ($)	1,713	10,212	1,424	2,014**	2,845***	2,487**	-	1,692*
			(882.7)	(926.4)	(1,088)	(1,038)		(863.0)
Number of employers worked for (N)	1,713	1.45	0.206**	0.226**	0.119	0.196*	-	-
			(0.094)	(0.094)	(0.085)	(0.101)		
Number of NAICS sectors worked in (N)	1,713	1.03	0.109*	0.124**	0.070	0.111*	-	-
			(0.058)	(0.057)	(0.054)	(0.063)		
Received any UI benefits	1,713	0.058	0.003	0.004	0.006	0.009	-	-
			(0.012)	(0.013)	(0.012)	(0.014)		
Amount of UI benefits received ($)	1,713	222.0	48.85	47.03	26.98	86.04	-	33.24
			(65.69)	(73.13)	(66.02)	(93.95)		(65.73)
Self-reported outcomes from post-endline (15 month) survey								
Currently employed	680	0.404	0.024	0.035	-	0.040	0.032	0.035
			(0.039)	(0.039)		(0.049)	(0.038)	(0.039)
Hourly wage at main job ($; among the employed)	680	14.49	-0.011	0.177	-	0.242	0.356	0.100
			(0.674)	(0.743)		(0.728)	(0.721)	(0.685)
Total jobs currently held (N)	680	0.484	0.024	0.091	-	0.026	0.093	-0.017
			(0.104)	(0.126)		(0.108)	(0.132)	(0.055)
Weekly work hours (N)	680	13.01	-0.109	0.306	-	-0.406	0.133	0.541
			(1.64)	(1.65)		(2.08)	(1.63)	(1.48)
Total monthly earnings ($)	680	709.8	-107.8	-114.9	-	-	-107.3	-114.9
			(236.7)	(237.5)			(232.8)	(237.5)
Actively searched for job in past 4 weeks	680	0.543	0.040	0.015	-	0.060	0.021	0.015
			(0.044)	(0.046)		(0.043)	(0.045)	(0.046)
No covariates			X					
Includes benchmark covariates				X	X		X	X
Includes outcome in 4 quarters before enrollment					X			
Post-double LASSO covariate selection						X		
Includes nonresponse weights							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 for the adult sample. The nonresponse weights used in column (5) are based on propensity scores from a logit model that includes the benchmark set of baseline characteristics as predictors of nonresponse. Robust standard errors are in parentheses. ***p <0.01, **p <0.05, *p <0.1

Table A15: Robustness of effects of free fares relative to no discount on health care utilization among the adult sample within the first 540 days after enrollment

Outcome (N = 9,544)	Control mean	(1)	(2)	(3)	(4)	(5)
Received any health care	0.914	0.002 (0.007)	0.002 (0.007)	0.002 (0.007)	-	-0.006 (0.007)
A. Physical health care						
Has at least one claim						
Any physical health care	0.900	<0.001 (0.008)	<0.001 (0.007)	<0.001 (0.007)	-	-0.005 (0.008)
Non-ER outpatient	0.877	0.003 (0.008)	0.002 (0.008)	0.002 (0.008)	-	-0.001 (0.009)
ER outpatient	0.615	-0.008 (0.012)	-0.008 (0.012)	-0.006 (0.012)	-	-0.006 (0.013)
Non-ER inpatient	0.091	0.005 (0.007)	0.004 (0.007)	0.005 (0.007)	-	-0.004 (0.009)
ER inpatient	0.082	-0.007 (0.007)	-0.007 (0.007)	-0.005 (0.007)	-	-0.004 (0.007)
Days with at least one claim (N)						
Any physical health care	33.63	1.64 (1.62)	1.73 (1.57)	1.25 (0.850)	1.22 (0.818)	1.24 (0.909)
Non-ER outpatient	20.36	1.30 (1.49)	1.34 (1.47)	0.906 (0.783)	0.841 (0.741)	0.712 (0.821)
ER outpatient	2.26	-0.056 (0.103)	-0.059 (0.102)	-0.021 (0.080)	-0.005 (0.067)	0.126 (0.104)
Non-ER inpatient	0.498	0.165 (0.152)	0.168 (0.156)	0.227 (0.199)	0.032 (0.035)	0.006 (0.213)
ER inpatient	0.682	-0.095 (0.088)	-0.091 (0.087)	-0.047 (0.079)	-0.018 (0.053)	-0.125 (0.103)
Prescription fills (N)	17.99	0.157 (0.625)	0.199 (0.604)	0.079 (0.582)	0.205 (0.544)	0.685* (0.404)
Days covered by a prescription (N)	222.3	4.62 (5.20)	5.05 (5.04)	1.73 (3.27)	1.73 (3.27)	4.29 (3.55)
B. Behavioral health care						
Has at least one claim						
Any behavioral health care	0.665	-0.006 (0.012)	-0.006 (0.012)	-0.004 (0.011)	-	-0.013 (0.012)
Non-crisis	0.606	-0.004 (0.012)	-0.004 (0.012)	-0.003 (0.012)	-	-0.009 (0.012)
Crisis	0.361	-0.008 (0.012)	-0.008 (0.012)	-0.003 (0.012)	-	-0.006 (0.013)
Substance use treatment	0.122	-0.001 (0.008)	-0.001 (0.008)	-0.002 (0.007)	-	0.010 (0.008)
Days with at least one claim (N)						
Any behavioral health care	23.50	-1.86 (1.38)	-1.84 (1.35)	-1.14 (0.851)	-1.55** (0.756)	1.44 (0.901)
Non-crisis	14.10	-0.692 (1.10)	-0.663 (1.10)	-0.012 (0.576)	-0.640 (0.464)	0.701 (0.639)
Crisis	1.55	0.062 (0.174)	0.065 (0.177)	0.180 (0.180)	0.056 (0.077)	0.242 (0.183)
Substance use treatment	6.47	-1.30* (0.714)	-1.30* (0.702)	-1.37** (0.580)	-0.870* (0.444)	0.703 (0.622)
Prescription fills (N)	3.78	0.013 (0.216)	0.008 (0.210)	-0.064 (0.203)	-0.041 (0.190)	0.128 (0.162)
Days covered by a prescription (N)	89.26	3.10 (4.17)	3.14 (4.03)	3.20 (2.53)	3.20 (2.53)	5.46** (2.63)
Cost of care to managed care org. ($)	3,415	-568.7* (299.5)	-568.4* (294.7)	-191.7 (243.1)	-81.23 (168.8)	809.2** (382.3)
No covariates		X				
Includes benchmark covariates			X	X	X	
Includes outcome in 365 days before enrollment				X	X	
Winsorize continuous outcomes at p99					X	
Post-double LASSO covariate selection						X

Notes: Table presents the robustness of the effect of being assigned to free fares relative to no discount on health care utilization for the adult sample, as measured in the first 540 days after enrollment. Data comes from Medicaid claims. The 'received any health care' outcome in the first row represents the likelihood that the participant received any type of Medicaid-funded health care in the first 540 days post-enrollment. The 'days with at least one claim' outcome counts the cumulative number of days on which the participant had at least one claim in the first 540 days post-enrollment. The 'days covered by a prescription' outcome counts the cumulative number of days in the first 540 days post-enrollment for which the participant had a remaining dose from a filled prescription. The 'cost of care to managed care org' outcome measures the cumulative dollar amount of claims that providers have billed to the Allegheny County Medicaid behavioral health managed care organization. The estimates in column (1) are from a regression of the outcome on an indicator for treatment status, with no covariate adjustment. Column (2) adjusts for the benchmark set of covariates used throughout the main text. Column (3) additionally adjusts for the outcome measured in the 365 days prior to enrollment. Column (4) additionally winsorizes continuous-valued outcomes at the 99th percentile. Column (5) uses the post-double LASSO method to select the model covariates. Robust standard errors are in parentheses. ***p <0.01, **p <0.05, *p <0.1

Table A16: Effect of free fares on mobility outcomes by baseline employment status

	Employed				Unemployed				Not working - Other reason		
	N	Control mean	Effect		N	Control mean	Effect		N	Control mean	Effect
A. From travel diaries											
Number of places visited yesterday (N)	2,059	3.43	-0.550***		1,187	4.65	-1.17**		1,351	3.22	-0.158
			(0.169)	[0.196]			(0.503)	[0.045]			(0.255)
Likelihood of taking at least one trip yesterday											
Car trip	2,076	0.365	0.006		1,201	0.319	0.002		1,365	0.340	-0.013
			(0.016)	[0.805]			(0.019)	[0.797]			(0.018)
Public transportation trip	2,073	0.623	0.008		1,198	0.572	0.015		1,364	0.505	0.007
			(0.016)	[0.836]			(0.022)	[0.850]			(0.021)
Walk or bike trip	2,073	0.477	-0.068***		1,196	0.480	-0.024		1,362	0.446	-0.075***
			(0.017)	[0.086]			(0.021)	[0.123]			(0.021)
Left the house for work yesterday	2,067	0.601	-0.025		1,190	0.294	0.013		1,358	0.199	-0.023
			(0.016)	[0.146]			(0.019)	[0.152]			(0.020)
Did not leave the house yesterday	2,067	0.090	0.029***		1,190	0.156	0.003		1,358	0.182	0.030**
			(0.009)	[0.141]			(0.014)	[0.183]			(0.014)
B. From smartphone GPS data											
Number of trips per week (N)											
Car trips	128	14.86	-1.99		90	13.85	2.90		95	10.69	-6.57**
			(1.77)	[0.448]			(3.45)	[0.041]			(3.15)
Public transportation trips	128	3.91	0.139		90	3.12	3.49***		95	3.19	0.721
			(1.16)	[0.456]			(1.20)	[0.339]			(1.14)
Walk or bike trips	128	5.35	-0.106		90	6.00	-0.319		95	3.19	0.276
			(0.961)	[0.629]			(1.17)	[0.720]			(0.855)
Total trips	128	24.18	-2.62		90	23.03	4.79*		95	17.13	-5.29
			(2.66)	[0.287]			(2.78)	[0.018]			(3.50)
Unique POI's visited per day (N)	128	1.68	-0.204		90	1.57	0.326*		95	1.12	-0.270
			(0.201)	[0.243]			(0.176)	[0.080]			(0.263)
Time spent traveling per day (hours)	128	1.34	-0.043		90	1.43	-0.214		95	1.12	-0.140
			(0.191)	[0.671]			(0.265)	[0.522]			(0.203)
Total distance traveled per day (miles)	128	13.99	-1.09		90	12.87	6.38**		95	8.23	-8.07***
			(1.60)	[0.717]			(2.65)	[0.114]			(2.46)

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 A17: Heterogeneity in effects of free fares relative to no discount on focal study outcomes, by assorted baseline sub-groups (pt. 1)

	Lives in PRT 7-day freq. svc. walkshed		Sex		Race	
	No	Yes	Male	Female	Non-White	White
A. Public transit trips per week (N; from GPS data)						
N	204.0	151.0	102.0	157.0	146.0	157.0
Control mean	3.36	3.68	3.84	3.31	3.63	3.33
Treatment effect	1.70**	0.815	0.142	1.79*	0.494	2.92***
SE	(0.691)	(1.65)	(1.27)	(0.923)	(1.33)	(0.866)
P-value of diff.	[0.899]		[0.943]		[0.213]	
B. Had any paid employment in Q1 - Q6 after enrollment (from UI data)						
N	4,008	3,125	1,754	3,127	4,102	3,085
Control mean	0.667	0.665	0.569	0.704	0.726	0.555
Treatment effect	0.008	-0.012	0.010	-0.006	-0.004	0.003
SE	(0.011)	(0.015)	(0.018)	(0.011)	(0.011)	(0.015)
P-value of diff.	[0.250]		[0.354]		[0.718]	
C. Total earnings in Q1 - Q6 after enrollment ($; from UI data)						
N	4,008	3,125	1,754	3,127	4,102	3,085
Control mean	17,347	17,184	12,910	19,009	18,854	14,362
Treatment effect	183.8	320.6	-1,365	616.3	186.7	12.31
SE	(512.0)	(632.8)	(890.9)	(451.4)	(480.0)	(735.9)
P-value of diff.	[0.861]		[0.064]		[0.901]	
D. Number of days with a non-ER outpatient claim in first 540 days after enrollment (N; from Medicaid claims)						
N	4,047	3,159	1,770	3,164	4,158	3,114
Control mean	20.59	19.94	19.36	20.75	21.26	18.65
Treatment effect	0.525	1.58	1.87	0.740	1.27	0.285
SE	(0.979)	(1.28)	(1.67)	(0.914)	(0.982)	(1.38)
P-value of diff.	[0.533]		[0.713]		[0.531]	

Notes: This table reports heterogeneity in the effect of free fares versus no discount on select outcomes across sample sub-groups defined by baseline characteristics. The 'children enrolled' sub-group indicates whether the adult participant had one or more children who were also enrolled in the study. The coefficient reported in row 'Treatment effect' comes from a regression of the outcome of interest on a treatment indicator. The p-value of the difference between columns 1 and 2, 3 and 4, and 5 and 6, are calculated by regressing the outcome variable on a treatment variable, an indicator for being in the even numbered column, and the interaction of these two variables. The p-value of the interaction term is reported in row 'P-value of diff.'. 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), lives within the PRT 7-day frequent service walkshed (y/n), and the outcome measured in the year prior to enrollment. Robust standard errors are in parentheses. ***p <0.01, **p <0.05, *p <0.1

Table A18: Heterogeneity in effects of free fares relative to no discount on focal study outcomes, by assorted baseline sub-groups (pt. 2)

	Has access to a car		Employment status		Above 75p earnings	
	No	Yes	Unemployed	Employed	No	Yes
A. Public transit trips per week (N; from GPS data)						
N	250.0	131.0	90.00	113.0	240.0	132.0
Control mean	4.03	1.71	3.12	3.91	2.73	5.71
Treatment effect	1.37*	1.94	3.49***	0.139	1.54**	-0.529
SE	(0.797)	(1.86)	(1.20)	(1.16)	(0.725)	(2.53)
P-value of diff.	[0.822]		[0.456]		[0.925]	
B. Had any paid employment in Q1 - Q6 after enrollment (from UI data)						
N	5,108	3,125	1,695	2,175	4,681	3,108
Control mean	0.657	0.709	0.578	0.931	0.565	0.967
Treatment effect	0.006	-0.038	0.034*	-0.017	-0.005	0.037
SE	(0.010)	(0.026)	(0.021)	(0.021)	(0.010)	(0.028)
P-value of diff.	[0.155]		[0.071]		[0.349]	
C. Total earnings in Q1 - Q6 after enrollment ($; from UI data)						
N	5,108	3,125	1,695	2,175	4,681	3,108
Control mean	16,212	22,171	10,212	29,581	9,932	39,173
Treatment effect	7.12	-930.3	2,845***	-1,076	-89.48	-6,430**
SE	(436.6)	(1,396)	(1,088)	(821.2)	(963.6)	(2,754)
P-value of diff.	[0.584]		[0.025]		[0.005]	
D. Number of days with a non-ER outpatient claim in first 540 days after enrollment (N; from Medicaid claims)						
N	5,159	3,155	1,713	2,196	4,687	3,111
Control mean	20.53	19.60	16.21	11.34	23.47	11.03
Treatment effect	0.589	0.603	-0.234	0.655	1.36	-0.226
SE	(0.861)	(2.65)	(1.39)	(1.67)	(0.889)	(2.13)
P-value of diff.	[0.516]		[0.708]		[0.121]	

Notes: This table reports heterogeneity in the effect of free fares versus no discount on select outcomes across sample sub-groups defined by baseline characteristics. Outcome data is winsorized at the 99th percentile if it comes from a survey question that permitted an unbounded numeric response. The 'above 75p earnings' grouping indicates whether the participant's earnings in the calendar quarter prior to their study enrollment quarter was above the 75th percentile of the full sample, according to Pennsylvania unemployment insurance (UI) wage records. The coefficient reported in row 'Treatment effect' comes from a regression of the outcome of interest on a treatment indicator. The p-value of the difference between columns 1 and 2, 3 and 4, and 5 and 6, are calculated by regressing the outcome variable on a treatment variable, an indicator for being in the even numbered column, and the interaction of these two variables. The p-value of the interaction term is reported in row 'P-value of diff.'. 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), lives within the PRT 7-day frequent service walkshed (y/n), and the outcome measured in the year prior to enrollment. Robust standard errors are in parentheses. ***p <0.01, **p <0.05, *p <0.1

Table A19: Heterogeneity in effects of free fares relative to no discount, by whether home address is shared with at least one other participant

	Shares address with another participant		Shares address with another participant of greater discount level	
	Yes	No	Yes	No
A. PRT farecard taps per week (N; from farebox data)				
N	763	5,367	289	5,841
Control mean	0.275	0.302	0.271	0.302
Treatment effect	5.12***	4.72***	4.76***	4.77***
SE	(0.323)	(0.105)	(0.099)	(0.108)
P-value of diff.	[0.215]		[0.462]	
B. PRT trips last week (N; from midline survey data)				
N	277	2,239	96	2,420
Control mean	11.67	9.62	12.14	9.65
Treatment effect	0.781	0.554	0.747	-0.556
SE	(1.19)	(0.491)	(0.474)	(0.998)
P-value of diff.	[0.621]		[0.119]	
C. PRT spending last week ($; from midline survey data)				
N	255	1,961	89	2,127
Control mean	38.00	32.53	38.76	32.65
Treatment effect	-15.52***	-17.94***	-17.25***	-20.17***
SE	(4.66)	(1.58)	(1.55)	(4.02)
P-value of diff.	[0.515]		[0.249]	
D. Likelihood of taking a PRT trip yesterday (from travel diary data)				
N	518	4,117	178	4,457
Control mean	0.685	0.562	0.699	0.565
Treatment effect	-0.040	0.014	0.016	-0.084***
SE	(0.030)	(0.011)	(0.011)	(0.028)
P-value of diff.	[0.052]		[0.000]	

Notes: This table explores the extent of potential treatment spillovers by looking at the effects of free fares versus no discount on various measures of public transit usage, disaggregated by whether the participant listed an address on their study application that was shared with at least one other participant. We permitted only one adult per SNAP household to participate, in order to mitigate the risk of treatment spillovers. However, multiple SNAP households can live in the same home, and 12.5% of the 9,544 adults in our sample shared a baseline home address with at least one other adult participant. Among these adults, 40.9% shared a home address with someone who was assigned to a greater discount level. As shown in Panel D, the impact of free fares on the likelihood of taking a PRT trip yesterday is positive among individuals who do not live with another study participant and negative among individuals who do live with another participant. The third column ('Shares address with another participant of greater discount level' = 'yes') reports impacts among a sub-sample comprised of all free fares group members and only the control group members who live with a half-fares or free fares group member. The fourth column ('Shares address with another participant of greater discount level' = 'no') reports impacts among a sub-sample comprised of all free fares group members and only the control group members who *do not* live with a half-fares or free fares group member. Across the four outcomes in Panels A through D, the free-fares treatment was no less impactful when only using control group members who had within-household access to a fare discount. This suggests little to no treatment spillovers among co-household members. Robust standard errors are in parentheses. ***p <0.01, **p <0.05, *p <0.1

Table A20: Local average treatment effects (LATE) of free fares relative to no discount on number of public transportation trips per week

Outcome	N	Control mean	Effect	First-stage F stat	First-stage R-squared
Study-issued farecard taps per week (from PRT admin data)	6,130	0.298	5.17*** (0.104)	34,440	0.849
"In the past week, how many trips have you taken on a PRT bus or the T in Allegheny County? Count a one-way ride as one trip					
From midline survey (6 months)	2,516	11.52	-0.784 (1.27)	18,548	0.885
From endline survey (11 months)	2,688	12.90	-1.50 (1.26)	22,687	0.897
From post-endline survey (15 months)	2,696	11.95	-0.735 (2.20)	19,210	0.881
Response value × 7: "How many bus or light rail trips did you take yesterday? Count a one-way journey as one trip." (from post-endline survey)	2,613	1.85	-0.092 (0.195)	19,024	0.883
Public transit trips per week (from GPS data)	298	3.38	1.51** (0.587)	1,440	0.897

Notes: Table presents estimates of the local average treatment effect (LATE) of receiving free fares relative to no discount on the number of public transportation trips per week for the adult sample. Estimates are from a two-stage least squares regression that uses treatment status as an instrument for taking at least one free-fare boarding, 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), and lives within the PRT 7-day frequent service walkshed (y/n). Compliers in the free-fares group are defined as the participants who used a free-fares ConnectCard for at least one boarding according to farecard administrative records. N indicates the number of participants across the free fares and control groups that have non-missing data for the given outcome. Robust standard errors are in parentheses. ***p <0.01, **p <0.05, *p <0.1

B Comparing data sources on travel behavior

We use three complementary data sources to measure participants' travel behavior on a given day. This section explores the level of agreement between the three sources on various mobility measures. These comparisons may be informative for future researchers who are considering whether to invest in smartphone GPS data collection to measure travel behavior. This analysis also adds to a literature that has compared the accuracy of surveys versus smartphone location data for measuring spatial mobility (Bricka et al., 2009; P. Stopher et al., 2007; Cools et al., 2021; Li et al., 2024; Ruktanonchai et al., 2018).

We collected three sources of data on the adult participants' public transportation ridership on a given day:

1. **Administrative tap data from PRT:** This data covers all study-issued farecards. It includes the date and time of the boarding, as well as the geolocation of the boarding and the route of the bus being boarded. This data has the advantage of capturing all boardings without relying on participant self-reporting. However, the data does not capture transit trips in which the person paid using another method or did not pay at all. It also includes trips taken by other people with whom the study participant may have shared their farecard. These factors make the data an imperfect measure of transit ridership.

2. **Travel diary surveys:** The high-frequency text message-based travel diaries included the question "Did you use the bus/light rail for any trips yesterday?". The midline and endline surveys also included this question. The question only captures the extensive margin of transit ridership on a given day. However, the post-endline (15-month) survey included a more detailed travel diary module that additionally asked "How many public transportation trips did you take yesterday?". The survey data records the date when the respondent answered this specific question, allowing us to infer the date that the participant was mentally referencing in their answer. Limitations to this data potentially include memory error, researcher demand effects, and the usual measurement concerns associated with surveys.

3. **Google Maps smartphone location history data:** This data comes from a JSON file exported from the person's Google Maps app. The data records movements of the phone and includes timestamped locations and estimated modes of travel for each movement spell. Google does not disclose its algorithms for inferring modes of travel, but it generally considers factors such as the speed and distance of the trip, nearby roads and traffic patterns, and other data from the phone's internal sensors.[48] Each trip includes a probability that the estimated travel mode is correct. Li et al. (2024) cross-checked Google Maps mode estimates against verified diary responses for specific travel journeys. They found that Google's estimates were correct for 97.7% of car trips, 97.7% of walking trips, 82.8% of biking trips, and 89.9% of local public transportation trips.

[48] https://policies.google.com/technologies/location-data?hl=en-US

Farecard tap data vs. GPS data vs. travel diaries for measuring public transit trips. Figure B1 explores the rates of concordance between the three data sources when measuring whether the person took at least one public transportation trip on a given day. Panel A compares the GPS data with the farecard tap data. The two sources gave the same reading on 78.9% of person-days among the control group and on 82.3% of person-days among the free fares group. Rates of agreement range from 67% and 75% between the GPS data and the travel diaries (Panel B), and from 48% to 62% between the travel diaries and the farecard tap data (Panel C).

The gray bars in Figure B1 Panels A and C show the limitations of the farecard tap data for measuring a person's ridership. The farecard data recorded a boarding on only 5.9% of the days when a control group member's GPS data recorded a transit trip. This is to be expected because the control group had no incentive to use their study-issued farecard to pay for their boardings once their $10 balance ran out. The less-than-100% concordance for the gray bars reflects a combination of card sharing and people not using their study-issued farecard to pay for a boarding (or simply evading the fare). As expected, the undercounting becomes less severe as the fare discount gets larger.

At the same time, the red bars in Figure B1 Panels A and B suggest that the Google Maps data fails to capture some fraction of public transit trips. Google Maps inferred a transit trip on only 67.4% of the days when a free fares group member tapped their assigned farecard. This group had the strongest incentive to use their assigned farecard for all trips, meaning that this less-than-100% concordance likely stems more from lapses in the GPS data rather than from card-sharing.

Figure B2 compares the level of agreement between our three data sources when counting the number of public transit trips taken on a given day. The 45 degree line indicates a perfect correlation between data sources. In Panel A, the correlation between a person's number of farecard taps and their number of GPS transit trips on the same day becomes closer to one-to-one as the fare discount increases.

Travel diaries vs. GPS data for other mobility measures. We further explore the concordance between the travel diaries and GPS data for other measures of daily mobility. Each diary asked participants if they took a car trip, a transit trip, or a walk/bike trip yesterday. The diary also asked whether the person left the house at all yesterday, how many total places they went, and whether they took a trip for each of the following reasons: Work, school, groceries, leisure, health care, social services, and other.

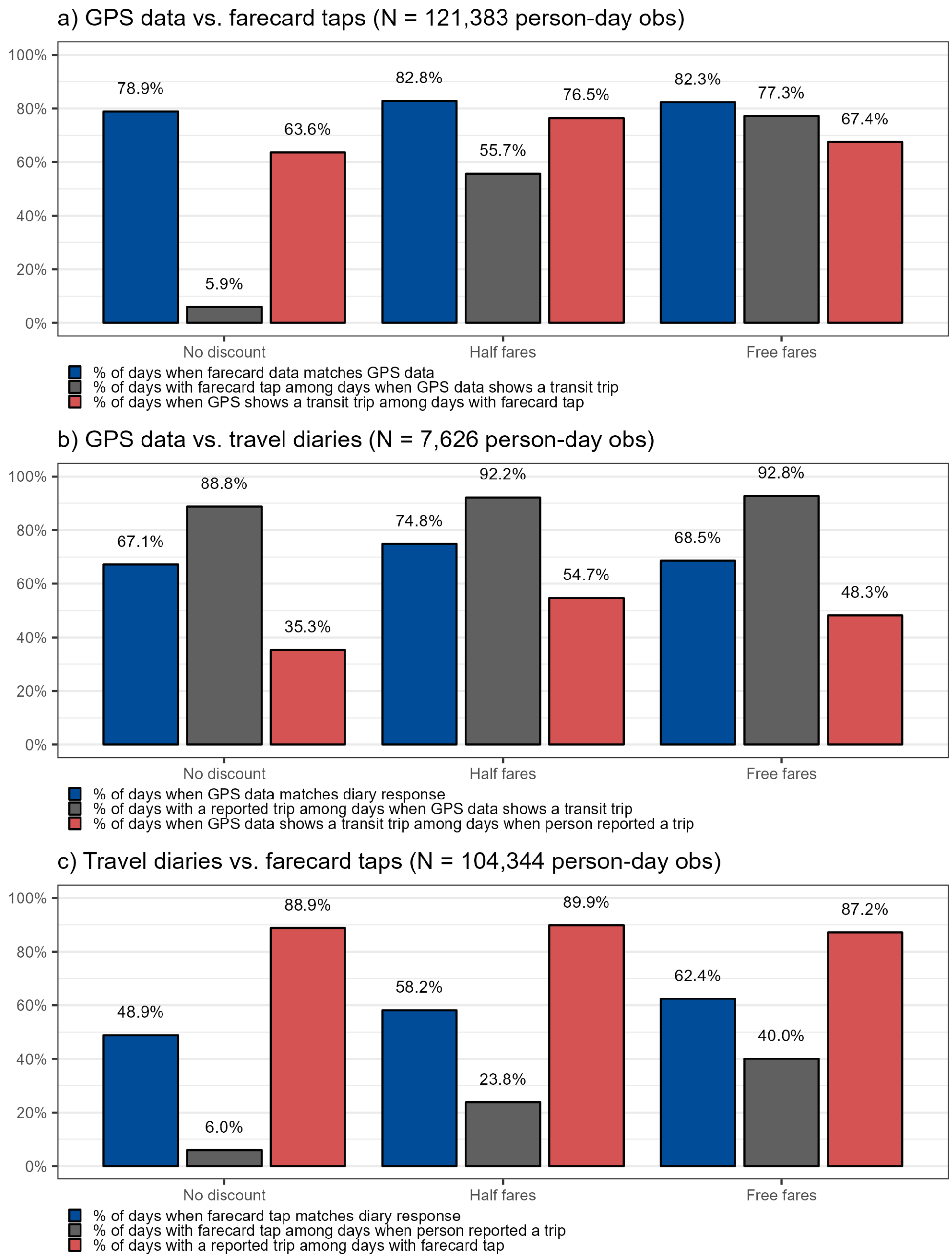
Table B1 compares these measures between the GPS data and diary data for the same person on the same day. The GPS data counted fewer distinct daily places visited than the travel diaries: The GPS-based counts of the number of places visited were only 44.7% to 64.0% of the travel diary-based counts, depending on the study arm. The two sources agreed 59.7% to 63.1% of the time on whether the person left home on a given day, 68.5% to 74.3% of the time on whether the person took a car trip, and 90.8% to 93.7% of the time on whether the person went to school.

Internal consistency of travel diary responses. Figure B3 looks at diaries in which the person reported not leaving the house yesterday. The figure plots the percentage of these diaries in which the person also reported taking a trip yesterday. Such responses are contradictory because it is not possible to take a trip without leaving the house. The rates of contradictory responses were generally below 5% and did not systematically differ across survey waves or discount groups. The rates also appear to be uncorrelated with the mode of the trip reported in the diary (car, public transit, or walk/bike) or with the reported reason for the trip (groceries, school, work).

Takeaways. Our validations show that high-frequency, short-recall travel diaries are a useful complement to smartphone location data when measuring an individual's daily travels. The two sources show a relatively high rate of agreement in certain cases, such as on days when the person's GPS data recorded a public transit trip (see the gray bars in Figure B1 Panel B). Diaries may capture the extensive margin of daily transit ridership more reliably than GPS data, as implied by the free-fares red bar in Figure B1 Panel C being 20 percentage points larger than the same bar in Panel A. On the other hand, GPS data may do a better job at avoiding over-reporting of transit trips: the free fares group actually tapped their card on only 40% of days when they self-reported taking a transit trip, versus on 77% of days when their GPS data recorded a transit trip.

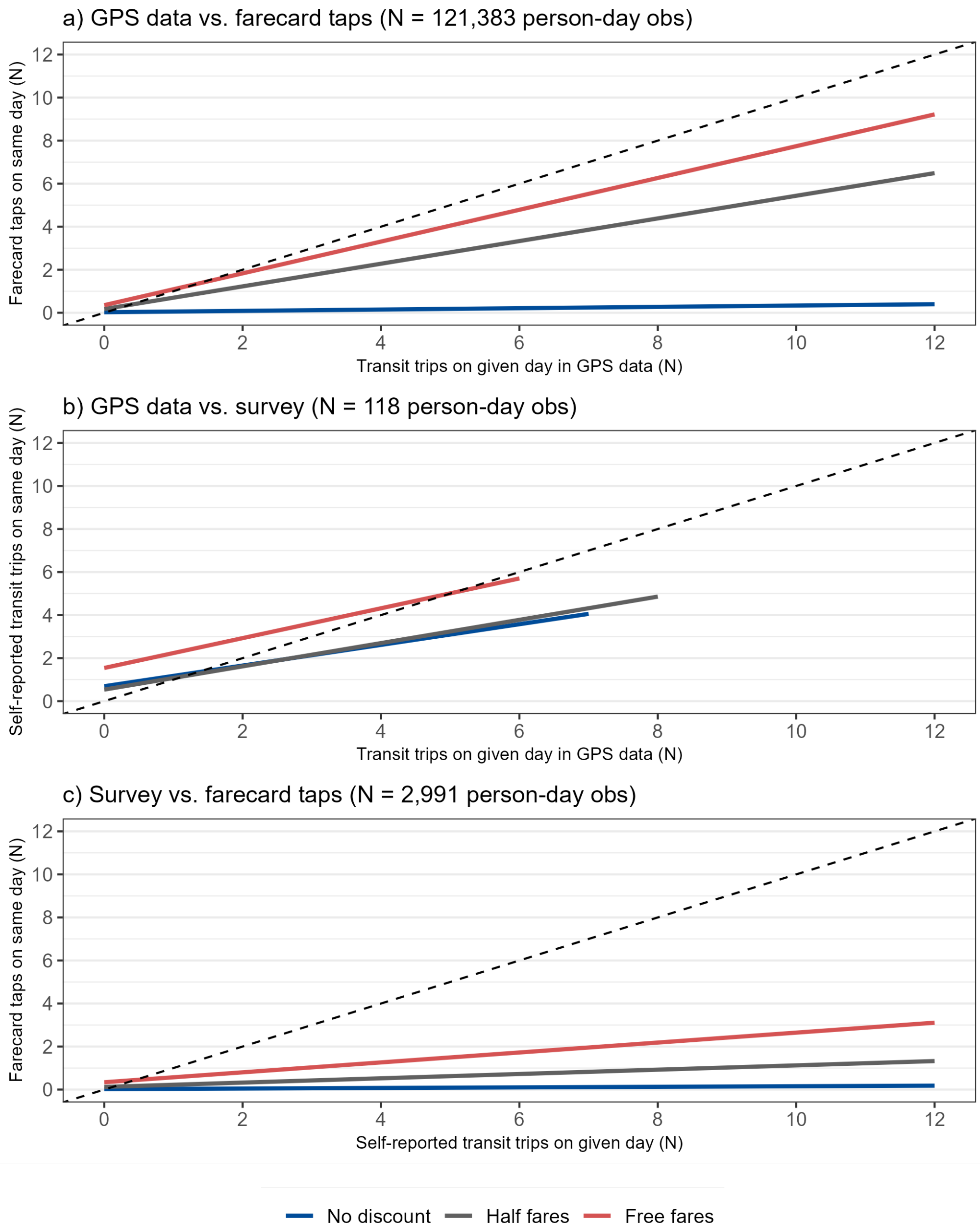
Without a source of ground truth about a person's daily trip-taking, we do not know whether the imperfect concordance between the diaries and GPS data means that one source's measurement properties are strictly better than the other. In any case, the lower-tech text message diaries are more user-friendly than the Google Maps data collection process that we employed, which required participants to navigate several menus on their phones.

Figure B1: Cross-validation of having at least one public transit trip on a given day



Notes: Figure shows rates of concordance between three different data sources that measure whether the participant took a public transit trip on a given day. Panel A compares the Pittsburgh Regional Transit (PRT) administrative farecard tap data with the smartphone Google Maps location history (GPS) data, aligning the two data sources by date. Panel B compares the GPS data with participants' responses to the travel diary question "Did you take a PRT trip yesterday?", aligning the two data sources by date. Panel C compares the farecard tap data with the travel diary responses, again aligning the two data sources by date. Blue bars show the percentage of all observed days on which the two data sources give the same indication of whether or not the person took a PRT trip on that day.

Figure B2: Cross-validation of number of public transit trips on a given day



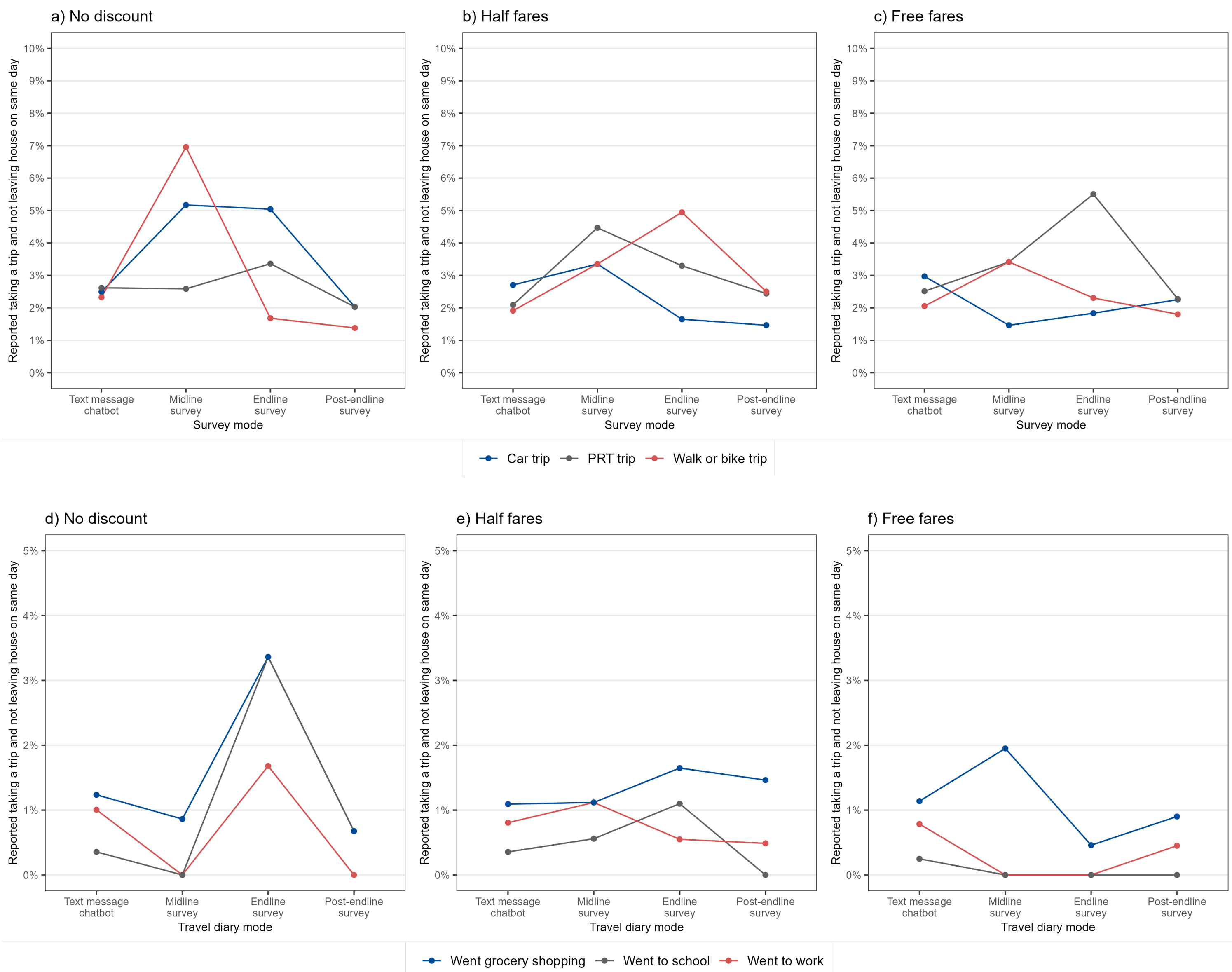
Notes: Figure shows pairwise correlations between three different data sources that measure the number of public transit trips that a participant took on a given day. Panel A compares the Pittsburgh Regional Transit (PRT) administrative farecard tap data with the smartphone Google Maps location history (GPS) data, aligning the two data sources by date. Panel B compares the GPS data with participants' responses to the post-endline survey question "How many PRT trips did you take yesterday?", aligning the two data sources by date (The post-endline survey was the only survey in the entire study in which we asked participants to report the number of transit trips they took on a given day). Panel C compares the farecard tap data with the post-endline survey responses, again aligning the two data sources by date. The correlation lines are fitted to the underlying data using a bivariate OLS regression.

Table B1: Concordance between travel diary data and smartphone GPS data for same person on same day

	No discount		Half fares		Free fares	
	N	Concordance	N	Concordance	N	Concordance
Took at least one trip on given day (%)						
By car	1,838	0.743	2,701	0.715	3,087	0.685
By public transportation	1,838	0.671	2,701	0.748	3,087	0.685
By walk or bike	1,838	0.668	2,701	0.674	3,087	0.613
Number of trips taken on given day (N)						
By car	28	1.53	40	0.829	49	4.26
By public transportation	28	0.733	40	0.540	49	0.295
By walk or bike	28	1.00	40	0.743	49	0.629
Left home at least once on given day (%)	1,789	0.613	2,626	0.631	2,998	0.597
Visited place on given day (%)						
School	1,838	0.908	2,701	0.937	3,087	0.915
Grocery store	1,838	0.615	2,701	0.624	3,087	0.569
Health care facility	1,838	0.867	2,701	0.876	3,087	0.830
Total number of places visited on given day (N)	1,838	0.447	2,701	0.640	3,087	0.574

Notes: Table presents rates of concordance between a participant's travel diary responses and their smartphone GPS data on the same day. For the binary measures, the concordance is the percentage of person-days on which the two data sources match. For the continuous-valued measures of mobility, the concordance is the mean value across the GPS person-days divided by the mean value across the travel diary person-days. Column N reports the number of person-days that the concordance rate is based on. The questions about the number of trips taken on a given day were only asked in the post-endline survey, not in the higher-frequency text message travel diaries.

Figure B3: Percentage of travel diaries in which respondent said they took a trip yesterday, only among diaries in which respondent said they did not leave the house yesterday (i.e. a contradictory answer)



Notes: Calculations based on data from travel diaries collected via text message and via the three waves of follow-up surveys.

C Survey response rates and nonresponse bias

C.1 Post-endline survey

All adult 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 vast 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 Tango reward via email for the offered amount.

In this section we focus on the post-endline survey. Table C1 presents the post-endline completion rates by fare discount and survey incentive amount. Overall, 42.6% of study participants completed the survey. Across the three discount arms, the \$20 incentive group was 5.8 percentage points more likely than the \$10 incentive group to complete the survey.

Table C1: Post-endline survey completion rates, by incentive amount

Discount group	Total	\$20 incentive	\$10 incentive	\$20 versus \$10 diff.
0%	0.361	0.397	0.325	0.072***
				(0.017)
50%	0.418	0.441	0.396	0.045***
				(0.017)
100%	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 vast majority of questions in the midline 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 C2 presents the differential response rates to certain questions within the survey. Across each question shown in the table, the 50% discount group was more likely to provide a response than the control group, and the 100% discount group was more likely to provide a response than the 50% group. Response rates also varied across questions. For example, 31.8% of the control group responded to the question about monthly savings, while 35.9% responded to the question asking how many PRT trips you took in the past week.

Table C2: Post-endline survey response rates, by discount group

Survey question	Total respondents	Control group response rate	Response rate differences		
			50% discount vs. control	100% discount vs. control	100% vs. 50% discount
A. Transportation questions					
PRT trips in past week (N)	4,048	0.359	0.058*** (0.012)	0.136*** (0.012)	0.079*** (0.012)
B. Employment questions					
Currently employed	3,871	0.345	0.054*** (0.012)	0.128*** (0.012)	0.075*** (0.012)
Weekly work hours (N)	3,871	0.345	0.054*** (0.012)	0.128*** (0.012)	0.075*** (0.012)
Total monthly earnings ($)	3,868	0.345	0.054*** (0.012)	0.128*** (0.012)	0.074*** (0.012)
C. Financial questions					
Cannot afford $400 expense	3,729	0.332	0.052*** (0.012)	0.123*** (0.012)	0.071*** (0.012)
Behind with finances	3,675	0.327	0.052*** (0.012)	0.121*** (0.012)	0.069*** (0.012)
Monthly savings ($)	3,567	0.318	0.051*** (0.012)	0.116*** (0.012)	0.066*** (0.012)
D. Health and well-being questions					
Current health good or better	3,807	0.342	0.050*** (0.012)	0.121*** (0.012)	0.070*** (0.012)
Life satisfaction rating (0-10)	3,797	0.341	0.050*** (0.012)	0.120*** (0.012)	0.069*** (0.012)
Feeling anxious last 2 weeks	3,647	0.329	0.047*** (0.012)	0.114*** (0.012)	0.067*** (0.012)
I have finished the survey	4,064	0.361	0.057*** (0.012)	0.137*** (0.012)	0.080*** (0.012)

Notes: Table presents the response rates to various post-endline (15-month follow-up) survey questions by fare discount group. The 'total respondents' column reports the total number of adult participants who completed the given survey question across the three study arms. The vast 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. Robust standard errors are in parentheses. ***p <0.01, **p <0.05, *p <0.1

Table C3 explores the extent of selection into post-endline survey completion on observable baseline characteristics. Survey completers were 9.9 percentage points more likely to be female than the non-completers, 7.6 percentage points more likely to be White, and 12.8 percentage points more likely to have more than a high school degree.

Table C3: Selection into post-endline survey completion on baseline characteristics

	Completers	Non-completers	Difference
A. Demographics			
Female	0.782	0.683	0.099***
			(0.009)
Age	39.37	39.64	-0.270
			(0.256)
Race			
Black	0.536	0.622	-0.086***
			(0.010)
White	0.384	0.308	0.076***
			(0.010)
Other	0.057	0.046	0.012**
			(0.005)
Hispanic	0.039	0.030	0.009**
			(0.004)
Children in household (N)	1.14	1.13	0.006
			(0.029)
Highest education			
Less than high school	0.062	0.093	-0.032***
			(0.005)
High school	0.487	0.587	-0.100***
			(0.010)
More than high school	0.444	0.316	0.128***
			(0.010)
B. Transportation			
Owns a car	0.067	0.051	0.017***
			(0.005)
PRT trips last week (N)	9.37	10.45	-1.08***
			(0.267)
PRT spending last week ($)	27.18	31.62	-4.44***
			(0.641)
C. Employment (from baseline survey)			
Employed past 12 months	0.613	0.598	0.014
			(0.010)
Currently employed	0.443	0.417	0.026**
			(0.010)
Hours worked per week at main job (N)	30.17	31.15	-0.984***
			(0.352)
Hourly wage at main job ($)	13.64	13.38	0.260**
			(0.116)
D. Employment in quarter prior to enrollment (from UI records)			
Total earnings ($)	2,384.93	2,206.41	178.52***
			(69.14)
Received nonzero UI benefits	0.035	0.029	0.007*
			(0.004)
Test for joint orthogonality			
F stat			1.911
p-value			0.014
N	**3,689**	**5,855**	

Notes: This table compares the mean baseline characteristics between the adult participants who completed the post-endline (15 month) survey and those who did not. The vast 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. The joint F test is done using randomization inference. ***p <0.01, **p <0.05, *p <0.1

Table C4 explores whether the sample of post-endline survey respondents remains balanced across randomization arms on certain relevant baseline characteristics. The respondents do not demonstrate worse balance than the full study sample on most characteristics shown in the table.

Table C5 reports intent-to-treat impacts on outcomes from the post-endline survey, with extreme value (i.e. "Manski") bounds on the impact estimate. The upper bound assumes that all nonresponders in the treatment group had the highest outcome that is observed across the two study arms being contrasted, and all nonresponders in the comparison group had the lowest observed outcome across the two groups being contrasted. The lower bound assumes the opposite, meaning that all nonresponders in the treatment group had the lowest observed outcome and all nonresponders in the comparison group had the highest observed outcome. These bounds represent the worst case of item-level nonresponse bias in either direction, showing what the impact estimate would be if those who answered the question gave either maximally higher or maximally lower response values than those who did not answer the question. These bounds are most informative for the survey questions that take binary responses. The bounds are too wide to be informative for the questions that take continuous-valued responses, such as total monthly earnings and monthly savings.

Table C4: Randomization balance among post-endline survey respondents

	No discount		Half fares		Free fares		
	N	Mean	N	Mean	N	Mean	Free fares vs. no discount diff.
A. Demographics							
Female	1,137	0.796	1,356	0.777	1,571	0.785	-0.011 (0.016)
Age	1,137	38.75	1,356	39.94	1,571	39.43	0.685 (0.461)
Race							
Black	1,137	0.549	1,356	0.532	1,571	0.565	0.016 (0.019)
White	1,137	0.380	1,356	0.379	1,571	0.356	-0.024 (0.019)
Other	1,137	0.056	1,356	0.058	1,571	0.057	<0.001 (0.009)
Hispanic	1,137	0.039	1,356	0.034	1,571	0.041	0.003 (0.008)
Children in household (N)	1,137	1.14	1,356	1.08	1,571	1.22	0.087* (0.052)
Highest education							
Less than high school	1,137	0.051	1,356	0.071	1,571	0.071	0.020** (0.009)
High school	1,137	0.481	1,356	0.498	1,571	0.495	0.013 (0.019)
More than high school	1,137	0.461	1,356	0.424	1,571	0.426	-0.034* (0.019)
B. Transportation							
Owns a car	1,137	0.076	1,356	0.066	1,571	0.064	-0.011 (0.010)
PRT trips last week (N)	1,137	9.24	1,356	8.86	1,571	9.06	-0.184 (0.386)
PRT spending last week ($)	1,137	27.51	1,356	27.60	1,571	26.85	-0.656 (1.05)
C. Employment (from baseline survey)							
Employed past 12 months	1,137	0.628	1,356	0.617	1,571	0.622	-0.006 (0.019)
Currently employed	1,137	0.451	1,356	0.455	1,571	0.446	-0.005 (0.019)
Hours worked per week at main job (N)	513	29.34	617	30.48	701	30.83	1.49** (0.613)
Hourly wage at main job ($)	513	13.79	617	13.65	699	13.56	-0.225 (0.217)
D. Employment in quarter prior to enrollment (from UI records)							
Total earnings ($)	1,130	2,393	1,346	2,386	1,557	2,488	94.89 (130.5)
Received nonzero UI benefits	1,130	0.031	1,346	0.042	1,557	0.030	-0.001 (0.007)
Total survey respondents	**1,137**		**1,356**		**1,571**		

Notes: Table presents mean baseline characteristics across study groups among the adult participants who completed the post-endline (15 month) survey. The vast 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 characteristics in panels A, B, and C come from the baseline survey. The characteristics in panel D come from Pennsylvania unemployment insurance (UI) records. Baseline survey items that permitted unbounded continuous-valued responses are winsorized at the 99th percentile. Robust standard errors are in parentheses. ***p <0.01, **p <0.05, *p <0.1

Table C5: Impacts of fare discounts on various post-endline survey outcomes, with extreme value bounds

Outcome	N	Control mean	Treatment effect: Half fares	Treatment effect: Free fares	Free vs. half fares
A. Transportation outcomes					
PRT trips last week (N)	4,048	9.39	-0.328 [-32; 30]	0.462 [-30; 27]	0.790** [-28; 26]
PRT spending last week ($)	3,474	33.53	-5.64** [-703; 641]	-17.09*** [-1,408; 1,124]	-11.45*** [-1,285; 1,124]
B. Employment outcomes					
Employed	3,871	0.523	-0.022 [-0.635; 0.620]	-0.020 [-0.598; 0.584]	0.002 [-0.564; 0.565]
Unemployed and seeking work	3,871	0.177	0.013 [-0.643; 0.612]	-0.005 [-0.636; 0.546]	-0.017 [-0.594; 0.534]
Hourly wage at main job ($)	1,781	14.92	-0.196 [-24; 24]	-0.276 [-24; 23]	-0.080 [-23; 23]
Weekly work hours (N)	3,871	17.13	-1.13 [-112; 105]	-1.77** [-109; 90]	-0.638 [-103; 92]
Total monthly earnings ($)	3,868	623.88	-69.84* [-3,708; 3,405]	-73.65* [-3,672; 3,029]	-3.81 [-3,368; 3,029]
C. Financial outcomes					
Cannot afford $400 expense	3,729	0.502	-0.002 [-0.645; 0.636]	0.017 [-0.600; 0.612]	0.018 [-0.570; 0.590]
Behind with finances	3,675	0.419	0.011 [-0.650; 0.641]	0.007 [-0.623; 0.601]	-0.004 [-0.592; 0.580]
Monthly savings ($)	3,567	67.52	2.06 [-1,307; 1,316]	0.174 [-1,239; 1,255]	-1.88 [-922; 898]
D. Health and well-being outcomes					
Current health good or better	3,807	0.552	-0.015 [-0.639; 0.625]	-0.042** [-0.614; 0.581]	-0.027 [-0.583; 0.563]
Life satisfaction rating (0-10)	3,797	5.78	-0.014 [-6; 6]	0.034 [-6; 6]	0.048 [-6; 6]
Feeling anxious last 2 weeks	3,647	0.312	-0.031 [-0.670; 0.624]	-0.019 [-0.650; 0.579]	0.012 [-0.604; 0.578]

Notes: Table presents extreme value bounds (also known as "Manski" bounds) for the estimates of the effect of being assigned to each treatment status (50% discount or 100% discount) on various self-reported outcomes for the adult sample. Data comes from the midline survey, which took place six months after the participant enrolled in the study. 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), and lives within the PRT 7-day frequent service walkshed (y/n). The extreme value bounds are in brackets below the estimates. The upper bound assumes that all nonresponders in the treatment group had the highest outcome that is observed across the two groups being contrasted, and all nonresponders in the comparison group had the lowest observed outcome across the two groups being contrasted. The lower bound assumes the opposite, meaning that all nonresponders in the treatment group had the lowest observed outcome and all nonresponders in the comparison group had the highest observed outcome. Column N indicates the number of individuals across the three study arms that have non-missing data for the given outcome. ***p <0.01, **p <0.05, *p <0.1

Recent research has demonstrated that traditional methods for addressing survey nonresponse bias may not be adequate if the nonresponse 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., 2022; 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 C6. The differences in item-level response rates ranged from 4.6 percentage points (hourly wage at main job) to 6.5 percentage points (behind with finances). These significant differences in response rates raise the potential for selection bias in the survey results on the dimension of the incentive amount.

Table C6: 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. $10 diff.
A. Transportation questions					
PRT trips last week (N)	4,771	0.453	4,773	0.395	0.058*** (0.010)
PRT spending last week ($)	4,771	0.389	4,773	0.339	0.049*** (0.010)
B. Employment questions					
Employed	4,771	0.436	4,773	0.376	0.060*** (0.010)
Unemployed and seeking work	4,771	0.436	4,773	0.376	0.060*** (0.010)
Hourly wage at main job ($)	4,771	0.209	4,773	0.164	0.046*** (0.008)
Weekly work hours (N)	4,771	0.436	4,773	0.376	0.060*** (0.010)
Total monthly earnings ($)	4,771	0.435	4,773	0.376	0.059*** (0.010)
C. Financial questions					
Cannot afford $400 expense	4,771	0.423	4,773	0.359	0.064*** (0.010)
Behind with finances	4,771	0.418	4,773	0.353	0.065*** (0.010)
Monthly savings ($)	4,771	0.405	4,773	0.342	0.063*** (0.010)
D. Health and well-being questions					
Current health good or better	4,771	0.429	4,773	0.369	0.060*** (0.010)
Life satisfaction rating (0-10)	4,771	0.429	4,773	0.367	0.062*** (0.010)
Feeling anxious last 2 weeks	4,771	0.413	4,773	0.351	0.062*** (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. Participants were randomly offered either $10 or $20 for completing the survey. The vast majority of questions in the survey did not force a response. Participants were thus able to respond to some questions but not others. Robust standard errors are in parentheses. ***p <0.01, **p <0.05, *p <0.1

We next test for selection bias by comparing mean response values to certain survey questions between the two incentive groups. Table C7 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 1.51 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 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 C7. The mean differences between the marginal and always-responders are inflated by the relatively small differences in item 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.

Nevertheless, the standard errors of the differences in mean answers between the $10 and $20 incentive groups are small enough to rule out substantial selection bias for at least some of the survey questions in Table C7. Other differences in response values are less precisely measured and may not preclude substantial selection, such as the difference in total self-reported monthly earnings. The relatively small differences in item-level response rates shown in Table C7 also provide some reassurance that selection bias is limited: Doubling the $10 incentive to $20 increased response rates by roughly four to six percent, depending on the survey question. Such small increases suggest there is not much room for selection on unobservables having to do with the time value of money.

Table C7: 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. $10 difference	Marginal responders vs. always-responders difference
A. Transportation questions						
PRT trips last week (N)	2,162	9.48	1,886	9.55	-0.066 (0.301)	-0.513 (2.48)
PRT spending last week ($)	1,854	24.66	1,620	24.82	-0.156 (1.89)	-1.23 (16.05)
B. Employment questions						
Employed	2,078	0.520	1,793	0.489	0.031* (0.016)	0.227* (0.131)
Unemployed and seeking work	2,078	0.172	1,793	0.181	-0.009 (0.012)	-0.069 (0.096)
Hourly wage at main job ($)	999	14.81	782	14.37	0.438* (0.225)	2.01* (1.18)
Weekly work hours (N)	2,078	16.69	1,793	15.18	1.51** (0.662)	11.00** (5.40)
Total monthly earnings ($)	2,075	595.3	1,793	518.2	77.09** (31.83)	565.7** (268.7)
C. Financial questions						
Cannot afford $400 expense	2,016	0.492	1,713	0.518	-0.027 (0.016)	-0.178 (0.115)
Behind with finances	1,992	0.429	1,683	0.406	0.023 (0.016)	0.147 (0.111)
Monthly savings ($)	1,933	72.69	1,634	63.20	9.50** (4.77)	61.27** (33.06)
D. Health and well-being questions						
Current health good or better	2,046	0.525	1,761	0.525	<0.001 (0.016)	0.002 (0.122)
Life satisfaction rating (0-10)	2,045	5.83	1,752	5.80	0.025 (0.092)	0.177 (0.659)
Feeling anxious last 2 weeks	1,971	0.289	1,676	0.287	0.002 (0.015)	0.011 (0.101)

Notes: This table compares respondents' answers to certain post-endline (15 month) survey questions between the high ($20) and low ($10) incentive groups. The vast majority of questions in the survey did not force a response. Participants were thus able to respond to some questions but not others. 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

C.2 Text message travel diaries

All adult study participants received a text message three days after they enrolled in the study that invited them to participate in the travel diary survey task. This message included a randomized offer of either a $1 or $2 payment for each completed diary. Eighty-seven study participants were not invited to the task because they listed the same phone number on their application as another participant and thus could not be uniquely identified in the Allegheny County Department of Human Services text messaging system. These 87 participants are excluded from all analyses in this section.

Those who opted into the task received a 14-month stream of text message-based travel diary surveys. They received a survey every three days for the first two months of their study enrollment, then once per month for the next ten months, then once per week for the next two months.

As with the follow-up surveys, our travel diary surveys used randomized incentive payments. Participants were randomly assigned to one of two incentive offers: the low incentive group was offered \$1 for each completed diary, and the high incentive group was offered \$2 per completed diary. Participants received payment for their completed diaries on a monthly basis in the first two months of their study enrollment. Then they received one payment at the end of their twelfth month of enrollment that covered all diaries completed in months three through 12. Then they received payments on a monthly basis again for the final two months of the task.

The midline, endline, and post-endline follow-up surveys also included a module with the same questions as in the text message-based travel diaries. There were 1,164 study participants who completed the travel diary module in one or more of the follow-up surveys but did not respond to any of the text message-based travel diaries. These follow-up survey-based diary responses are incorporated into all tables and figures throughout this paper that concern the travel diaries. However, we exclude these 1,164 participants from the below analysis of travel diary response rates in order to avoid conflating the attrition dynamics of the follow-up surveys and the text message-based diaries.

Table C8 presents the text message-based travel diary participation rates for the overall sample and disaggregated by fare discount group. Among the full sample, 61% of study participants completed at least one travel diary. Those who completed at least one diary went on to complete 18.4 diaries on average. The rates of completing at least one diary differed significantly across the three discount groups, ranging from 55.2% in the control group to 66.3% in the free fares group. The three groups also differed in their mean numbers of diaries completed, conditional on completing at least one diary. The task participants in the free fares group completed 2.9 more diaries on average than the control group.

Table C8: Travel diary participation by discount level

					Mean differences		
	Full sample	No discount	Half fares	Free fares	Half fares vs. no discount	Free fares vs. no discount	Free fares vs. half fares
Completed at least 1 diary	0.613	0.552	0.622	0.663	0.070*** (0.012)	0.111*** (0.012)	0.041*** (0.012)
Number of diaries completed (N), among those who completed at least 1	18.43	16.89	18.30	19.82	1.409*** (0.450)	2.934*** (0.452)	1.524*** (0.437)

Notes: This table presents the travel diary survey participation rates by fare discount group. We consider a participant to have completed a travel diary if they answered all five questions in the diary. Robust standard errors are in parentheses. ***p <0.01, **p <0.05, *p <0.1

Table C9 presents the travel diary participation rates by the per-diary incentive amount. The \$2 incentive group was 4.5 percentage points more likely than the \$1 incentive group to complete at least one diary. The \$2 incentive group completed 0.77 more diaries on average than the \$1 group, conditional on completing at least one diary. The difference in rates of completing at least one diary between incentive amounts was largest among the half-fares treatment group and was smallest among the free fares treatment group.

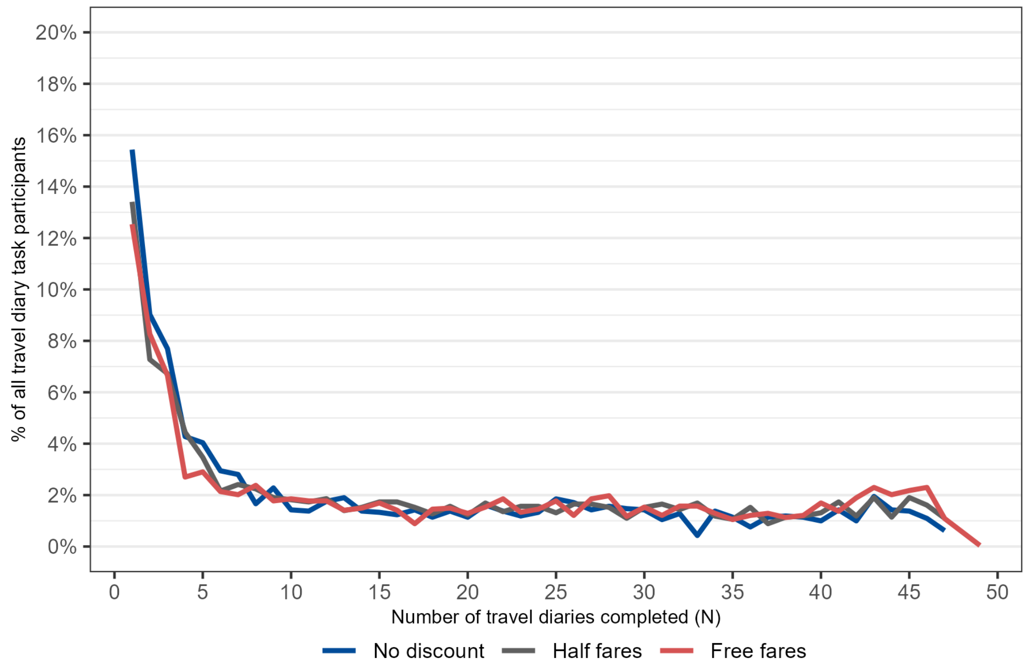
Table C9: Travel diary participation by incentive amount

Discount group	\$1 incentive	\$2 incentive	\$2 versus \$1 diff.
A. Completed at least one diary			
No discount	0.529	0.575	0.046***
			(0.018)
Half fares	0.592	0.651	0.059***
			(0.017)
Free fares	0.649	0.678	0.029*
			(0.017)
Total	0.590	0.635	0.045***
			(0.010)
B. Number of diaries completed, among those who completed at least 1 (N)			
No discount	16.19	17.52	1.324**
			(0.655)
Half fares	17.74	18.81	1.072*
			(0.616)
Free fares	19.76	19.87	0.106
			(0.618)
Total	18.02	18.79	0.771**
			(0.365)

Notes: This table presents the travel diary survey participation rates by fare discount group and by diary incentive amount. Each participant was randomly assigned at the beginning of the study to receive either \$1 or \$2 for each diary that they completed. We consider a participant to have completed a travel diary if they answered all five questions in the diary. Robust standard errors are in parentheses. ***p <0.01, **p <0.05, *p <0.1

Figure C1 presents the distribution of diary completions per person, among the participants who completed at least one diary. The modal respondent completed only one diary. The median number of diaries completed was 13, and the mean was 16.4. The distribution of the number of diary completions per person was similar across the three fare discount groups.

Figure C1: Distribution of the number of travel diaries completed per person, among those who completed at least one diary, by fare discount group



Notes: This figure presents the distribution of the number of travel diaries completed per person, among the study participants who completed at least one diary. A diary completion is defined as answering all five questions in the diary.

Table C10 compares the baseline characteristics of subjects who responded to at least one travel diary with the characteristics of subjects who did not respond to any diaries. Those who completed at least one diary were 10.9 percentage points more likely than the non-completers to be female, 5.1 percentage points more likely to be White, and 10.9 percentage points more likely to have some post-high school education.

Table C11 explores whether the subset of study participants that answered at least one text message travel diary remained balanced across randomization arms on certain relevant baseline characteristics. The diary respondents do not demonstrate worse balance than the full study sample on most characteristics shown in the table.

Table C10: Selection into travel diary surveys on baseline characteristics

	Completed a diary	Did not complete a diary	Difference
A. Demographics			
Female	0.765	0.657	0.108*** (0.010)
Age	39.22	40.01	-0.790*** (0.265)
Race			
Black	0.567	0.626	-0.058*** (0.010)
White	0.357	0.304	0.052*** (0.010)
Other	0.052	0.046	0.006 (0.005)
Hispanic	0.037	0.027	0.009*** (0.004)
Children in household (N)	1.18	1.06	0.120*** (0.029)
Highest education			
Less than high school	0.070	0.097	-0.027*** (0.006)
High school	0.515	0.598	-0.083*** (0.010)
More than high school	0.409	0.301	0.108*** (0.010)
B. Transportation			
Owns a car	0.062	0.050	0.013*** (0.005)
PRT trips last week (N)	9.99	10.03	-0.036 (0.281)
PRT spending last week ($)	28.93	31.36	-2.42*** (0.693)
C. Employment (from baseline survey)			
Employed past 12 months	0.629	0.570	0.059*** (0.010)
Currently employed	0.447	0.400	0.047*** (0.010)
Hours worked per week at main job (N)	30.63	31.01	-0.385 (0.362)
Hourly wage at main job ($)	13.62	13.26	0.360*** (0.119)
D. Employment in quarter prior to enrollment (from UI records)			
Total earnings ($)	2,393.55	2,122.25	271.30*** (68.64)
Received nonzero UI benefits	0.031	0.031	0.001 (0.004)
Test for joint orthogonality			
F stat			0.691
p-value			0.764
N	**5,792**	**3,663**	

Notes: This table compares the mean baseline characteristics between the participants who completed at least one travel diary and those who did not complete any diaries. We consider a participant to have completed a diary if they responded to all five questions in the diary. The statistical significance of the difference in mean characteristics between the diary completers and non-completers is calculated by regressing the characteristic on a dummy variable that equals 1 if the participant completed at least one diary. Robust standard errors are in parentheses. The joint F test is done using randomization inference. ***p <0.01, **p <0.05, *p <0.1

Table C11: Randomization balance among participants who completed at least one travel diary

	No discount		Half fares		Free fares		Free fares vs. no discount diff.
	N	Mean	N	Mean	N	Mean	
A. Demographics							
Female	1,724	0.766	1,997	0.771	2,071	0.760	-0.007 (0.014)
Age	1,724	38.89	1,997	39.43	2,071	39.30	0.418 (0.390)
Race							
Black	1,724	0.567	1,997	0.565	2,071	0.569	0.002 (0.016)
White	1,724	0.363	1,997	0.354	2,071	0.354	-0.009 (0.016)
Other	1,724	0.047	1,997	0.051	2,071	0.057	0.010 (0.007)
Hispanic	1,724	0.034	1,997	0.038	2,071	0.038	0.004 (0.006)
Children in household (N)	1,724	1.17	1,997	1.13	2,071	1.25	0.076* (0.046)
Highest education							
Less than high school	1,724	0.061	1,997	0.074	2,071	0.074	0.013* (0.008)
High school	1,724	0.528	1,997	0.516	2,071	0.504	-0.024 (0.016)
More than high school	1,724	0.407	1,997	0.403	2,071	0.417	0.011 (0.016)
B. Transportation							
Owns a car	1,724	0.064	1,997	0.062	2,071	0.062	-0.003 (0.008)
PRT trips last week (N)	1,724	10.04	1,997	9.48	2,071	9.67	-0.371 (0.362)
PRT spending last week ($)	1,724	29.60	1,997	28.44	2,071	28.59	-1.01 (0.993)
C. Employment (from baseline survey)							
Employed past 12 months	1,724	0.642	1,997	0.625	2,071	0.621	-0.021 (0.016)
Currently employed	1,724	0.448	1,997	0.447	2,071	0.446	-0.002 (0.016)
Hours worked per week at main job (N)	773	30.09	892	30.77	924	30.93	0.840 (0.536)
Hourly wage at main job ($)	773	13.71	892	13.48	922	13.66	-0.050 (0.177)
D. Employment in quarter prior to enrollment (from UI records)							
Total earnings ($)	1,708	2,369	1,980	2,364	2,053	2,436	67.20 (109)
Received nonzero UI benefits	1,708	0.026	1,980	0.036	2,053	0.031	0.005 (0.005)
Total diary respondents	**1,724**		**1,997**		**2,071**		

Notes: Table presents mean baseline characteristics across study groups among the adult participants who completed at least one text message-based travel diary. We define completion of a diary as answering all 5 questions in the diary. The characteristics in panels A, B, and C come from the baseline survey. The characteristics in panel D come from Pennsylvania unemployment insurance (UI) records. Baseline survey items that permitted unbounded continuous-valued responses are winsorized at the 99th percentile. Robust standard errors are in parentheses. ***p <0.01, **p <0.05, *p <0.1

Finally, we test for selection bias by comparing the mean response values to certain survey questions between the two incentive groups. Table C12 compares the mean answers in the low and high incentive groups and tests whether the difference is zero. Respondents in the high incentive group were two percentage points (5.6%) more likely than the low incentive group to report taking a car trip yesterday. The high incentive group was also 2.9 percentage points (7.6%) more likely to report leaving the house to go to work, and 1.8

percentage points (11.0%) less likely to report not leaving the house yesterday.

The rightmost column in Table C12 compares 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), again following the methods in Coffman et al. (2019). As was the case for the midline surveys, the mean differences between the marginal diary responder and always-responders are inflated by the relatively small differences in item response rates between the low and high incentive groups. The lack of a large response to incentives makes it difficult to assess how different the marginal responders are from the always-responders. Nevertheless, the standard errors of the differences in mean answers between the \$1 and \$2 incentive groups are small enough to rule out substantial selection bias for most of the survey questions in Table C12.

Table C12: Comparing travel diary response values of low and high incentive groups

	Low incentive (\$10)		High incentive (\$20)			
	Item response rate	Mean	Item reponse rate	Mean	\$20 vs. \$10 difference	Marginal responders vs. always-responders difference
Number of places visited yesterday	0.590	3.31	0.637	3.36	0.055 (0.157)	0.747 (2.46)
Did you use the following mode for any trips yesterday?						
Car	0.598	0.360	0.644	0.379	0.020** (0.008)	0.277** (0.146)
Pittsburgh Regional Transit	0.597	0.583	0.643	0.592	0.009 (0.009)	0.120 (0.121)
Walk or bike	0.596	0.459	0.642	0.456	-0.002 (0.009)	-0.031 (0.138)
Reason for leaving house yesterday						
For work	0.594	0.380	0.639	0.408	0.029*** (0.010)	0.413** (0.176)
For school	0.594	0.110	0.639	0.117	0.007 (0.006)	0.105 (0.095)
For groceries	0.594	0.449	0.639	0.467	0.018** (0.008)	0.264** (0.143)
For health care	0.594	0.141	0.639	0.147	0.006 (0.006)	0.081 (0.093)
For leisure	0.594	0.221	0.639	0.235	0.014* (0.007)	0.201* (0.125)
For social services	0.594	0.062	0.639	0.068	0.006 (0.004)	0.089 (0.066)
For other reason	0.594	0.323	0.639	0.330	0.007 (0.008)	0.106 (0.133)
Did not leave house yesterday	0.594	0.164	0.639	0.146	-0.018*** (0.006)	-0.257** (0.119)

Notes: This table compares respondents' answers to the travel diary survey questions between the high (\$20) and low (\$10) incentive groups. 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. The 'item response rate' columns report the share of study participants who answered the given diary question at least once. 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

C.3 Smartphone GPS data sharing

All adult study participants received a text message three days after they enrolled in the study that invited them to participate in the voluntary smartphone Google Maps data-sharing task. Interested participants clicked a link that walked them through the process of configuring their Google Maps app settings to collect their location history at all times. Study participants continued receiving the task invitation on a monthly basis until they either opted into the task or said they were not interested.

Each month, we sent a message to a randomly-selected subset of the individuals within each fare discount group who had opted into the task. The message invited them to transmit their Google Maps location history data to the research team. The message contained instructions for exporting the data from Google and uploading it to a Qualtrics survey. Participants received $1 for each day covered by their data in the request month, for a maximum monthly payment of $31.

Starting in April 2024, we expanded the data collection effort and began sending the monthly data request message to all adult study participants, including those who had no previously opted into the task. We also changed the data transmission process starting in this month. Instead of uploading their data to a Qualtrics survey, participants now uploaded their data to Google Drive and shared it with a Google account managed by the research team. We also revised the compensation scheme so that each participant received $10 if their data covered at least 10 days in the request month, and $0 otherwise. The GPS data-sharing task concluded in May 2024, which was up to 18 months after random assignment for some participants.

Table C13 presents the GPS task participation rates for the full sample and for each fare discount group. Participation rates were low overall, with only 4.9% of the adult sample sharing Google Maps data that covered at least one day from the time period after they enrolled in the study. Participation rates varied across the three discount groups, ranging from 4.2% of the control group to 5.7% of the free fares group. The difference in rates of task participation was statistically significant between the free fares group and control group, but not between the half-fares group and the control group. Among those who shared their data, the location history covered an average of 272 days from the time period after they enrolled in the study. The data shared by the free fares task participants covered an average of 35.8 more post-enrollment days than the data shared by the no-discount task participants.

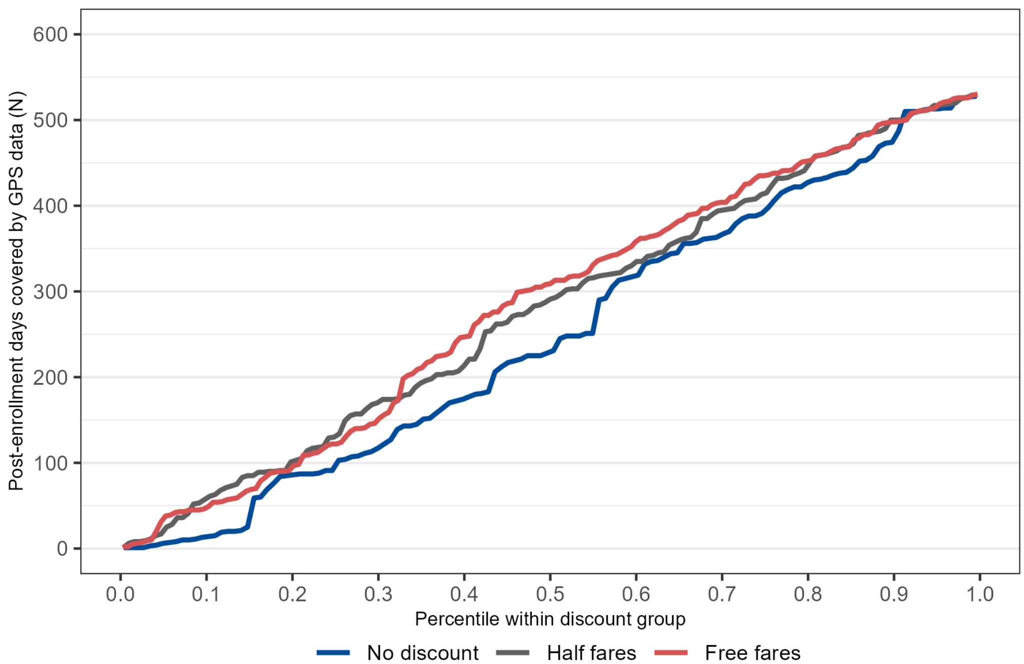
Table C13: GPS data sharing participation, by discount group

					Mean differences		
	Full sample	No discount	Half fares	Free fares	Half fares vs. no discount	Free fares vs. no discount	Free fares vs. half fares
Shared any data	0.049	0.042	0.049	0.057	0.007 (0.005)	0.015*** (0.005)	0.008 (0.006)
Days covered by data (N), among those who shared any data	272.17	248.78	277.52	284.53	28.74 (19.40)	35.75* (19.08)	7.01 (17.66)

Notes: Table presents measures of participation in the GPS data-sharing task by fare discount group. The first row reports the fraction of participants that shared GPS data that covered at least one day in the time period after they enrolled in the study. The second row reports the mean number of post-enrollment days covered by the participant's GPS data, conditional on sharing data that covered at least one post-enrollment day. Robust standard errors are in parentheses. ***p <0.01, **p <0.05, *p <0.1

Figure C2 plots the number of post-enrollment days covered by each GPS task participant's data. Compared with the free fares and half fares groups, the control group members tended to share GPS data that covered fewer days of their study enrollment. The median number of days covered by GPS data was approximately 225 among the control group and 300 among the half fares and free fares group. The half fares and free fares task participants had similar distributions of GPS day coverage.

Figure C2: Distribution of number of post-enrollment days covered by GPS data for each task participant, by discount group



Notes: Figure presents the distribution of the number of days covered by GPS data for each GPS data-sharing task participant. The analysis is limited to the individuals who shared at least one post-enrollment day of GPS data. Calculations are based on smartphone Google Maps location history data.

Table C14 compares the baseline characteristics of the study participants who took part in the GPS data-sharing task with those who did not. The participants who elected to share their GPS data were 5.5 percentage points less likely than the non-sharers to be female, 21.8 percentage points more likely to be White, and 13.9 percentage points more likely to have some post-high school education.

Table C14: Selection into GPS data-sharing task on baseline characteristics

	Shared GPS data	Did not share GPS data	Difference
A. Demographics			
Female	0.669	0.724	-0.055**
			(0.022)
Age	38.60	39.59	-0.989**
			(0.459)
Race			
Black	0.379	0.600	-0.221***
			(0.023)
White	0.544	0.327	0.218***
			(0.023)
Other	0.074	0.049	0.025**
			(0.012)
Hispanic	0.025	0.034	-0.008
			(0.007)
Children in household (N)	0.953	1.14	-0.189***
			(0.058)
Highest education			
Less than high school	0.053	0.083	-0.030***
			(0.011)
High school	0.436	0.554	-0.118***
			(0.023)
More than high school	0.498	0.359	0.139***
			(0.024)
B. Transportation			
Owns a car	0.070	0.056	0.013
			(0.012)
PRT trips last week (N)	10.03	10.04	-0.003
			(0.583)
PRT spending last week ($)	26.57	30.08	-3.51***
			(1.24)
C. Employment (from baseline survey)			
Employed past 12 months	0.587	0.605	-0.018
			(0.023)
Currently employed	0.424	0.427	-0.003
			(0.023)
Hours worked per week at main job (N)	28.41	30.88	-2.47***
			(0.749)
Hourly wage at main job ($)	13.64	13.47	0.165
			(0.273)
D. Employment in quarter prior to enrollment (from UI records)			
Total earnings ($)	2,107.97	2,284.09	-176.12
			(149.48)
Received nonzero UI benefits	0.019	0.032	-0.012*
			(0.007)
Test for joint orthogonality			
F stat			1.044
p-value			0.405
N	**472**	**9,072**	

Notes: This table compares the mean baseline characteristics between the adult study participants who took part in the GPS data-sharing task and those who did not. We define participation in the GPS task as sharing data that covers at least one day in the time period after the person joined the study. The statistical significance of the difference in mean characteristics between the GPS task participants and non-participants is calculated by regressing the characteristic on a dummy variable that equals 1 if the participant took part in the GPS task. Robust standard errors are in parentheses. Joint F test is done using randomization inference. ***p <0.01, **p <0.05, *p <0.1

Table C15 explores whether the subset of study participants that elected to share their GPS data remained balanced across randomization arms on certain relevant baseline characteristics. The GPS sharers do not demonstrate worse balance than the full study sample on most characteristics shown in the table.

Table C15: Randomization balance among participants in the GPS data-sharing task

	No discount		Half fares		Free fares		
	N	Mean	N	Mean	N	Mean	Free fares vs. no discount diff.
A. Demographics							
Female	132	0.705	159	0.660	181	0.652	-0.053 (0.053)
Age	132	37.34	159	39.32	181	38.88	1.54 (1.08)
Race							
Black	132	0.402	159	0.346	181	0.392	-0.009 (0.056)
White	132	0.538	159	0.566	181	0.530	-0.007 (0.057)
Other	132	0.083	159	0.069	181	0.072	-0.012 (0.031)
Hispanic	132	0.038	159	0.019	181	0.022	-0.016 (0.020)
Children in household (N)	132	0.864	159	0.899	181	1.07	0.203 (0.134)
Highest education							
Less than high school	132	0.045	159	0.031	181	0.077	0.032 (0.027)
High school	132	0.455	159	0.390	181	0.464	0.010 (0.057)
More than high school	132	0.492	159	0.553	181	0.453	-0.039 (0.057)
B. Transportation							
Owns a car	132	0.083	159	0.069	181	0.061	-0.023 (0.030)
PRT trips last week (N)	132	8.40	159	9.35	181	10.86	2.45** (1.15)
PRT spending last week ($)	132	22.54	159	26.29	181	28.80	6.26** (2.73)
C. Employment (from baseline survey)							
Employed past 12 months	132	0.621	159	0.579	181	0.569	-0.052 (0.056)
Currently employed	132	0.417	159	0.453	181	0.403	-0.013 (0.056)
Hours worked per week at main job (N)	55	27.62	72	29.54	73	27.88	0.259 (1.98)
Hourly wage at main job ($)	55	13.86	72	13.10	72	14.00	0.141 (0.723)
D. Employment in quarter prior to enrollment (from UI records)							
Total earnings ($)	130	2,269	155	2,128	180	1,966	-303.8 (369.8)
Received nonzero UI benefits	130	0.031	155	0.019	180	0.011	-0.020 (0.017)
Total GPS task participants	**132**		**159**		**181**		

Notes: Table presents mean baseline characteristics across study groups among the adult participants who chose to take part in the GPS data-sharing task. We define participation in the GPS task as sharing data that covers at least one day in the time period after the person joined the study. The characteristics in panels A, B, and C come from the baseline survey. The characteristics in panel D come from Pennsylvania unemployment insurance (UI) records. Baseline survey items that permitted unbounded continuous-valued responses are winsorized at the 99th percentile. Robust standard errors are in parentheses. ***p <0.01, **p <0.05, *p <0.1

Table C16 disaggregates the treatment effects on certain focal study outcomes by whether the study participant shared their smartphone GPS data. The GPS sharers had larger treatment effects than the non-sharers on the number of times per week that they tapped their study-issued farecard (Panel A) and their likelihood of self-reporting that they took a PRT trip yesterday (Panel B). GPS sharers also experienced negative effects on cumulative earnings in the first four quarters after enrollment, while the non-sharers experienced a positive effect on this outcome. These differences raise the possibility that the participants who opted to share their GPS data were self-selected on characteristics that correlate with their responsiveness to the fare discounts, at least in terms of travel behavior.

Table C16: Heterogeneity in impacts on various outcomes, by whether the participant shared their smartphone Google Maps location history data

	Half fares vs. no discount		Free fares vs. no discount	
	Didn't share GPS	Shared GPS	Didn't share GPS	Shared GPS
A. Farecard taps per week (N; from PRT farecard tap data)				
Control mean	0.297	0.332	0.297	0.332
Treatment effect	1.44***	3.50***	4.69***	5.87***
SE	(0.067)	(0.554)	(0.101)	(0.427)
P-value of diff.	[<0.001]		[0.003]	
B. Likelihood of taking a PRT trip yesterday (from travel diary data)				
Control mean	0.580	0.519	0.580	0.519
Treatment effect	-0.012	0.016	0.002	0.066
SE	(0.011)	(0.044)	(0.011)	(0.040)
P-value of diff.	[0.799]		[0.075]	
C. Cumulative earnings in first 4 quarters after enrollment ($; from UI records)				
Control mean	11,138	10,714	11,138	10,714
Treatment effect	344.3	-1,125	397.1	-1,717
SE	(334.9)	(1,607)	(341.3)	(1,638)
P-value of diff.	[0.220]		[0.680]	
D. Number of days with a non-ER outpatient claim in first 365 days after enrollment (N; from Medicaid claims)				
Control mean	13.65	12.48	13.65	12.48
Treatment effect	0.155	-2.09	0.595	0.674
SE	(0.961)	(5.47)	(0.995)	(5.81)
P-value of diff.	[0.352]		[0.689]	

Notes: This table disaggregates the treatment effects on various study outcomes by whether the participant opted to share their smartphone Google Maps location history data. The coefficient reported in row 'Treatment effect' comes from a regression of the outcome of interest on a treatment indicator. The p-values of the differences in impacts between the GPS sharers and non-sharers are calculated by regressing the outcome on a treatment indicator, an indicator for sharing GPS data, and the interaction of these two variables. The p-value of the interaction term is reported in row 'P-value of diff.'. All regressions also 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). Robust standard errors are in parentheses. ***p <0.01, **p <0.05, *p <0.1

D Details of cost effectiveness calculations

In this appendix, we calculate and discuss the costs and benefits of providing free public transportation fares to working-age SNAP recipients.

D.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 control group took an average of 3.47 transit trips per week according to GPS data. But 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.[49] When counting only the payable trips, the control group took 2.08 trips per week, or 108.16 trips per year. The policy thus cost PRT 108.16 × \$2.75 = \$297.44 in foregone fare revenue per person per year. Among the baseline-unemployed sub-group, control group participants took 1.98 payable transit trips per week, for a cost to PRT of 1.98 × 52 × \$2.75 = \$283.14 per person per year.

The Allegheny County Department of Human Services 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 an annual administrative cost per participant of (25 × \$25 × 52) / 9,544 = \$3.41.

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.[50]

Summing these costs yields a total direct cost of \$297.44 + \$3.41 = \$300.85 per person per year for the average participant, and \$283.14 + \$3.41 = \$286.55 for the average baseline-unemployed participant.

[49]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.

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

D.2 Cost-effectiveness of eliminating car trips by expanding transit service

Beaudoin and Lawell (2018) estimate that a 1,000,000 increase in a public transit system's total annual vehicle revenue-miles (VRM) leads to 43 fewer daily automobile vehicle miles traveled (VMT) per freeway lane-mile (see Table 2 column 3 in their paper). Equivalently, an increase of 63.71 VRM eliminates 1 VMT per lane-mile. Allegheny County has 12,625.85 lane-miles of roadways.[51] An increase of 63.71 VRM in Allegheny County would therefore eliminate 12,625.85 VMT, so a 0.005 VRM increase would eliminate 1 VMT. The Pittsburgh Regional Transit system had 20,178,341 total VRM (in the form of fixed-route bus and light rail service) in 2023 at an operating cost of \$487,483,000 net of fare revenue, for a total public cost of \$24.16 per VRM.[52] It would therefore cost $\$24.16 \times 0.005 = \$0.1219$ to eliminate 1 VMT in Allegheny County via an expansion of transit service.

D.3 Marginal value of public funds

In this section, we calculate the marginal value of public funds (MVPF) of providing free public transportation fares. 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 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.

Our study estimates the effect of free fares on a broad array of behavioral outcomes. Most of these effects are not statistically different from zero, and even if they were, many of them lack monetary valuations of fiscal cost or willingness to pay (WTP). We therefore limit our MVPF calculation to the components for which free fares had statistically detectable treatment effects and for which credible valuations are available.

We present two versions of the MVPF: one for the full sample and another for the sample members who were unemployed at baseline.

D.3.1 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 must instead use an ex post valuation of their WTP that is based on any downstream benefits the person derives from the subsidy.

[51] This number was provided by a Pennsylvania Department of Transportation official.

[52] The VRM number comes from the Federal Transit Administration National Transit Database. The operating cost number comes from Pittsburgh Regional Transit (2024).

Our data gives some indications that 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 steadily in the first five months of the study before leveling off (Appendix Figure A5). 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.[53] Furthermore, free fares had a four-times 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 A6 panel A). 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.

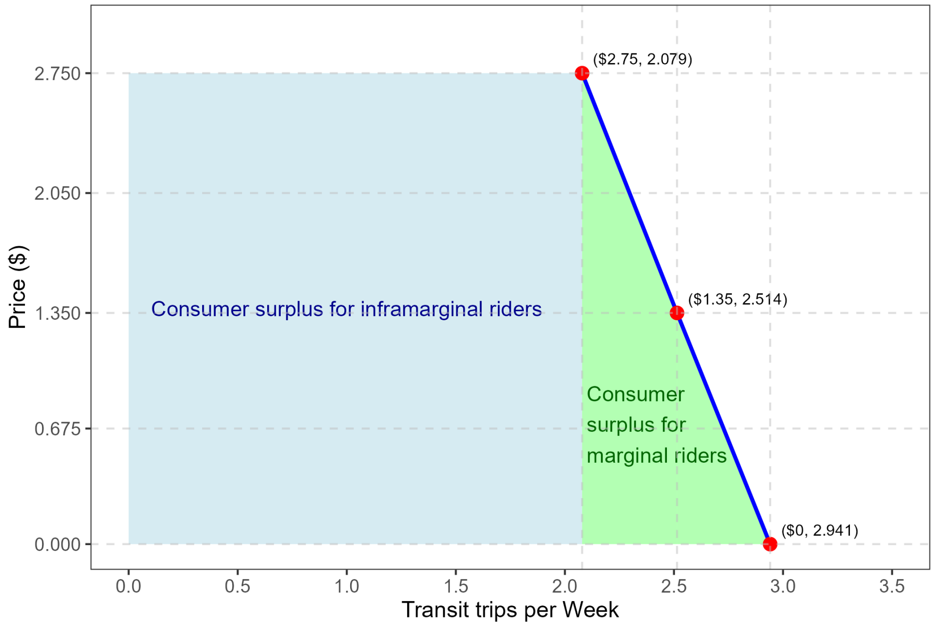
On the other hand, each of our follow-up surveys included the question "Would you be willing to pay $X for a month of unlimited PRT trips?", where X is a random integer between 1 and 97 (a regular-price monthly pass costs $97.50). There are no systematic changes in the shape of these unincentivized WTP curves for the treated participants 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, 73% of control group respondents said they would be willing to pay X = $30, which corresponds to the monetary value of the number of payable transit trips that the free fares group actually took per year ($359). Put differently, most 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.[54]

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.

[53]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.

[54]The minimal observed effects of fare discounts on most downstream socioeconomic outcomes could imply in and of itself that participants were already taking their privately optimal number of transit trips at baseline. By this logic, a low-income person would find a way to take more transit trips under regular fares if they knew that the additional trips would improve their life. Our survey data shows at least some evidence of liquidity or credit constraints, as 23.7% of respondents said that the cost of fares prevents them from riding more often.

Figure D1: Transit demand curve, based on effects of fare discounts on number of payable PRT trips per week



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. 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 2.08 payable trips per week according to GPS data. Half fares added 0.435 payable trips per week (SE = 0.442) and free fares added another 0.427 payable trips per week (SE = 0.425). These treatment effects are not reported in any table or figure. They are based on the same model specification as in the bottom row of Table 3.

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 recipient 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 D1). The demand curve linearly interpolates between the three observed price effects. Free fares provide consumer surplus of 2.08 × $2.75 = $5.73 for the 2.08 payable weekly trips that the person would take under regular prices, 0.44 × $2.05 = $0.90 for the 0.44 additional payable weekly trips induced when fares fall to $1.35, and 0.43 × $0.675 = $0.28 for the additional payable weekly trips induced when fares become free, for a total annual per capita WTP of ($5.73 + $0.90 + $0.28) × 52 = $359.32. The same calculation for the baseline-unemployed sub-group amounts to $286.84.

Ex post benefits approach: Free fares recipients spent 66.04 fewer hours traveling per year than the control group, according to GPS data. They reported a mean hourly wage of $14.61 in the post-endline survey. If we assume that people value an hour of travel time at 50% of their hourly wage, then the annual WTP for less travel is 0.5 × $14.61 × 66.04 = $482.42. The WTP for the baseline-unemployed sub-group is $1,575.79.

The baseline-unemployed sub-group gains additional 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 through six quarters (T = 6), discounted at quarterly gross rate 1 + r where we set r = 0.01. Any effects that persist beyond six quarters would make this valuation even higher. The net present value is:

$$(1 - 0.0765 - 0.0307 - 0.1) \times 0.6 \times \sum_{t=1}^{T=6} \frac{\hat{\beta}^{t,earnings}}{(1+0.01)^{t-1}} = \$1,315.08,$$

and the equivalent annual WTP is:

$$\frac{\$1,315.08 \times 0.01 \times (1.01)^6}{(1.01)^6 - 1} = \$226.55$$

Society's WTP. This consists of any externalities of free fares for third parties. Free fares led participants to travel 529.25 fewer miles by car per year. Society benefits from this reduction in car travel. We monetize three negative externalities of car travel: carbon emissions, traffic congestion, and car accidents.

Carbon emissions: The average passenger vehicle emits 400 grams of CO_2 per mile (U.S. Environmental Protection Agency, June 2023), so free fares reduced annual CO_2 emissions by 400 × 529.25 = 211,700 grams, or 0.233 tons per person. We place a monetary cost on CO_2 emissions following the U.S. Environmental Protection Agency's 2023 estimate of $193 per ton (U.S. Environmental Protection Agency, 2023).[55] The social WTP for reduced CO_2 is then $193 × 0.233 = $44.97 per study participant per year.

Traffic congestion: Traffic congestion cost the U.S. economy an estimated $70.4 billion in 2023 in the form of lost time (Pishue, June 2024), and U.S. residents drove a total of 3.2637 trillion miles in 2023 (U.S. Federal Highway Administration, 2023). Congestion thus cost an average of $70.4 billion / 3.2637 trillion = $0.0215 per mile. The social WTP for less traffic is $0.0215 × 529.25 = $11.38 per participant per year.

Car accidents: Car accidents cost the U.S. an estimated $340 billion in 2019 (Blincoe et al., February 2023). Residents drove a total of 3.2691 trillion miles in that year (U.S. Federal Highway Administration, 2019). Accidents therefore cost an average of $340 billion / 3.2691 trillion = $0.104 per mile, or $0.12 inflated to 2023 dollars using the CPI-U. The social WTP for reduced accidents is $0.12 × 529.25 = $63.51 per participant per year.

The total social WTP for reducing these three externalities of car travel is $44.97 + $11.38 + $63.51 = $119.86 per participant per year. Among the baseline-unemployed sub-group, free fares reduced car travel by 788.32 miles per year, for a total social WTP of

[55] This cost of carbon is also used by Hahn et al. (2024) in their recent environmental policy MVPF review.

$178.63.[56]

Society's WTP for free fares would be even larger if we include other observed effects that have uncertain valuations. For example, free fares increased the standardized test scores of child study participants by an estimated 0.135 SD units (Appendix Table A9 panel B). Assuming that a one SD increase in test scores increases a child's lifetime earnings by 10% (Kline & Walters, 2016), this effect would substantially increase the MVPF.

D.3.2 Net cost to the government

The MVPF denominator includes the direct cost of free fares to the government plus any fiscal externalities associated with the effects of the policy. The direct cost is $300.85 per person per year for the full sample and $286.55 for the baseline-unemployed sub-group, as calculated in Section D.1 above. Fiscal externalities could theoretically include government cost savings associated with reduced car travel, such as savings on road maintenance or accident damage. We are not aware of credible monetary values for these effects, so we conservatively omit them from our benchmark calculation.

The government collects additional tax revenue on the increased earnings of the baseline-unemployed sub-group. The net present value of this revenue is equal to:

$$(0.0765 + 0.0307 + 0.1) \times \sum_{t=1}^{T=6} \frac{\hat{\beta}^{t,earnings}}{(1+0.01)^{t-1}} = \$574.02,$$

and the equivalent annual revenue is:

$$\frac{\$574.02 \times 0.01 \times (1.01)^6}{(1.01)^6 - 1} = \$99.05$$

The annual per capita net cost to the government is $300.85 for the full sample and $286.55 - $99.05 = $187.50 for the baseline-unemployed sub-group.

D.3.3 MVPF results

The MVPF results are summarized in Appendix Table D1. Offering free transit fares to all working-age SNAP recipients has an MVPF of 1.59 when measuring private WTP using revealed preference, and an MVPF of 2.00 when measuring private WTP using ex post benefits. For *unemployed* SNAP recipients, the MVPF is 2.48 and 10.57 for these two approaches.

[56]Free fares could also cause some amount of *increased* carbon emissions from public transit vehicles if the additional transit ridership leads PRT to run more frequent bus service. We abstract from this possibility as our MVPF calculations are partial-equilibrium.

Table D1: Marginal value of public funds (MVPF) of free public transportation fares

	Measuring private WTP by revealed preference	Measuring private WTP by ex post benefits
A. For all working-age SNAP recipients		
Willingness to pay		
Value of free fares (for recipient)	\$359.32	-
Less time spent traveling (for recipient)	-	\$482.42
Reduced automobile externalities (for third parties)	\$119.86	\$119.86
Net cost		
Direct cost of fare subsidies	\$300.85	\$300.85
MVPF	**1.59**	**2.00**
B. For unemployed SNAP recipients		
Willingness to pay		
Value of free fares (for recipient)	\$286.84	-
Less time spent traveling (for recipient)	-	\$1,575.79
Increased labor earnings (for recipient)	-	\$226.55
Reduced automobile externalities (for third parties)	\$178.63	\$178.63
Net cost		
Direct cost of fare subsidies	\$286.55	\$286.55
Increased income tax revenue	-\$99.05	-\$99.05
MVPF	**2.48**	**10.57**

Note: All values are per free-fares recipient per year

E Study materials

E.1 Study recruitment flier

Figure D1: The flier that was used to advertise the Allegheny County Discounted Fares Pilot program

Join the Allegheny County Discounted Fares Pilot Program!

The Allegheny County Department of Human Services (DHS) is seeking Supplemental Nutrition Assistance Program (SNAP) recipients ages 18 through 64 to participate in a 12-month pilot program to understand the impact of transportation affordability on low-income residents.

Who qualifies for the Allegheny County Discounted Fares Pilot Program?

Eligible participants:

- Currently reside in Allegheny County
- Were receiving SNAP benefits on September 30, 2022
- Are between the ages of 18 and 64
- Do not have another household member ages 18 through 64 who is already participating in this pilot

How does the pilot work?

Participation in the pilot is voluntary but includes agreeing to share data and completing occasional surveys. Eligible participants will be randomly assigned to one of three groups:

1. **Free fares:** This group will receive unlimited free fares on all PRT trips for 12 months.
2. **50% discount:** This group will receive a ConnectCard that reduces the cost of all PRT trips by half (50%) for 12 months, and is pre-loaded with $10.
3. **No discount:** This group will receive a ConnectCard pre-loaded with $10 but will not receive a fare discount.

Why is it a pilot rather than a permanent program?

A pilot is a short-term opportunity to learn from participants with the goal of informing the design on a permanent program.

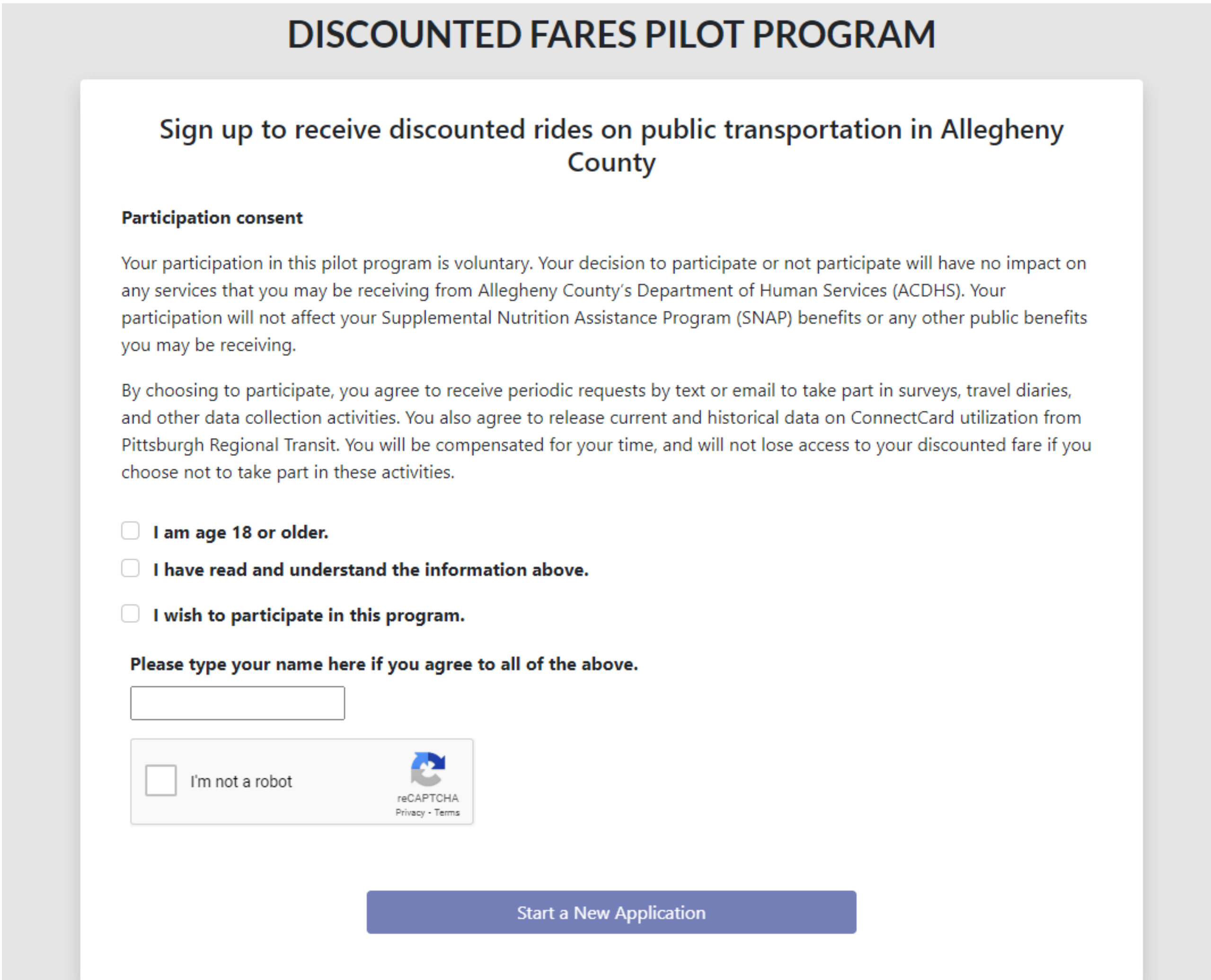
DHS wants to understand how local residents may benefit from lowering the cost of public transit. This will include examining the impact on ridership and whether there is increased access to jobs, services and other resident needs.

To learn more and apply, visit:
DiscountedFares.alleghenycounty.us

Allegheny County
Discounted Fares
Pilot Program

E.2 Study application

Figure D2: Study application consent form



DISCOUNTED FARES PILOT PROGRAM

Sign up to receive discounted rides on public transportation in Allegheny County

Participation consent

Your participation in this pilot program is voluntary. Your decision to participate or not participate will have no impact on any services that you may be receiving from Allegheny County's Department of Human Services (ACDHS). Your participation will not affect your Supplemental Nutrition Assistance Program (SNAP) benefits or any other public benefits you may be receiving.

By choosing to participate, you agree to receive periodic requests by text or email to take part in surveys, travel diaries, and other data collection activities. You also agree to release current and historical data on ConnectCard utilization from Pittsburgh Regional Transit. You will be compensated for your time, and will not lose access to your discounted fare if you choose not to take part in these activities.

- [ ] **I am age 18 or older.**
- [ ] **I have read and understand the information above.**
- [ ] **I wish to participate in this program.**

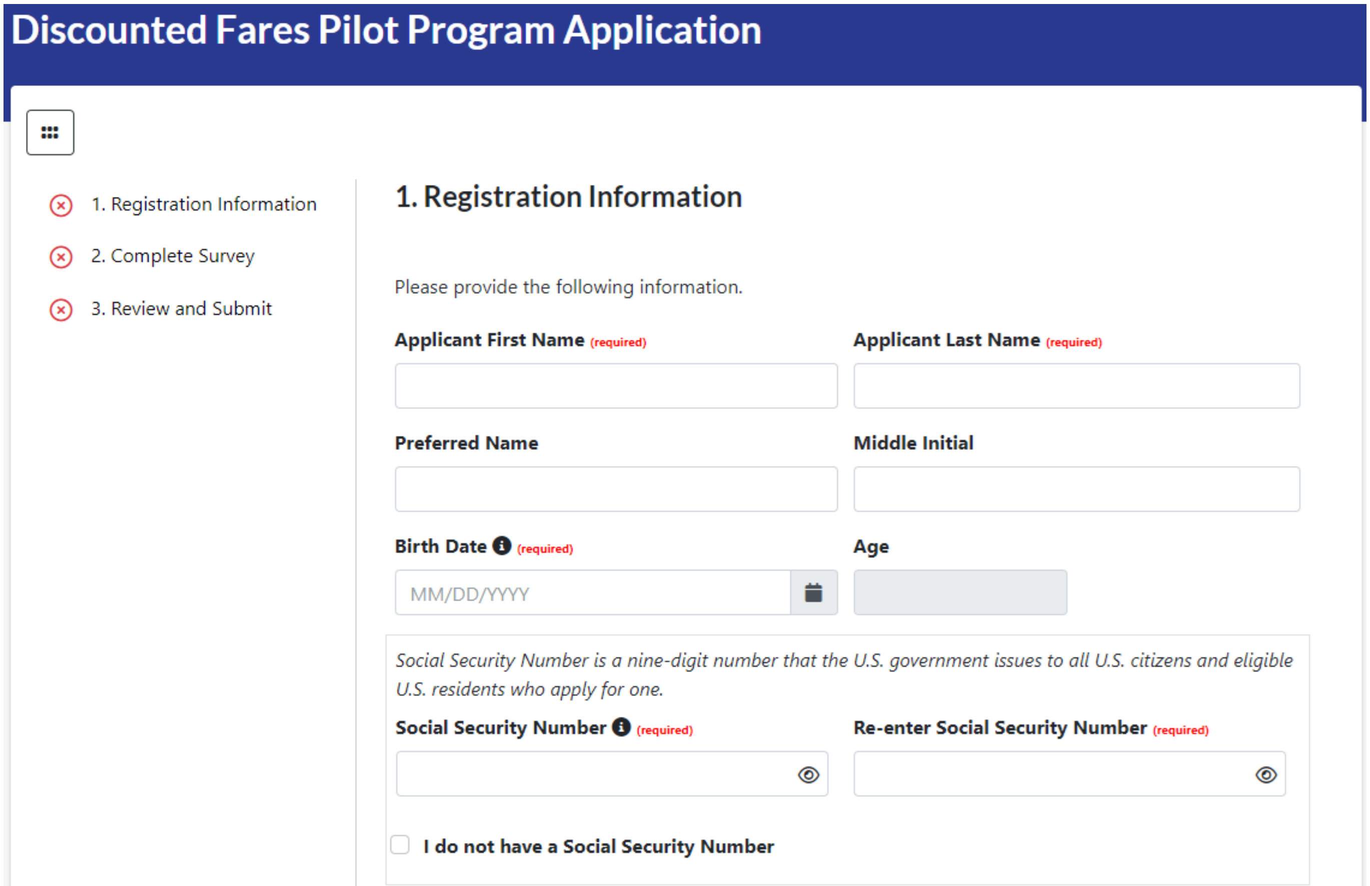
Please type your name here if you agree to all of the above.

I'm not a robot

reCAPTCHA
Privacy - Terms

Start a New Application

Figure D3: First section of study application form



Discounted Fares Pilot Program Application

1. Registration Information
2. Complete Survey
3. Review and Submit

1. Registration Information

Please provide the following information.

Applicant First Name (required)

Applicant Last Name (required)

Preferred Name

Middle Initial

Birth Date (required)

MM/DD/YYYY

Age

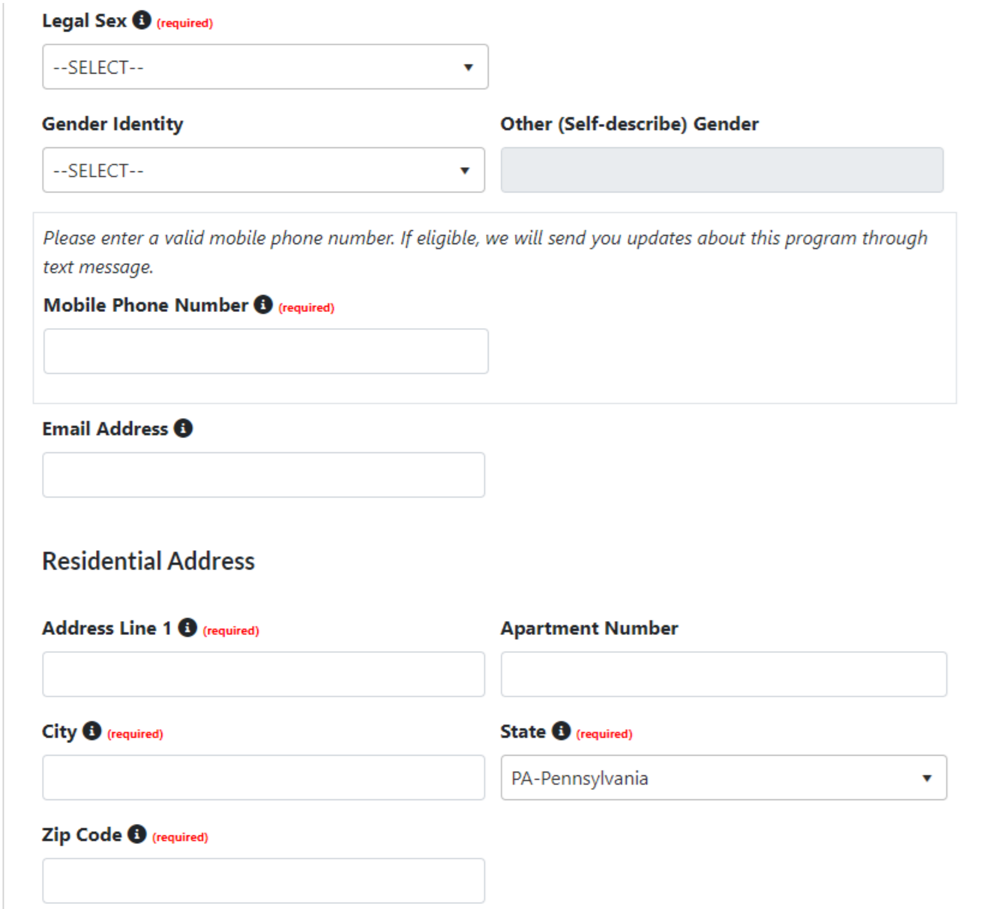
Social Security Number is a nine-digit number that the U.S. government issues to all U.S. citizens and eligible U.S. residents who apply for one.

Social Security Number (required)

Re-enter Social Security Number (required)

I do not have a Social Security Number

Figure D4: Second section of study application form



Legal Sex (required)

--SELECT--

Gender Identity

--SELECT--

Other (Self-describe) Gender

Please enter a valid mobile phone number. If eligible, we will send you updates about this program through text message.

Mobile Phone Number (required)

Email Address

Residential Address

Address Line 1 (required)

Apartment Number

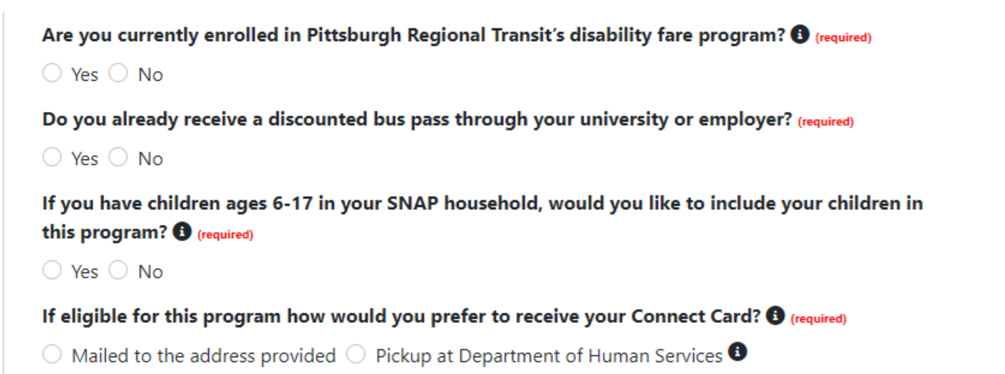
City (required)

State (required)

PA-Pennsylvania

Zip Code (required)

Figure D5: Third section of study application form



Are you currently enrolled in Pittsburgh Regional Transit's disability fare program? (required)

Yes No

Do you already receive a discounted bus pass through your university or employer? (required)

Yes No

If you have children ages 6-17 in your SNAP household, would you like to include your children in this program? (required)

Yes No

If eligible for this program how would you prefer to receive your Connect Card? (required)

Mailed to the address provided Pickup at Department of Human Services

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