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

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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 either 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 decrease in private vehicle trips. Half-price fares yield no change in transit ridership. There is suggestive evidence that fare reductions decrease the overall frequency and spatial breadth of travel, implying the need for other measures when quantifying improvements in mobility. Our confidence intervals rule out increases of more than 3.2 percentage points in the likelihood of being employed during the first year, and we rule out increases in first-year earnings of more than $864. We find minimal downstream effects on health care consumption, social services receipt, or self-reported health and well-being. Fare prices appear to play a limited role in the socioeconomic lives of poor families.

Keywords: Public transportation, transit subsidies, randomized controlled trial

JEL: H4, H7, I3, R4, R5

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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 a variety of other socioeconomic outcomes among low-income households. We enrolled a sample of 9,544 adults age 18 to 64 who receive Supplemental Nutrition Assistance (SNAP) benefits in Allegheny County, Pennsylvania, a large county that contains the city of Pittsburgh. Each adult came from a different SNAP beneficiary household. Participants were randomly assigned to one of three conditions, each with equal probability. The first treatment group received farecards that provided a 50% discount on all public transportation trips. The second treatment group received farecards that provided a 100% discount (i.e. free fares) on all trips. The control group received farecards that contained \$10 but no further discount. The discounts for the two treated groups lasted for 16 to 19 months, depending on when the individual enrolled in the study.

We first explore the effects of the fare discounts on mobility and travel behavior. Our

[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.

preferred estimates of the effect of fare discounts on public transit ridership come from Google Maps location history (i.e. 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 (s.e. 0.716) trips per week, a 43% increase relative to no discount. Half-price fares yielded no detectable change in transit ridership. To put the monetary value of free fares in context, 1.48 additional transit trips per week for 12 months under status quo prices would cost roughly $212, which represents 2.3% of the mean sample member's annualized earnings in the quarter before study enrollment.

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 private vehicle trip on a given day, and reduced total weekly private vehicle travel by 1.7 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 private vehicle. These patterns of substitution are echoed 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 may have actually *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. 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 on a given day, and was 18.7% more likely to not leave their house at all on a given day. The possibility that lower transportation costs may reduce some dimensions of total mobility constitutes a novel finding in the literature on urban travel. While the potential mechanisms behind these effects require further study, the results imply that increased spatial movement by itself is not necessarily a positive outcome. Part of the utility that low-income residents derive from cheaper transit fares could take the form of somehow being able to leave home less often or visit fewer distinct places to satisfy their needs.

Fare discounts provided direct financial relief and improved participants' travel capabilities. The recipients of free fares reported spending \$17.09 less than the control group per week on public transportation at 15 months after enrollment. The half fares group reported \$5.64 lower spending per week than the control group. Both discount levels yielded improvements in transportation insecurity according to a validated questionnaire. The concept of transportation insecurity refers to the experience of being unable to move from place to place in a safe or timely manner. The free fares treatment reduced the share of post-endline (15-month follow-up) survey respondents that exhibited moderate-to-high insecurity by 11.9 percentage points, while the half fares treatment reduced moderate-to-high insecurity by 4.7 percentage points.

With these first-stage effects on travel behavior 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.

According to Pennsylvania unemployment insurance (UI) wage records, we find no detectable effect on the cumulative likelihood of being employed in the first four complete calendar quarters after joining the study. The 95% confidence interval allows us to reject that free fares cause a decline in the probability of employment of more than 0.4 percentage points or an increase of more than 3.2 percentage points relative to the control group over the first four calendar quarters. We also rule out increases in cumulative earnings of more than \$864 (7.8% of the control mean) for free-fares relative to no discount over the first four quarters. We observe little heterogeneity across baseline subgroups in the treatment effects on cumulative employment and earnings in the first four quarters. Machine learning-based heterogeneity analyses do not reveal any clusters of participant characteristics that are correlated with especially large effects on these outcomes. We also fail to reject the sharp null hypothesis that the effect of free fares versus regular prices on these outcomes is zero for every participant. These findings suggest that the null average treatment effects on these outcomes are generally applicable across the entire study sample, rather that being heavily influenced by particular types of participants. Looking at self-reported employment outcomes, free fares led to a 1.4-hour (8.2%) reduction in weekly labor supply relative to no discount. The fare discounts did not produce statistically detectable changes in self-reported hourly wages, commute times, or job search intensity. Fare prices have an economically small influence on the short-run labor market outcomes of low-income working-age adults.

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 minus one or plus two percentage points on the likelihood of having at least one Medicaid claim within the first 365 days of study participation. Free fares caused a 26.8% increase in the likelihood of having at least one inpatient hospital stay in the first 365 days that did not begin with an emergency room visit. The free fares recipients also had 6.3% more days than the control group with a behavioral health care claim, 20.3% more days with a crisis-oriented behavioral health care claim, and 23.2% fewer days with a claim for substance use treatment. Despite these changes in consumption of certain types of health care, we observe little to no 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. We find no detectable effects on the likelihood of receiving public benefits in the twelfth month after study enrollment.

Among the minor-age youth study participants, fare discounts had no effect on the overall likelihood of receiving health care. We also find no detectable effects on employment or earnings for 16 and 17 year-olds in the first year after enrollment. Free fares appear to have caused students to miss two more days of school per academic year than the control group. Both discounts led to small increases in mean standardized test scores in the 2023-2024 school year.

In sum, our findings demonstrate that the cost of fares influences low-income individuals' choices of which transportation mode to use for their travels. However, this does not translate into meaningful improvements in downstream socioeconomic outcomes for the average participant in the domains of employment, health, or well-being. Whether due to relatively inelastic demand for public transit, poor transit service quality, or the broader difficulty of moving poor individuals out of current equilibria, fare prices by themselves appear to play only a minor role in the economic lives of disadvantaged residents.

Our study contributes to several bodies of literature in urban and labor economics. First, we build upon existing experimental studies of the effects of fare subsidy policies. One of the first such studies, Phillips (2014) finds evidence that a short-term transportation subsidy in Washington D.C. increases job search intensity for the recently unemployed, with suggestive evidence that this effect translates into decreased unemployment duration.

More recent experiments in Boston (Rosenblum, 2020), and Seattle (Brough, Freedman, & Phillips, 2022, 2024) find evidence of increased use of provided public transit farecards as a result of subsidized fares, with mixed results on healthcare consumption and limited effects on employment and other socioeconomic outcomes.[2] We extend this work by providing longer-term subsidies that last for a full 16 to 19 months – compared to previous studies' maximum of 6 months – allowing respondents to potentially make higher fixed-cost behavioral changes in response to sustained fare reductions. Our use of two separate treatment arms also enables us to test for non-linearities in the elasticity of demand for public transit.

Our measurement of transit trips using GPS data provides a particularly important contribution. Prior experiments measured transit ridership primarily using administrative boardings data from study-issued farecards. In our setting, we find that measuring ridership in this way produces inflated treatment effects because participants do not use their assigned farecard for all transit boardings, and the undercounting of true transit trips is most acute among the control group. Our GPS-based measurements of ridership result in much smaller, yet arguably more credible estimates of the price elasticity of demand for public transit than have been found in prior experiments. Beyond this measurement issue, our large sample size of 9,544 adults and 4,928 children allows us to detect effects on mobility and downstream outcomes that are well within the range of existing estimates. Furthermore, 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 yield a more complete picture of the impacts of transit subsidies on low-income households.

Second, this paper contributes to a growing literature that uses smartphone geolocation data to explore travel patterns in cities (G. E. Kreindler & Miyauchi, 2023; Miyauchi et al., 2022; Athey et al., 2021). Urban economic theory considers mobility to be critical for residents to take advantage of the agglomeration effects of cities (Combes & Gobillon, 2015; Glaeser & Kahn, 2004). We collect Google Maps location history files from the smartphones of a subset of our adult sample at regular intervals throughout the experiment. This data enables us to explore the effect of fare discounts on the travel behavior of low-income riders at a high level of spatial and temporal resolution, including details on the mode of travel and trip itineraries. Our study utilizes several different sources of mobility data: high-frequency travel diaries administered via text message, GPS data, and administrative card tap data. By comparing these three methods, we show that high-frequency travel diaries with short

[2]See Franklin (2018), Bull et al. (2021), Gravert and Collentine (2021), Cats et al. (2017), Busch-Geertsema et al. (2021), Guzman and Hessel (2022), and Munoz and Sandoval (2022) for additional studies on the effects of free or reduced-price transit fares in various contexts, including some randomized experiments.

recall times (e.g., asking about yesterday's travel) can achieve high accuracy when compared with GPS data (See Figure A15). This finding is significant as it suggests that researchers can obtain reliable mobility data using low-tech solutions like daily text messages, without the need to rely on smartphone-based GPS tracking.

Third, we add to the literature on spatial mismatch, which considers the extent to which differential access to jobs across neighborhoods is responsible for persistent urban poverty and disparities in labor market outcomes (Kain, 1968, 1992; Holzer et al., 1994; Ihlanfeldt & Sjoquist, 1998). Much of the work on spatial mismatch has focused on the employment effects of expanding public transit infrastructure (Gobillon et al., 2007; Tyndall, 2021; Holzer et al., 2003) or having access to a personal automobile (Blumenberg & Pierce, 2017; Raphael & Rice, 2002). Our estimates of the effect of fare discounts on employment, earnings, and job search shed light on how transportation costs influence access to jobs for low-income people. We reproduce the finding from Brough et al. (2024) that free fares have little to no effect on employment or earnings within the first year. At the same time, our finding of no effect on self-reported job search activity contrasts with prior work that has documented positive impacts of transit subsidies on job search behavior (Phillips (2014), Franklin (2018), and Abebe et al. (2021)). Our results also contribute to the longstanding question of how in-kind transfers affect poor individuals' labor supply (Moffitt, 2016). Our finding of no labor supply response among working-age adults in poverty echoes the null effects found in studies of other means-tested transfers such as SNAP (Cook & East, 2023) and Medicaid (Baicker et al., 2014).

In terms of policy implications, our analysis suggests that reducing transit fares alone is not sufficient to improve the economic outcomes of low-income families. While short-term fare subsidies yield direct improvements in transportation security, these improvements do not translate into measurable benefits in other domains of a person's life. However, this policy does yield environmental benefits for society as a whole, as we find evidence of participants shifting away from private vehicle use to public transportation.

2 The Allegheny County Context

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. With 39,207,577 unlinked passenger trips taken in 2023, PRT is the 26th largest public transportation agency in the U.S. by annual ridership. 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.[3]

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 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.

3 Experimental design

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.

3.1 Eligibility and recruitment

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

[3]Authors' calculations based on data from American Community Survey Table S0802 2022 5-year estimates.

SNAP household was allowed to participate.[4] 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.

ACDHS recruited participants by sending text messages to local residents who met the eligibility criteria according to administrative records. The messages contained a link to an online application portal. The text message recipients who did not apply after the first outreach received a second text message two months later that again encouraged them to apply. ACDHS also sent text messages to newly-eligible residents after the SNAP eligibility criterion was expanded on January 26th, 2023. Applicants who were previously deemed ineligible 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 flyers that were disseminated in the community.[5]

3.2 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 [6] 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 imme-

[4] 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.

[5] The recruitment flyer is shown in Appendix Figure C1.

[6] Appendix Figures C2 through C8 provide screenshots of the consent form, screening application, and baseline survey.

diately randomly assigned to one of three study arms:

- Free fares on all PRT trips (100% discount)
- A 50% fare discount on all PRT trips
- 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. Given that each adult participant came from a different SNAP household, the random assignment was essentially conducted at the SNAP household level. Participants were immediately informed about their eligibility for the study and their assigned fare discount level. Thus, all participants were randomized on the same date that they enrolled in the study.

Participants indicated in their application whether they wished to receive their ConnectCard by mail or pick it up in person. For those who chose mail delivery, ACDHS mailed the card within approximately one week of the person's 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.[7] These additional cards contained the same fare discount that the adult was assigned to. PRT offers an existing 50% discount for riders with disabilities. The study application asked applicants if they already receive this disability discount. Those who reported receiving this discount 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 50% discount group; they were instead told to continue using their existing disability farecard.

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

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

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.[8] 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.

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.[9] 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.[10] 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 will not be deactivated at any time. 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. Based on this timeline, 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 50% discount and the status quo control group was in effect for a total of 18 months.

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

[8] 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.

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

[10] 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.

sample contains a total of 14,472 individuals, including 9,544 adults.

4 Data and sample description

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

4.1 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 0% and 50% discount 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. Additionally, we receive data from PRT's third-party analytics vendor that uses the GPS location history of PRT vehicles to estimate the stop or station where each study-issued ConnectCard tap took place.

Second, we link participants to Pennsylvania unemployment insurance (UI) records. This dataset covers all UI-covered employment in Pennsylvania, which excludes jobs such as independent contracting and informal work. The data reports whether an individual had UI-covered 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 all other participants starting in the second quarter prior to random assignment, and is available for a subset of participants going back up 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.

4.2 Surveys and active data collection

Each study applicant completed a mandatory baseline survey immediately before random assignment. 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. Appendix Figures C6 through C8 present the full baseline survey instrument.

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). First, we administered text message-based travel diary surveys that asked participants five questions about their travels and whereabouts from the previous day (Appendix Section C.4 for a list of the five questions). 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.[11]

Second, we administered three rounds of lengthier 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 message, email, 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.

Third, 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 estimated modes of travel for each movement spell. 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 their location history covered at least 10 days in April 2024, and $0 otherwise.

4.3 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

[11] We use this randomization to test for non-response bias in Appendix B and B.2, following the procedure outlined in Dutz et al., 2022.

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 not surprising, 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.

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 reported baseline home addresses that are in suburban areas where PRT service is less frequent and less accessible.

5 Empirical strategy

We estimate the effects of the fare discounts using regressions of the form:

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

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 obtain a consistent estimate of the average treatment effect in the presence of heterogeneous effects (Lin, 2013; Gibbons et al., 2018). The coefficients β_1 and β_2 are the parameters of interest and represent the intent-to-treat effects, or the average treatment 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 (yes/no).[12] 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, with one observation per participant in each regression. 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 confirmatory outcomes: 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 A3 and A6, respectively. All other treatment effect estimates that we present should be considered exploratory. Any statistically significant effects beyond these two pre-specified outcomes are suggestive and worthy of future confirmatory research due to the possibility of false positive tests. In addition to unadjusted p-values, we report sharpened false discovery rate (FDR) q-values to adjust for multiple hypothesis testing (Benjamini et al., 2006; Anderson, 2008). The q-values are only reported for full-sample average treatment effects, and the adjustments are based on the number of hypothesis tests within each table.

We also explore heterogeneity in effects across sample subgroups defined by baseline characteristics. We examine heterogeneity along certain demographic and socioeconomic dimensions that are relevant to our study context. We also use machine learning inference methods developed in Wager and Athey (2018) and Athey et al. (2019) to explore hetero-

[12]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.

geneity across the full set of pre-enrollment variables available in our data. These data-driven methods are suited to our research setting, as we have high-dimensional administrative data over which to search for clusters of characteristics that are associated with particularly large treatment effects.

6 Results

6.1 Farecard use

We begin by examining the use of the study-issued ConnectCards through which participants accessed their fare subsidies. Figure 2 shows the percentage of adult and child participants in each study group that ever tapped their assigned ConnectCard on a PRT vehicle. Among the 9,173 adult participants for whom we are able to observe ConnectCard taps, 85% tapped their assigned ConnectCard at least once.[13] In the free-fares group, 92% of adults tapped their assigned card at least once, compared with 82% in the half-fares group and 81% 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 in the midline survey that they never received their ConnectCard, suggesting that some mailed cards were delivered properly but still failed to reach the participant for some reason. While it is not clear why the remaining non-users never tapped their card, these results confirm that most treated participants successfully gained access to the intervention and made use of their fare subsidy for at least one trip.[14]

Panel A in Table 3 reports the average treatment effects on study-issued ConnectCard taps per week. A tap corresponds to a single boarding of a PRT vehicle, including boardings that are free transfers. Relative to the control group, the half fares group had 1.52 more taps of their assigned ConnectCard per week and the free fares group had 4.76 more taps per week. The counts of study-issued farecard taps do not provide a reliable measure of a person's true 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

[13] We are not able to observe ConnectCard 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 because their study-issued card number was not recorded properly in the study database.

[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.

evaded the fare. Second, some participants shared their cards with other people, in which case the farecard taps reflect some trips taken by people besides the intended participant.[15] 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.

6.2 Mobility and travel behavior

Table 4 presents our preferred estimates of the effect of the fare subsidies on mobility and travel behavior. The outcomes in this table are measured from smartphone Google Maps location history data that was collected from a subset of adult participants. Google Maps infers the mode of travel being used whenever the phone is in motion (e.g. bus, car, train, bike). This information allows us to estimate treatment effects separately by travel mode and explore substitution across modes.

Free fares increased public transit ridership relative to status quo fares. On the extensive margin, 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. 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. Altogether, free fares increased the weekly number of public transit trips by 1.48 from a base of 3.47 trips per week. These positive 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 (see Table A13). The positive effects grew in magnitude over the first five months of study participation before mostly stabilizing in months six through 12 (see Figure A2). 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 A11). 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.[16] The participants who rode public transit least often at baseline may have had a slightly larger ridership response to free fares than the participants who rode most often, although

[15]Four percent of post-endline survey respondents in the free fares group reported sharing their card with other people (Appendix Table A1). Card sharing may partly explain why participants in the free fares group reported spending a non-zero amount of money last week on transit despite having access to unlimited free trips (see Table 3 Panel B.) Card sharing also poses the threat of treatment spillovers in our setting. Appendix Table A20 provides some evidence on the extent of such spillovers.

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

this difference is not consistent across ridership data sources (Appendix Figure A10).[17]

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. The positive ridership 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. At the same time, 1.48 added transit trips per week is an arguably small increase in terms of economic magnitude. We return to this point when discussing our results in Section 7.

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 to detect significant effects (an increase of 1.045 trips per week is over 30% of the control mean).[18] 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.

Table 5 translates the treatment effects on public transit ridership into demand elasticities and compares them with the estimated elasticities from other recent fare reduction experiments. This highlights a key methodological contribution of our study. Measuring ridership using farecard taps, our treatment effects imply an elasticity of 10 when going from full to half price and 1.75 when going from half price to free. The elasticities are much smaller when measuring ridership using GPS data, and are a fraction of the size of the estimates from recent studies in D.C. and Seattle. Prior experiments measured transit ridership primarily using the boarding data from study-issued farecards. However, as mentioned above, such data likely has reliability issues due to individuals sharing their assigned cards and taking some trips using other payment modes or not paying at all. As an alternative measure of transit ridership, prior studies have asked participants to self-report how many transit trips they take. Each of our follow-up surveys asked respondents how many one-way

[17]Participants who rode public transit least often at baseline can be considered marginal 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.

[18]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 B.3. 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.

PRT trips they took in the past week. The control group reported a mean weekly number of transit trips that is more than double the number of farecard taps among the free fares group, and the effect of fare discounts is negative according to this measure (see Table 3 Panel B). These self-reported trip counts may be inflated by researcher demand effects and could be distorted by memory error or ambiguity in the wording of the question. Smartphone GPS data, in contrast, has the benefit of recording all transit trips with a device that stays in close proximity to the person being studied. We find the elasticity of demand for public transit to be much smaller than previously estimated when using a measure of trip-taking that is arguably more reliable than farecard usage or the self-reported number of trips taken per week.[19]

The positive effect of free fares on transit ridership consisted mostly of travel mode substitution rather than new trips. According to the GPS results in Table 4, free fares caused a 5.6 percentage-point reduction (from a base of 52%) in the likelihood of taking at least one private vehicle trip on a given day relative to the control group. This category covers all types of automobile travel, including ridehailing trips, carpooling, and rides in another person's car. Free fares also appear to have reduced the number of private vehicle trips per week by 1.7 from a base of 13.39, although the 95% confidence interval includes zero. Free fares increased the mean distance traveled by public transit (0.974 miles per day, or 6.8 miles per week) and decreased the mean distance traveled by private vehicle (-1.45 miles per day, or -10.15 miles per week). Similarly, free fares increased the time spent traveling by public transit (5.6 minutes per day, or 39 minutes per week) and decreased the time spent traveling by car (-10.8 minutes per day, or 75.6 minutes per week).

The travel diary survey responses in Panel C of Table 3 provide supporting evidence of mode substitution. Recipients of free fares reported taking 0.188 fewer car trips (from a base of 0.929 trips) than the control group on a given day. These participants were also 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 taking at least one public transit trip on a given day. The travel diaries also show evidence of substitution away from self-powered travel, as respondents were 4.6 percentage points (9.8%) less likely than the control group to report taking at least one walking or biking

[19] Panel A in Appendix Figures A15 and A16 illustrates the measurement challenges that arise when counting transit trips using farecard taps versus GPS data. The gray bars in Figure A15 show that farecard taps fail to capture some of a person's transit trips, and this undercounting becomes more severe as the fare discount gets smaller. This is not surprising because the control group had no incentive to continue using their assigned ConnectCard once the initial $10 balance ran out. The red bars in Figure A15 provide evidence of farecard sharing, as some days with a farecard tap are not corroborated in the person's GPS data. Figure A16 shows that the correlation between a person's number of farecard taps and their number of transit boardings in GPS data on a given day becomes closer to one-to-one as the fare discount increases.

trip on a given day.[20] Free fares had a negligible effect on the total number of trips taken per week across all modes. Nor did free fares produce statistically significant changes in the number of visits per week to various types of places such as grocery stores, convenience stores, restaurants, or schools. Free fares led participants to shift away from cars and self-powered travel and towards greater use of public transportation for their travel needs, but may not have led them to take many new trips that they otherwise would not have taken.

In fact, we observe some evidence that free fares reduced the frequency and spatial breadth of a person's travels by certain measures. According to the travel diary results in Table 3 Panel C, the free fares group reported visiting 0.551 (14.9%) fewer places on a given day 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. Diary respondents in both the free fares and half fares groups reported lower rates of leaving the house on a given day than the control group for all trip purposes listed in the diary (work, school, groceries, leisure, health care, social services, and "other"). These results are all highly statistically significant after adjusting for multiple testing and are robust to alternative model specifications (Appendix Table A12). The GPS results in Table 4 further show negative point estimates for the effects on several measures of overall mobility, although these estimates are noisy and less robust due to the smaller sample size of GPS sharers (Appendix Table A13). The GPS-based 95% confidence intervals rule out an increase of more than 3.1 total trips per week (14.3%) and an increase of more than one minute spent traveling per day (1.2%) for free fares relative to no discount. Together, the travel diaries and GPS data provide very little evidence that fare discounts increase the overall breadth or frequency of travel. We discuss potential explanations for this perhaps surprising result in Section 7.

According to the GPS-based outcomes in Table 4, the free fares group spent 11 fewer minutes (-0.182 hours) traveling per day across all modes of transportation, a 14% reduction from the control mean. Free fares recipients may have likewise traveled less distance per week overall, with the 95% confidence interval ranging from 27.5 fewer miles to 9.8 more miles traveled per week. Additionally, the free fares group left their home 18.9% fewer times per day than the control group. Free fares may have even caused participants to stay closer to home in their travels than the control group, with an estimated 1.52-mile (7%) reduction in the mean daily maximum distance from home that a person reached.

Other results in Table 3 provide further detail on the effects of fare discounts on transportation affordability and accessibility. The free-fares treatment reduced mean self-reported weekly spending on PRT trips by $17.09 (51.0%) relative to the control group, with a $5.64

[20] Appendix Figure A1 shows the effects on these travel diary-based outcomes by month over the first 14 months of study participation.

(16.8%) decrease for the half-fares treatment relative to control.[21] The magnitude of these reductions in spending decreased over time for the half fares group but remained relatively stable for the free fares group (Appendix Figure A8 Panel A). The post-endline survey included the six-item Transportation Security Index (TSI-6) instrument developed by Murphy et al. (2024).[22] As shown in Table 3 Panel B, 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. 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. This suggests that transportation issues persist for many low-income people even when fare prices are zero, 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.

Taken together, our travel results demonstrate that fare discounts, especially free fares, provide a financially meaningful subsidy that alters travel behavior along several margins. Treated participants substituted away from cars and, more suggestively, from self-powered modes of travel, while making greater use of public transportation. At the same time, we find little evidence that discounts led to more frequent or widespread travel overall. Recipients of free fares may have even traveled less by certain measures. If we assume that increased overall travel is the sole channel through which fare discounts can produce socioeconomic benefits, then the scant evidence of greater travel may lead us to expect similarly modest effects on downstream outcomes. We now turn to those effects.

[21] 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 midline survey in Appendix Section B and for the travel diaries in Appendix Section B.2. Although the three study arms had significantly different rates of overall midline survey completion and item-level completion, we find suggestive evidence that the likelihood of completing the midline 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.

[22] 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?

6.3 Labor market outcomes

The fare discounts produced small and insignificant effects on labor market outcomes in the first year after enrollment according to administrative UI records. Table 6 Panel A presents average treatment effects on employment-related outcomes for the adult sample measured cumulatively over the first four complete calendar quarters after the person enrolled in the study. The first row shows that 63.2% of the control group had paid employment at some point in the first four quarters. The fare discounts did not significantly affect the likelihood of having paid employment over this time period. The 95% confidence interval for the effect of free fares rules out an increase of more than 3.2 percentage points and a decrease of more than 0.4 percentage points. The impact of fare discounts on cumulative earnings in the first four quarters was indistinguishable from zero, with the 95% confidence interval for free fares spanning from -\$188 to \$864. The upper bound of this interval represents 7.8% of the control group's mean earnings over the first four quarters. The earnings impact estimates include individuals who had no earnings in the time period. We cannot rule out null effects for the average participant on the likelihood of receiving UI benefits in the first four quarters, or on the mean amount of UI benefits received over this period.

The effects of free fares on employment and earnings remain stable when adjusting for different sets of covariates and when winsorizing earnings at the 99th percentile (Appendix Table A14). The average treatment effects on these outcomes also do not substantially differ by sex, race, or baseline employment status (Appendix Tables A16 and A17). There is suggestive evidence that cumulative earnings effects over the first four quarters were larger among participants who had access to a car at baseline and larger among those who had earnings above the 75th percentile in the quarter before enrollment.

Follow-up surveys add nuance to the null effects on UI-based employment outcomes. Table 6 Panel B shows the effects on self-reported employment outcomes according to the endline (11-month) survey. All outcomes in Panel B include response values of zero unless otherwise noted. Neither discount level affected the likelihood of being employed, as the free fares confidence interval rules out a decrease of more than 4.8 percentage points and an increase of more than 2.2 percentage points. Free fares caused an estimated 1.38-hour (8.2%) decrease in weekly labor supply. Among survey respondents who reported actively searching for a job in recent weeks, the half-fares treatment reduced the number of jobs to which they applied by an estimated 19%. Neither of these marginally-significant effects maintain significance after adjusting for multiple testing.

The UI-based and survey-based measures of employment and earnings correspond closely in mean outcome levels (Appendix Table A14). The control group had mean quarterly UI earnings of \$11,120 / 4 = \$2,780 over the first four quarters (Panel A). This almost exactly matches their mean self-reported quarterly earnings of $2,782 from the endline survey (Panel C). Similarly, 50.8% of the control group had UI employment in the fourth quarter after enrollment, and 52.4% reported being employed in the endline survey. Conditional on being employed, the control group's self-reported mean quarterly earnings ($6,161) was higher than their mean fourth-quarter UI earnings ($5,923). This is not surprising because the self-reports include forms of employment that are not captured in UI records, such as self-employment and gig work. Despite these correspondences, the confidence intervals for the treatment effects on earnings are substantially different between the UI and self-reported data. As shown in Table A14, the 95% interval for the effect of free fares on self-reported quarterly earnings ranges from -$1,240 to $163. This compares with an interval of -$139 to $253 for the effect on UI earnings in the fourth quarter after enrollment (Panel B Column 2).[23] Given the smaller sample and the potential for selection bias in the survey responses, we favor the UI-based outcomes as the more reliable source of employment effects. Similar to Brough et al. (2024), our results show that fare discounts have economically limited effects on employment for low-income people.

To interpret our earnings impacts, it is useful to consider how the fare discounts affected the time and monetary costs of commuting to work.[24] Our surveys did not ask participants how much money they spent on commuting. However, the reductions in weekly PRT spending shown in Table 3, together with the fact that over 60% of employed survey respondents reported using public transit to get to work (Appendix Table A2), suggest that the treatment reduced the monetary cost of commuting on average. At the same time, fare subsidies could also make commuting faster by enabling a person to ride the bus instead of walking or biking. Indeed, the expanded set of self-reported employment outcomes in Appendix Table A2 shows that free fares led to substitution in modes of commuting, with an 8.9 percentage-point (15.3% of the control mean) increase in rates of primarily commuting by bus and a corresponding 5.4 percentage-point (50.5%) decrease in rates of commuting primarily by walking or biking. Rates of commuting primarily by car also decreased by 3.9 percentage points (22.9%). These shifts in commute mode, however, did not reduce participants' round-trip commute times on a typical day. The point estimate of the effect of free fares on daily commute time is positive and not distinguishable from zero. The effect on commute time also does not significantly differ by whether the person had access to a car at baseline.

[23]Prior studies have found that self-reported earnings for low-income individuals are often larger than earnings measured from UI records, but the differences do not usually cause significant discrepancies in estimates of workforce program impacts (Kornfeld & Bloom, 1999; Wallace & Haveman, 2007; Mastri et al., 2018; van Dok M. & Schaberg, 2023).

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

In a standard static labor supply model with non-linear preferences over consumption and leisure, it is straightforward to show that a reduction in the monetary cost of commuting reduces labor supply via an income effect, while a simultaneous reduction in commute time *increases* labor supply via an expansion of the time budget. With these opposing effects, the net effect on labor supply is ambiguous and depends on the worker's wage and the size of the commute time reduction per dollar of subsidy.[25] The economically small effects on UI earnings in our sample could therefore be a result of the competing effects of concurrent changes in the time and monetary costs of commuting.

The time-limited nature of our intervention may also partly explain the lack of substantial effects on labor market outcomes. It is possible that participants limited their employment response to the treatment because they knew that the fare discounts were temporary. This is suggested by the lack of a trend over time in the effects on self-reported hourly wages and monthly earnings (Appendix Figure A8) and on UI employment and earnings (Appendix Figure A3). The effects on these outcomes do not seem to result from delayed reactions or behavioral adjustments that take more than a year to materialize. Contrary to the spatial mismatch hypothesis, reducing the cost of public transit appears to have a negligible impact on the work lives of low-income working-age adults.

6.4 Health care use

Public transit subsidies had mixed effects on the use of health care, increasing the use of some types of health care while decreasing other types. Table 7 presents average treatment effects on the adult sample's use of Medicaid-funded health care within the first 365 days after enrolling in the study. The first row reports the likelihood of receiving any health care in this time period. Nearly 89% of the control group received care, and the discounts had a precisely-estimated null effect.[26]

When looking specifically at physical health care (Panel A in Table 7), the free fares group was 1.5 percentage points (26.8%) more likely than the control group to have at least one non-emergency room (ER) inpatient claim. This category of care covers overnight hospital stays that do not begin in the emergency room, such as scheduled operations. Apart from this relatively rare type of care, neither discount produced a detectable change in the consumption of physical health care along the extensive (the likelihood of having at

[25] Gutiérrez-i-Puigarnau and van Ommeren (2009) arrive at a different prediction using a multi-period model in which workers choose their labor supply along both the hourly and daily margins.

[26] Our treatment effects on health care are not biased by differential attrition from Medicaid. Appendix Figure A7 Panel D shows that rates of Medicaid enrollment among the study sample decreased over the first 12 months of study participation, but the decrease was uniform across the three study arms.

least one claim) or intensive (the number of days with a claim) margin.[27] 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 could indicate investments in one's basic health. Fare discounts also did not affect the number of prescription fills for physical health-related drugs, or the number of days on which a person had a remaining dose of a filled prescription. The null effects of free fares on most measures of physical health care are generally robust to adjusting for different covariate sets (Appendix Table A15). A statistically significant 4.1 percentage point (70.7%) increase in the likelihood of having an ER inpatient claim emerges when selecting covariates using a post-double LASSO procedure. The impacts on the likelihood of receiving any physical health care within a given month show no time trend over the first 12 months of study participation (Appendix Figure A4), and do not differ by whether the person received care in the year before joining the study (Appendix Table A21).

On the behavioral health care side (Panel B in Table 7), we again observe little to no effect of half fares on any measures of care utilization. Free fares, however, reduced the number of days on which a person received behavioral health care by 1.02 days from a base of 16.13 days. Looking within sub-types of behavioral health care, free fares increased the receipt of crisis-oriented care by 0.198 days (20.3%) and decreased the receipt of substance use treatment by 0.913 days (23.2%). When selecting covariates using post-double LASSO, we also detect an increase in the number of days covered by a behavioral health prescription and the total cost of behavioral health care that was billed to the Medicaid managed care organization in Allegheny County (Appendix Table A15). The impacts on the likelihood of receiving any behavioral health care within a given month show no trend over the first 12 months of study participation (Appendix Figure A4). However, some trends over time are evident when looking at the cumulative number of days with a behavioral health claim over time. Appendix Figure A6 shows a steady upward trend in the effect on the cumulative number of days with a crisis-related claim over the first 12 months, and a steady downward trend in the effect on the cumulative number of days with treatment for substance use disorder.

The expected effect of transit subsidies on health care utilization is theoretically ambiguous. Reduced fares could make it easier for low-income individuals to visit the doctor

[27] We measure the volume 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 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.

and address their health needs.[28] At the same time, the subsidies could provide financial benefits that lead to lower stress and adverse health experiences, thus lessening a person's need for health care. On this point, Brough et al. (2024) find that reducing public transit fares from half-price to free leads to a 5.6 percentage-point decrease in the likelihood of having any type of Medicaid claim in the first three months after random assignment. We find little evidence of changes in self-reported health at 15 months after enrollment, as shown in Table A3 and discussed further below. The health care impacts in our study setting are likely attenuated by the fact that 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 A10 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. Overall, the inconsistent pattern of effects that we observe across categories of care does not tell a clear story about the effect of public transportation costs on health care consumption.

6.5 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 three waves of follow-up surveys. Table A4 presents the average treatment effects on self-reported financial outcomes for post-endline 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. We also find little evidence of improvements on a variety of specific financial hardships experienced in the past 30 days.

The treatment had minimal effects on survey-based measures of health and subjective well-being at 15 months post-enrollment. These results are shown in Appendix Table A3. Neither subsidy level affected participants' overall life satisfaction or their likelihood of rating their current health as good, very good, or excellent. The half fares group was 14.7% (3 percentage points from a base of 20.4%) less likely than the control group to report that their health has gotten worse in the past six months, but the free fares group showed no detectable effect on this measure. The post-endline survey also included a battery of questions about

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

mental health symptoms, self-efficacy, and feelings of social connectedness. Fare discounts produced negligible, statistically insignificant effects on nearly all of these measures. We do find strong evidence of travel mode substitution in how participants reported getting to the doctor. Free fares recipients were 8.7 percentage points (15.9%) more likely than the control group to report taking public transit to their last medical appointment. They were also 2.3 percentage points (28.0%) less likely to report walking or biking and 3.5 percentage points (20.7%) less likely to report using a car. Half fares did not produce a similar pattern of mode substitution.

6.6 Receipt of public assistance and contact with criminal justice system

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 benefits is no longer necessary. We find no evidence of changes in rates of public benefits receipt as of the twelfth month after enrollment, as shown in Appendix Table A9 Panel C. There is also no time trend in the likelihood of receiving public benefits over the first 12 months after enrollment. It is noteworthy that only 83.7% of the control group still received SNAP benefits at 12 months after enrollment, given that every participant was receiving SNAP in the months immediately before joining the study (per the study's eligibility criteria). The decline in SNAP receipt by month 12 did not differ across study arms. Among participants who were still receiving SNAP benefits in the months after enrollment, free fares appear to have slightly increased their average monthly benefit allotment relative to the control group. Neither discount level affected the use of homeless shelters along the extensive or intensive margin in the first 365 days after study enrollment (Table A9 Panel A). Nor did either discount affect the likelihood of being involved in a child protective services referral (the process that initiates an investigation for child maltreatment).

Treatment effects on criminal activity are reported in Appendix Table A8. Nearly 8% of the adult study participants had at least one criminal charge filed against them in Allegheny County in the first 365 days after joining the study. Additionally, 4.3% of control group members spent time in the Allegheny County Jail during this time period. The relatively high rate of contact with the criminal justice system among our sample raises the possibility that transportation subsidies could facilitate additional crime. The subsidies could also lessen financial hardship in a way that reduces the motive to engage in criminal activity. We find that half-fare discounts 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 time spent in the County Jail along the extensive or intensive margin. Fare discounts also did not affect the overall likelihood of failing to appear at a criminal court hearing, a result that was also found in (Brough, Freedman, Ho, et al., 2022).

6.7 Effects on child outcomes

Our study included 4,949 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 financially 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 that are distinct from the benefits for adults. Older youth 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.

Appendix Table A1 provides some insight into the effects of the treatment on the travel behavior of the child sample. This table presents an expanded set of travel-related outcomes that were collected in the post-endline survey. 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. Both discount levels reduced this daily number of trips with children, although the effects are not statistically significant. Such reductions, if true, might suggest that the discounts enabled children to take more transit trips independently of their parents. At the same time, however, parents in the free-fares group were 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.

Although children were excluded from all surveys, we leverage administrative data to observe certain socioeconomic outcomes for the child sample. We focus our child analysis on three domains: health care use, school outcomes, and UI employment. Table A5 shows that, similarly to the adult sample, the fare subsidies did not affect children's overall likelihood of receiving health care in the first 365 days after enrollment. The subsidies had no effect 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, free fares increased children's likelihood of receiving behavioral health care, with a 3.2 percentage point (10.8%) increase in the likelihood of having at least one behavioral health claim and a 1.21-day increase (20.2%) in the number of days with such care. This increase could be interpreted as a positive sign of improved access to care, in light of the high prevalence of unmet mental health needs among economically vulnerable youth (Hodgkinson et al., 2017).

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 A6. Relative to the control group, free fares increased the number of days that students were absent from school by 2.11 days (17.8%) in the 2022-2023 school year (only looking at days after the child joined the study) and by 2.04 days (10.9%) in the 2023-2024 school year. These increases in days absent were driven by unexcused absences, suggesting that cheaper bus fares made it easier or more attractive for students to skip school. On a more positive note, there is some evidence of improvements in standardized test scores for students in elementary and middle school in the 2023-2024 school year. Free fares caused a 14.9 standard deviation-unit increase in standardized test scores across all subject tests, and half fares caused a 9.5 standard deviation-unit increase.

Finally, we examine the effect of the treatment on the labor market outcomes of youth study participants who were 16 or 17 years old at baseline. We limit the analysis to this age range because teenagers under 16 are less likely to be working in paid jobs that are covered by unemployment insurance. Appendix Table A7 presents the results. The 16 and 17 year-olds in the control group had a rate of employment in the first four quarters that was slightly *higher* than the employment rate among the adult control group members (66.8% versus 63.2%). Fare discounts did not have a detectable impact on cumulative employment or earnings among the 16 and 17 year-olds in the first four quarters after enrollment. The 95% confidence interval for the effect of free fares on cumulative Q1-Q4 earnings rules out increases of more than \$898 and decreases of more than \$959 (which is 25% of the control mean).

6.8 Exploring null effects

The full-sample average treatment effects of zero on several focal study outcomes raise the question of whether the treatment had a meaningful effect on these outcomes for any individual participant or subgroups of participants. We explore this in two ways. First, we use randomization inference to calculate exact p-values for the sharp null hypothesis that the treatment effect on a given outcome is zero for every participant (Imbens & Rubin, 2015). The results are shown in Appendix Table A23. We find no evidence against the sharp null hypothesis at conventional levels of significance for the effect of both half fares and free fares on self-reported hours worked per week, having any paid employment in Q1-Q4, total earnings in Q1-Q4, and the number of days with a non-ER outpatient claim in the first year. We can reject the sharp null hypothesis at the 10% significance level for the effect of half fares versus no discount on the number of public transit trips taken per week in the smartphone GPS data. However, this result is not consistent across the three test statistics shown in the table.

Second, we use machine learning methods from Athey et al. (2019) to estimate the conditional average treatment effect (CATE) of free-fares versus no discount for each individual sample member. This is done by training nonparametric causal forest models on a one-half partition of the full sample. The models draw upon hundreds of pre-enrollment characteristics that exist in our data, such as demographics and historical involvement with social services, while remaining agnostic as to the functional form of the relationship between these characteristics and the treatment effect. Each individual is held out from their particular CATE-estimating sample so their own outcome does not influence their estimated CATE. We then use the second-half partition of the sample to evaluate how much benefit there is to targeting treatment to participants with the largest estimated CATE's. This involves inputting the CATE's through a treatment targeting function, called the rank-weighted average treatment effect (RATE), which translates the CATE's into a treatment prioritization score. We then plot the average treatment effect within groups defined by the percentile of their prioritization score among the full sample. The resulting curves represent the targeting operator characteristic (TOC) (Yadlowsky et al., 2021).

Appendix Figure A14 presents the TOC curves for four select outcomes, looking at the effect of free fares relative to no discount. The outcomes in panels B, C, and D had an average treatment effect of zero for the full sample. Intuitively, these plots depict the hypothetical benefit of treating only the fraction q of the sample that is in the top qth percentile of CATE's. This benefit is visualized as the treatment effect for the qth percentile relative to the overall average treatment effect (ATE) for the full sample. We would expect the TOC curve to slope downward from left to right if the CATE's successfully identify a cluster of baseline characteristics that is associated with larger treatment effects than the full sample. The AUTOC statistic is the area under the TOC curve, which summarizes the ability of the estimated CATE's to rank individuals by treatment benefit. None of the

AUTOC statistics for the four curves are significant at conventional levels, suggesting there are no heterogeneous treatment effects within the covariate space over which we searched. The shape and insignificance of these curves is perhaps surprising, given our relatively large sample size and extensive set of baseline characteristics. We interpret Appendix Figure A14 as evidence that the treatment effects on these four outcomes are only weakly correlated with participants' observable pre-treatment characteristics. The effects of fare discounts on these outcomes may depend on idiosyncratic aspects of a person's life that cannot be quantified in our available data.

Based on the results of the sharp null tests and the machine learning heterogeneity analysis, we cannot rule out the possibility that the fare discounts had no effect for each and every individual participant on their earned income, their likelihood of being employed, and their number of days with a non-ER outpatient claim.

7 Discussion

Our fare subsidy treatments provided financial relief and improved certain dimensions of transportation affordability and security. They led to moderate increases in transit ridership that appear to stem mainly from substitution away from other modes of travel. The free fares treatment may have even reduced participants' spatial breadth and frequency of travel by some measures.

7.1 Elasticity of transit ridership

The elasticity of our sample's use of public transportation could have limited the effects on overall spatial movement. Several factors likely restricted the elasticity of our sample's ridership response to the price of transit. First, some participants had access to discounted PRT trips through other channels. A full 31.5% of midline survey respondents reported that they or someone else in their household receive a fare discount through PRT's disability half-fare program, 6-to-11 year-old half-fare program, senior free-fares program, or through their school or employer. All of these discounts are delivered through physical farecards that can easily be shared amongst friends and family members. The average effect of our treatment on weekly transit trips increases from 1.48 additional trips to 2.36 additional trips (SE 0.768) when subsetting the sample to only the midline survey respondents who did not report having access to another discount. This suggests that the existence of other fare discount programs indeed dampened the effect of our treatment.

The sharing of our study-issued farecards with other people further diminishes the effect of treatment for the targeted recipient. Only 4% of the free fares group reported sharing their card with others, yet the true prevalence of card sharing was likely much higher, given that only one adult per household received a discounted card.

PRT riders under status quo fare policy are not required to pay for boardings that take place within three hours of the previous boarding.[29] Such boardings are deemed "free transfers". According to GPS data, 35.4% of the control group's transit boardings throughout the study qualified as free transfers. This feature of the transit system means that a substantial portion of trips are already free. Moreover, riders will be less sensitive to the price of a transit trip if they are able to simply evade the fare. Our post-endline survey included a question that allows us to estimate aggregate rates of fare evasion while masking individual answers.[30] The responses indicate that 11.5% of sample adults evaded the fare in the past two weeks. The imperfect concordance shown in Panel A of Figures A15 and A16 between farecard taps and GPS-recorded transit trips on a given day likely indicates some degree of fare evasion, as participants did not always have a corresponding farecard tap on days when their GPS data recorded a transit boarding. The existence of several alternative fare discount programs in Pittsburgh, together with free transfers, fare evasion, and the sharing of assigned farecards, serves to dilute the strength of our subsidies relative to the status quo. Nonetheless, these factors would all be present in any large-scale implementation of transportation subsidies. From this perspective, any reduction in effect sizes due to these reasons reflects real-world effects of such a policy.

An additional limiting factor is that some of the study-issued free fare ConnectCards occasionally experienced a technical glitch in which they did not work when tapped on certain PRT vehicles. When these errors occurred, the farebox screen displayed a message to the vehicle driver that was identical to the message for an expired regular ConnectCard. Drivers often did not allow riders to board in these situations. We have no administrative data on the frequency of these glitches or how many attempted boardings were affected. However, 56% of post-endline survey respondents in the free fares group reported that their study-issued farecard failed to work at least one time. Among the people who reported this, 59% said that the issue happened "only a few times", 20% said it happened "about once every 10

[29] 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.

[30] 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).

taps", and 21% said it happened at least once every four taps. ACDHS alerted participants to this issue early in the study and told those affected to report the bus number so that PRT could try to fix the bus's farebox. The lingering threat of a random card malfunction may have dampened participants' use of the free fare cards. These malfunctions may also partly explain why 44.5% of post-endline survey respondents in the free fares group reported non-zero spending on public transit trips for just themselves despite nominally receiving unlimited free fares. This farebox glitch did not affect the half fares arm; our null results for this group suggest that these technical issues may not have had large impacts.

Even with a moderately-sized treatment effect relative to the control group, our sample's low baseline rate of public transit utilization leaves little room for large absolute increases in ridership. The control group took an average of only 3.47 transit trips per week over the course of the study according to GPS data.[31] This low volume of ridership is somewhat surprising when considering the sample's low socioeconomic status and the fact that participants presumably self-selected into the study because they perceived some benefit to getting a fare discount.

There could be fundamental limitations of public transportation services, whether specific to Pittsburgh or inherent to public transport in general, that prevent our sample of low-income riders from riding more frequently. On one hand, most study participants had convenient access to transit, with 78% reporting in the post-endline survey that they live less than a 10-minute walk from a transit stop or station. In this same survey, 57% reported that they usually wait less than 15 minutes at their home stop for the bus or train to arrive (Appendix Figures A12 and A13). Treatment effects on transit use also did not differ by whether the person lived near 7-day frequent transit service (see Table A19 Panel A). Yet at the same time, participants cited several reasons why they do not ride public transportation more often. According to the post-endline survey, 38% of respondents cited the weather as a primary reason, 31% reported that the service is not frequent enough, and 29% reported that it does not run early or late enough. These limitations of public transit are likely a key reason why 42% of the free fares group demonstrated moderate-to-high levels of transportation insecurity at 15 months post-enrollment despite facing no monetary cost to riding public transit. The quality and accessibility of transit services is a potentially important factor behind our sample's low baseline level of transit utilization and the elasticity of the response to lower fare prices. At a policy level, large-scale fare reductions may come with tradeoffs in terms of service quality, as U.S. transit agencies typically rely on passenger

[31] This number is far less than the 10 trips per week that participants reported taking in the baseline survey, our only other source of data on pre-treatment transit ridership.

revenue to cover a portion of operating expenses.[32]

7.2 Income effects

Our price intervention serves 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 the cash equivalent of our in-kind transfer would produce a similar effect. First, the strong pattern of travel mode switching implies that the increase in transit ridership resulted mostly from a substitution effect rather than an income effect. 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 $212 transfer (the annualized cash value of the effect of free fares on transit ridership) to public transit, it would translate into only 5 additional trips per year. This is a small fraction of the additional trips that we observe in response to free fares.

7.3 Reduction in overall mobility

The finding of some reductions in overall spatial movement stands out as a perhaps counterintuitive response to free fares. Why might free fares lead a person to travel less in terms of both distance and time spent in movement, while also leading them to visit fewer distinct places and leave their house less often? The robustness of these effects and their appearance in both the travel diary responses and the smartphone GPS data hints at a real signal about the underlying relationship between fare prices and total mobility. The decrease in total time spent traveling could arise from substituting bus trips for self-powered trips, as the bus is generally faster than walking or biking. Additionally, fare prices in Allegheny County do not depend on the distance of the trip. Free fares therefore do not directly incentivize riders to take farther transit trips, as would occur in cities where longer trips cost more than shorter trips. In future work, we plan to use the smartphone GPS data to further investigate the margins of adjustment that are driving the observed reductions in total mobility.

In any case, the lack of evidence for *increased* overall trip-taking suggests that greater spatial movement per se is not necessarily a positive outcome when assessing the benefits of transportation assistance. Part of the utility gain that low-income residents derive from

[32]Pittsburgh Regional Transit's fiscal year 2024 budget projects passenger revenue of approximately $47.9 million and operating expenses of $535.4 million (Pittsburgh Regional Transit, 2024).

cheaper transit fares could take the form of somehow being able to leave home less often or visit fewer distinct places to fulfill one's needs. This novel finding has implications for research on optimal urban transportation policies and their distributional effects (Parry & Small, 2009; Almagro et al., 2024; G. Kreindler et al., 2023). It also points to the need for alternative measures when quantifying improvements in a person's travel capabilities.

7.4 Downstream socioeconomic effects

One may ask why our intervention did not produce stronger socioeconomic effects. Our finding that more frequent travel is not the most relevant marker of improved mobility complicates the relationship between transportation costs and downstream outcomes. For example, if improved mobility capacity takes the form of less widespread travel, then our treatment would have perhaps needed to produce larger *decreases* in spatial movement in order to yield socioeconomic effects. Future work could investigate the theoretical linkages between the types of improvements in mobility that we observe in this study and outcomes like better health or higher earnings. Nonetheless, to the extent that transportation poses barriers for economic outcomes, a 16 to 19-month public transportation subsidy does not seem to address those barriers.

The time-limited nature of the treatment may also partly explain the muted impacts on downstream outcomes. 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 reduced-price transit. The treatment, for example, did not lead to higher rates of moving to a new home (estimates available upon request) or switching jobs (see Figure A3). The participants who anticipated shorter versus longer subsidy durations did not differ on these outcomes.[33]

Our treatment's modest socioeconomic impacts align with growing evidence that temporary cash or in-kind transfers for low-income families do not necessarily produce lasting positive effects. Recent studies of time-limited unconditional cash payments to families below the poverty line, for example, have found negligible effects on health, employment, and well-being (Jacob et al., 2022; Pilkauskas et al., 2023; Vivalt et al., 2024; Miller et al., 2024).

[33] To make this comparison, we use 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 of the subsidies for a three-month larger portion of their total time in the study than the earliest cohort of enrollees.

The benefits of interventions like free transportation may be too diffuse and individualized to register lasting improvements in economic outcomes for the average person, at least when the intervention is applied to a broad cross-section of low-income families such as in our study. More work is needed to understand the conditions under which a temporary in-kind transfer can shift a disadvantaged household to a new economic equilibrium.

7.5 Cost-benefit analysis

7.5.1 Comparing fare discounts to other policies

7.5.2 Marginal value of public funds

8 Conclusion

In this paper, we analyze the results of a randomized controlled trial that provided discounted public transportation fares to low-income working-age adults and their children. Among households receiving SNAP benefits in the Pittsburgh area, we compare the respective effects of free transit and half-price transit relative to status quo prices on an array of outcomes measured from administrative data and surveys. Recipients of free fares took 1.48 more transit trips per week than the control group, a 43% increase relative to the control mean. Half-price fares produced no discernible increase in transit ridership relative to regular prices. Free fares also caused participants to reduce their rates of walking, biking, or riding in a car for their daily travels. Half-price fares did not produce this same pattern of mode substitution. The positive effect of free fares on transit ridership appears to stem predominantly from shifts towards greater use of public transit for existing trips, rather than from taking new trips. We find little evidence of increased total mobility in response to fare discounts, with some evidence that overall mobility actually decreases when fare prices are reduced.

We do not detect significant effects on employment outcomes, rejecting increases in earnings of more than $864 for free fares relative to no discount in the first year after enrollment. For the adult participants, the treatment had no effect on the likelihood of receiving health care in the first year. We find limited evidence of improvements in downstream socioeconomic outcomes according to survey data. The subsidies did not affect recipients' likelihood of receiving public benefits, the average number of days they spent in jail, or their likelihood of failing to appear at a court hearing.

In sum, means-tested transportation subsidies produce certain measurable welfare gains for low-income riders, primarily in the form of improved transit affordability and security.

Fare prices play a significant role in shaping travel behavior, but they are only a minor factor in the broader economic outcomes of families in poverty.

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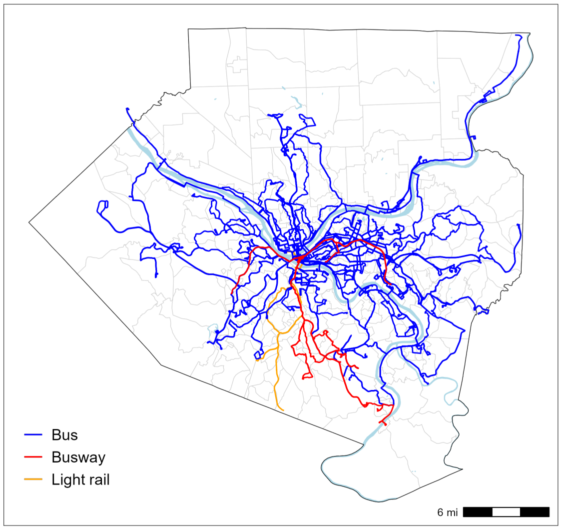
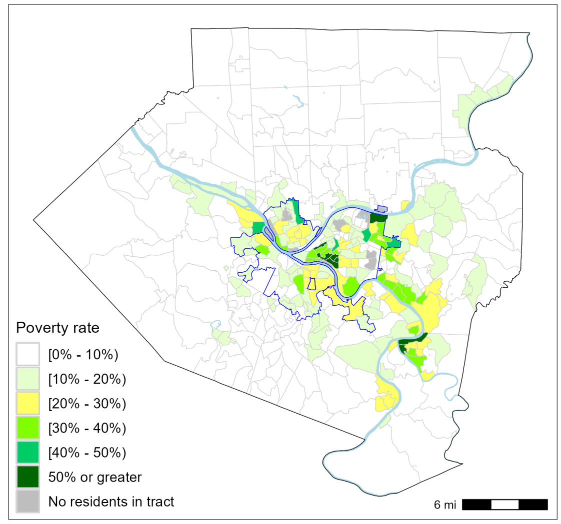
Figures

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

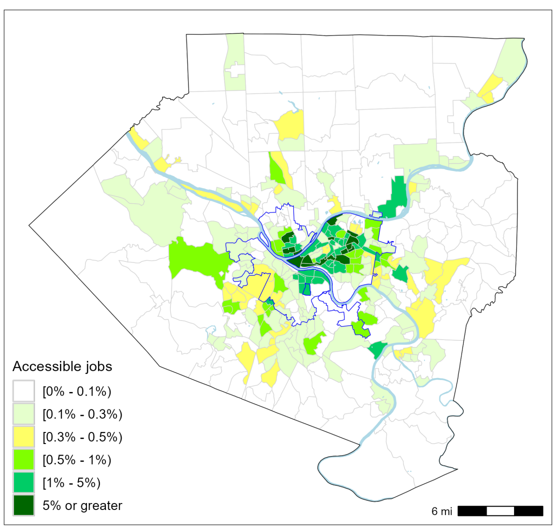
(a) Pittsburgh Regional Transit (PRT) service routes



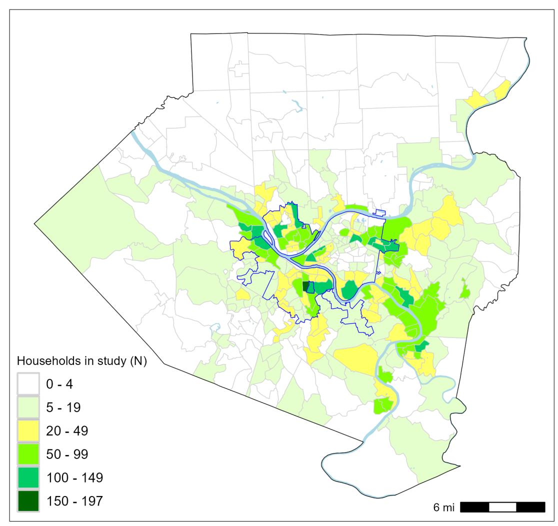
(b) Share of residents below poverty level, by census tract



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

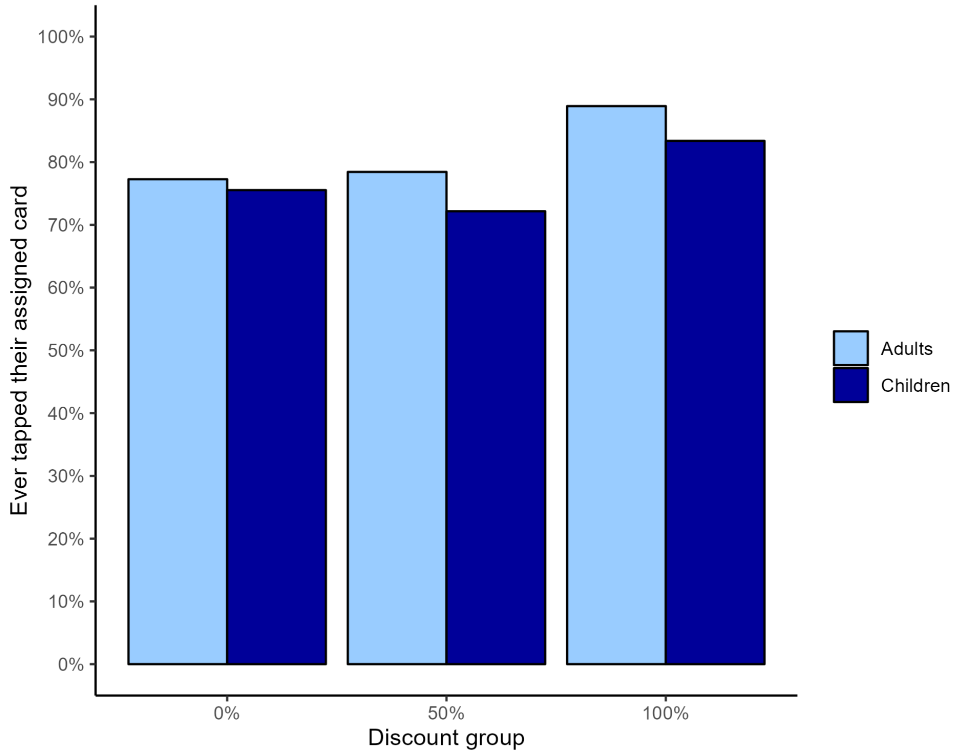


(d) Number of participating households by census tract



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: Share of study participants that ever used their assigned ConnectCard for a Pittsburgh Regional Transit boarding



Notes: Figure presents the share of study participants that have ever tapped their study-issued ConnectCard at least once. 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 because were randomly assigned to the 0% or 50% discount arm and they noted on their application that they already receive a 50% fare discount through the PRT disability fare program. It also excludes 21 participants (14 adults and 7 children) whose study-issued ConnectCard number was not recorded properly in the study database.

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

	No discount	Half fares	Free fares	Half fares vs. no discount diff.	Free fares vs. no discount diff.
A. Demographics					
Female	0.717	0.726	0.721	0.008 (0.011)	0.004 (0.011)
Age (years)	39.64	39.56	39.42	-0.079 (0.310)	-0.214 (0.312)
Race					
Black	0.588	0.591	0.588	0.003 (0.012)	<-0.001 (0.012)
White	0.346	0.332	0.334	-0.014 (0.012)	-0.012 (0.012)
Other	0.044	0.050	0.056	0.006 (0.005)	0.012** (0.006)
Hispanic	0.032	0.033	0.035	0.001 (0.004)	0.003 (0.005)
Highest education					
Less than high school	0.072	0.084	0.088	0.012* (0.007)	0.016** (0.007)
High school	0.560	0.552	0.532	-0.008 (0.012)	-0.028** (0.013)
More than high school	0.364	0.358	0.375	-0.006 (0.012)	0.011 (0.012)
B. Transportation					
No access to a car	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 ($)	30.36	30.02	29.32	-0.343 (0.807)	-1.04 (0.803)
Lives in PRT 7-day frequent service walkshed	0.357	0.360	0.359	0.003 (0.012)	0.003 (0.012)
C. Employment (from baseline survey)					
Employed past 12 months	0.611	0.598	0.603	-0.013 (0.012)	-0.008 (0.012)
Currently employed	0.432	0.424	0.425	-0.009 (0.012)	-0.007 (0.012)
Hours worked per week at main job (N)	30.41	30.91	30.96	0.501 (0.421)	0.556 (0.424)
Hourly wage at main job ($)	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	0.514	0.521	0.511	0.006 (0.013)	-0.003 (0.013)
Total earnings among those employed ($)	4,419	4,358	4,472	-61.04 (116)	52.87 (119)
Received nonzero UI benefits	0.028	0.035	0.031	0.007 (0.004)	0.003 (0.004)
Total sample size	**3,149**	**3,241**	**3,154**		

Notes: Table presents mean baseline characteristics for the adult 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 the bottom panel come from Pennsylvania unemployment insurance (UI) records. Allegheny County means are for 18 to 64 year-old residents and are calculated from ACS PUMS data or derived from ACS Table DP05 2021 1-year estimates. 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. Robust standard errors are in parentheses. ***p <0.01, **p <0.05, *p <0.1

Table 3: Impacts on travel behavior according to farecard taps and survey data

Outcome	N	Control mean	Treatment effect: Half fares	Treatment effect: Free fares	Free vs. half fares
A. Outcomes from PRT farecard tap data					
PRT farecard taps per week (N)	9,174	0.298	1.52***††† (0.067)	4.76***††† (0.098)	3.24***††† (0.116)
Proportion of days with > 0 taps	9,174	0.018	0.080***††† (0.003)	0.249***††† (0.004)	0.169***††† (0.005)
Mean taps per day on days with > 0 taps (N)	7,857	1.93	0.264***††† (0.024)	0.492***††† (0.024)	0.228***††† (0.023)
B. Outcomes from post-endline survey					
PRT trips last week (N)	4,048	11.95	-2.58† (2.00)	-0.696 (2.11)	1.88**†† (0.919)
PRT spending last week ($)	3,474	33.53	-5.64**††† (2.39)	-17.09***††† (2.80)	-11.45***††† (2.17)
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)
Still have study ConnectCard in possession	2,677	0.693	0.165***††† (0.030)	0.242***††† (0.028)	0.077***††† (0.015)
C. Outcomes 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)
Likelihood of taking at least one trip yesterday					
Car trip	7,041	0.346	-0.025**†† (0.011)	-0.029***††† (0.011)	-0.005 (0.010)
Walk or bike trip	7,022	0.469	-0.033**††† (0.013)	-0.046***††† (0.013)	-0.013† (0.012)
Public transportation trip	7,030	0.576	-0.015† (0.013)	0.026**†† (0.012)	0.040***††† (0.011)
Number of trips taken yesterday (only asked in post-endline survey travel diary module)					
Car trip	3,960	0.929	-0.105† (0.079)	-0.188**††† (0.073)	-0.083† (0.060)
Walk or bike trip	3,915	1.12	-0.127 (0.130)	-0.008 (0.148)	0.118 (0.137)
Public transportation trip	3,922	1.85	-0.069 (0.218)	-0.094 (0.194)	-0.026 (0.164)
Likelihood of leaving house yesterday					
For work	7,001	0.406	-0.028***††† (0.011)	-0.024**†† (0.011)	0.004 (0.010)
For school	7,001	0.131	-0.014*†† (0.007)	-0.011†† (0.007)	0.003 (0.006)
For groceries	7,001	0.508	-0.037***††† (0.011)	-0.028***††† (0.011)	0.009 (0.010)
For leisure	7,001	0.238	-0.022**†† (0.010)	-0.023**††† (0.010)	-0.001 (0.009)
For health care	7,001	0.170	-0.021***††† (0.007)	-0.009† (0.007)	0.012*†† (0.006)
For social services	7,001	0.084	-0.010*†† (0.005)	-0.018***††† (0.005)	-0.008*†† (0.004)
For other reason	7,001	0.281	-0.025***††† (0.010)	-0.013† (0.010)	0.013† (0.009)
Did not leave house yesterday	7,001	0.134	0.034***††† (0.008)	0.021***††† (0.007)	-0.012*†† (0.007)

Notes: Table presents estimates of the effect of being assigned to each treatment status (50% discount or 100% discount) on transportation use and travel behavior for the adult sample. Data in panel A comes from Pittsburgh Regional Transit (PRT) farecard transaction records. Data in panels B and C is self-reported. Column N indicates the number of participants 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. All treatment effect estimates are from a pooled cross-sectional 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 regressions in Panel C also include normalized weights for the number of travel diaries 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 4: Impacts on travel behavior according to smartphone Google Maps location history data

			Treatment effect		
Outcome	N	Control mean	Half fares	Free fares	Free vs. half fares
Likelihood of taking at least one trip on a given day (%)					
Public transportation	472	0.205	-0.012	0.052**	0.064***†
			(0.025)	(0.026)	(0.022)
Private vehicle	472	0.520	-0.014	-0.056*	-0.042
			(0.032)	(0.032)	(0.027)
Walk or bike	472	0.298	-0.027	0.022	0.048**
			(0.026)	(0.025)	(0.024)
All travel modes	472	0.702	-0.034	-0.039	-0.005
			(0.026)	(0.027)	(0.027)
Number of trips per week (N)					
Public transportation	472	3.47	-0.203	1.48**	1.69***††
			(0.637)	(0.716)	(0.502)
Private vehicle	472	13.39	0.441	-1.67	-2.11*
			(1.40)	(1.44)	(1.14)
Walk or bike	472	4.94	-0.204	0.385	0.589
			(0.508)	(0.513)	(0.492)
All travel modes	472	21.86	-0.065	-0.108	-0.043
			(1.47)	(1.65)	(1.30)
Number of trips per day on days with at least one trip (N)					
Public transportation	400	2.09	-0.006	0.290**	0.296***††
			(0.127)	(0.133)	(0.081)
Private vehicle	457	3.16	0.249	-0.099	-0.349**
			(0.193)	(0.200)	(0.160)
Walk or bike	438	1.97	-0.009	0.062	0.071
			(0.083)	(0.073)	(0.073)
All travel modes	462	4.20	0.096	0.152	0.056
			(0.189)	(0.205)	(0.161)
Number of trips per journey away from home (N)					
Public transportation	412	1.22	-0.608	-1.65*	-1.04
			(1.54)	(0.996)	(1.17)
Private vehicle	412	4.60	-2.50	-4.05	-1.55
			(4.35)	(2.66)	(3.41)
Walk or bike	412	1.77	-1.31	-1.78	-0.462
			(1.40)	(1.27)	(0.613)
All travel modes	412	7.63	-4.07	-7.15	-3.08
			(6.62)	(4.72)	(4.59)
Time spent traveling per day (hours)					
By public transportation	472	0.202	-0.007	0.093***	0.100***††
			(0.031)	(0.035)	(0.029)
By private vehicle	472	0.830	0.005	-0.180**	-0.186*
			(0.112)	(0.088)	(0.102)
By walking or biking	472	0.185	-0.017	-0.003	0.015
			(0.036)	(0.034)	(0.030)
All travel modes	472	1.30	-0.049	-0.182*	-0.133
			(0.119)	(0.101)	(0.110)
Total distance traveled per day (miles)					
By public transportation	472	1.57	0.337	0.974***††	0.637**
			(0.223)	(0.259)	(0.249)
By private vehicle	472	8.65	0.278	-1.45*	-1.73*
			(1.02)	(0.874)	(0.947)
By walking or biking	472	0.310	-0.052	-0.020	0.032
			(0.037)	(0.036)	(0.031)
All travel modes	472	12.03	-0.004	-1.26	-1.25
			(1.44)	(1.36)	(1.14)
Mean daily maximum distance from home (miles)	414	21.63	0.608	-1.52	-2.13
			(4.27)	(2.67)	(3.68)
Likelihood of leaving house on a given day (%)	414	0.461	0.007	-0.069	-0.076*
			(0.048)	(0.045)	(0.041)
Number of times left house per day (N)	414	0.703	0.033	-0.133*	-0.165**
			(0.083)	(0.073)	(0.072)
Time spent at home per day (hours)	414	11.91	1.58	-0.746	-2.32**
			(1.27)	(1.22)	(0.963)
Number of visits per week (N)					
Places to eat or drink	472	1.72	-0.035	-0.101	-0.066
			(0.253)	(0.246)	(0.205)
Grocery stores	472	0.717	0.134	0.089	-0.045
			(0.134)	(0.106)	(0.124)
Health care	472	0.289	0.095	0.043	-0.053

Table 4: Impacts on travel behavior according to smartphone Google Maps location history data *(continued)*

Outcome	N	Control mean	Treatment effect: Half fares	Treatment effect: Free fares	Free vs. half fares
			(0.063)	(0.054)	(0.062)
School	472	0.511	-0.065 (0.119)	-0.122 (0.113)	-0.057 (0.105)
Shopping (non-food)	472	3.04	0.355 (0.300)	0.058 (0.286)	-0.298 (0.308)
Gas stations and convenience stores	472	1.48	-0.065 (0.163)	-0.196 (0.168)	-0.131 (0.162)
Transportation facilities	472	1.62	-0.276 (0.336)	0.184 (0.351)	0.460* (0.236)
Private residences besides own home	472	<0.001	0.006 (0.006)	0.002 (0.002)	-0.004 (0.006)
Other types of locations	472	1.71	-0.071 (0.206)	0.075 (0.186)	0.146 (0.177)

Notes: Table presents estimates of the effect of being assigned to each treatment status (50% discount or 100% discount) on mobility outcomes measured from participants' smartphone Google Maps location history data. 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. Column N indicates the number of individuals across the three study arms that have non-missing data for the given outcome. Home locations could not be reliably estimated for 58 participants. Robust standard errors are in parentheses. ***p <0.01, **p <0.05, *p <0.1; † refers to comparable thresholds for FDR-adjusted q-value.

Table 5: Elasticities of demand for public transportation, compared with other fare discount experiments with low-income populations

	Present study, using farecard data (Pittsburgh)	Present study, using GPS data (Pittsburgh)	Rosenblum (2020) (Boston)	Brough et al. (2022) (Seattle)	Huberts & Oroxom (2024) (D.C.)
Full price to half price					
Point estimate	**10.00*** **	**-0.12**	0.58**	N/A	*Forthcoming*
95% CI	**[9.1, 10.9]**	**[-0.84, 0.60]**	[0.21, 0.95]		
Half price to free					
Point estimate	**1.75*** **	**0.52*** **	N/A	3.42***	*Forthcoming*
95% CI	**[1.63, 1.88]**	**[0.22, 0.82]**		[2.95, 3.88]	

Notes: Table presents the price elasticities of demand for public transportation, based on the results of recent fare discount experiments that treated low-income populations. ***p < 0.01, **p < 0.05, *p < 0.1

Table 6: Impacts on employment outcomes

Outcome	N	Control mean	Treatment effect: Half fares	Treatment effect: Free fares	Free vs. half fares
A. Cumulative outcomes in first 4 calendar quarters, from UI administrative records					
Had any paid employment	9,450	0.632	0.007 (0.009)	0.014 (0.009)	0.007 (0.009)
Number of quarters with employment (N)	9,450	2.04	0.033 (0.031)	0.054* (0.031)	0.022 (0.031)
Earnings ($)	9,450	11,120	235.0 (274.4)	338.4 (268.4)	103.4 (274.9)
Number of employers worked for (N)	9,450	1.31	0.066** (0.031)	0.021 (0.030)	-0.046 (0.031)
Number of 2-digit NAICS sectors worked in (N)	9,450	0.986	0.019 (0.020)	0.023 (0.020)	0.004 (0.020)
Received any UI benefits	9,450	0.068	-0.007 (0.006)	-0.001 (0.006)	0.006 (0.006)
Amount of UI benefits received ($)	9,450	249.4	-32.19 (29.16)	-21.44 (29.31)	10.75 (27.87)
B. Self-reported outcomes from 11-month follow-up survey					
Currently employed	3,888	0.524	-0.015 (0.018)	-0.013 (0.018)	0.002 (0.016)
Hourly wage at main job ($; excludes zeroes)	1,803	15.33	1.79 (2.11)	0.443 (0.695)	-1.35 (2.19)
Total jobs held (N)	3,888	0.589	0.325 (0.318)	-0.038 (0.076)	-0.363 (0.319)
Weekly work hours (N)	3,888	16.78	-0.322 (0.770)	-1.38* (0.737)	-1.06 (0.715)
Monthly earnings ($)	3,888	927.5	-131.2 (115.6)	-179.6 (119.3)	-48.35 (103.9)
Quarterly earnings ($)	3,888	2,782	-393.7 (346.7)	-538.7 (358.0)	-145.0 (311.7)
Jobs applied to in past 4 weeks (N), among active job seekers	1,417	11.04	-2.08* (1.19)	2.47 (4.26)	4.55 (4.16)

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 sample. The outcomes in panel A come from Pennsylvania unemployment insurance (UI) administrative records. These outcomes are measured cumulatively over the first four full calendar quarters after the quarter in which the person enrolled in the study. The outcomes in panel B are self-reported and come from the endline survey, which took place 11 months after random assignment. 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 estimates in panel A additionally adjust for the outcome measured in the four quarters prior to the quarter in which the person enrolled in the study. Column N indicates the number of individuals across the three study arms that have non-missing data for the given outcome. The UI data could not be obtained for 90 adult participants who do not have a social security number on file with the Allegheny County Department of Human Services. 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: Impacts on health care utilization among the adult sample within the first 365 days after enrollment

Outcome (N = 9,544)	Control mean	Treatment effect: Half fares	Treatment effect: Free fares	Free vs. half fares
Received any health care	0.889	0.007 (0.008)	0.003 (0.008)	-0.003 (0.008)
A. Physical health care				
Has at least one claim				
Any physical health care	0.871	0.002 (0.008)	<0.001 (0.008)	<0.001 (0.008)
Non-ER outpatient	0.835	0.002 (0.009)	0.004 (0.009)	0.002 (0.009)
ER outpatient	0.534	-0.014 (0.012)	-0.011 (0.012)	0.003 (0.012)
Non-ER inpatient	0.056	-0.002 (0.006)	0.015** (0.006)	0.016*** (0.006)
ER inpatient	0.058	-0.003 (0.006)	-0.001 (0.006)	0.001 (0.006)
Days with at least one claim (N)				
Any physical health care	22.79	0.086 (0.530)	0.461 (0.519)	0.376 (0.541)
Non-ER outpatient	13.60	-0.007 (0.482)	0.200 (0.466)	0.208 (0.486)
ER outpatient	1.58	-0.024 (0.058)	-0.009 (0.061)	0.015 (0.060)
Non-ER inpatient	0.244	0.025 (0.048)	0.210** (0.093)	0.186* (0.098)
ER inpatient	0.438	0.021 (0.065)	0.027 (0.065)	0.007 (0.069)
Prescription fills (N)	12.53	0.067 (0.408)	-0.054 (0.404)	-0.121 (0.400)
Days covered by a prescription (N)	155.7	0.839 (2.22)	0.833 (2.24)	-0.006 (2.21)
B. Behavioral health care				
Has at least one claim				
Any behavioral health care	0.601	<0.001 (0.012)	-0.002 (0.012)	<0.001 (0.012)
Non-crisis	0.542	-0.002 (0.012)	-0.009 (0.012)	-0.007 (0.012)
Crisis	0.294	-0.015 (0.011)	-0.005 (0.011)	0.010 (0.011)
Substance use treatment	0.103	<0.001 (0.007)	-0.003 (0.007)	-0.004 (0.007)
Days with at least one claim (N)				
Any behavioral health care	16.13	-0.810 (0.575)	-1.02* (0.568)	-0.207 (0.602)
Non-crisis	10.15	-0.126 (0.425)	-0.367 (0.401)	-0.241 (0.455)
Crisis	0.974	-0.011 (0.074)	0.198** (0.096)	0.209** (0.101)
Substance use treatment	3.93	-0.539 (0.378)	-0.913** (0.362)	-0.374 (0.334)
Prescription fills (N)	2.63	-0.099 (0.143)	-0.029 (0.143)	0.071 (0.138)
Days covered by a prescription (N)	62.90	0.925 (1.71)	1.95 (1.73)	1.03 (1.76)
Cost of care to managed care org. ($)	2,288	-150.1 (172.9)	-42.82 (169.2)	107.3 (183.5)

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 365 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 365 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 365 days post-enrollment. The 'days covered by a prescription' outcome counts the cumulative number of days in the first 365 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. 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

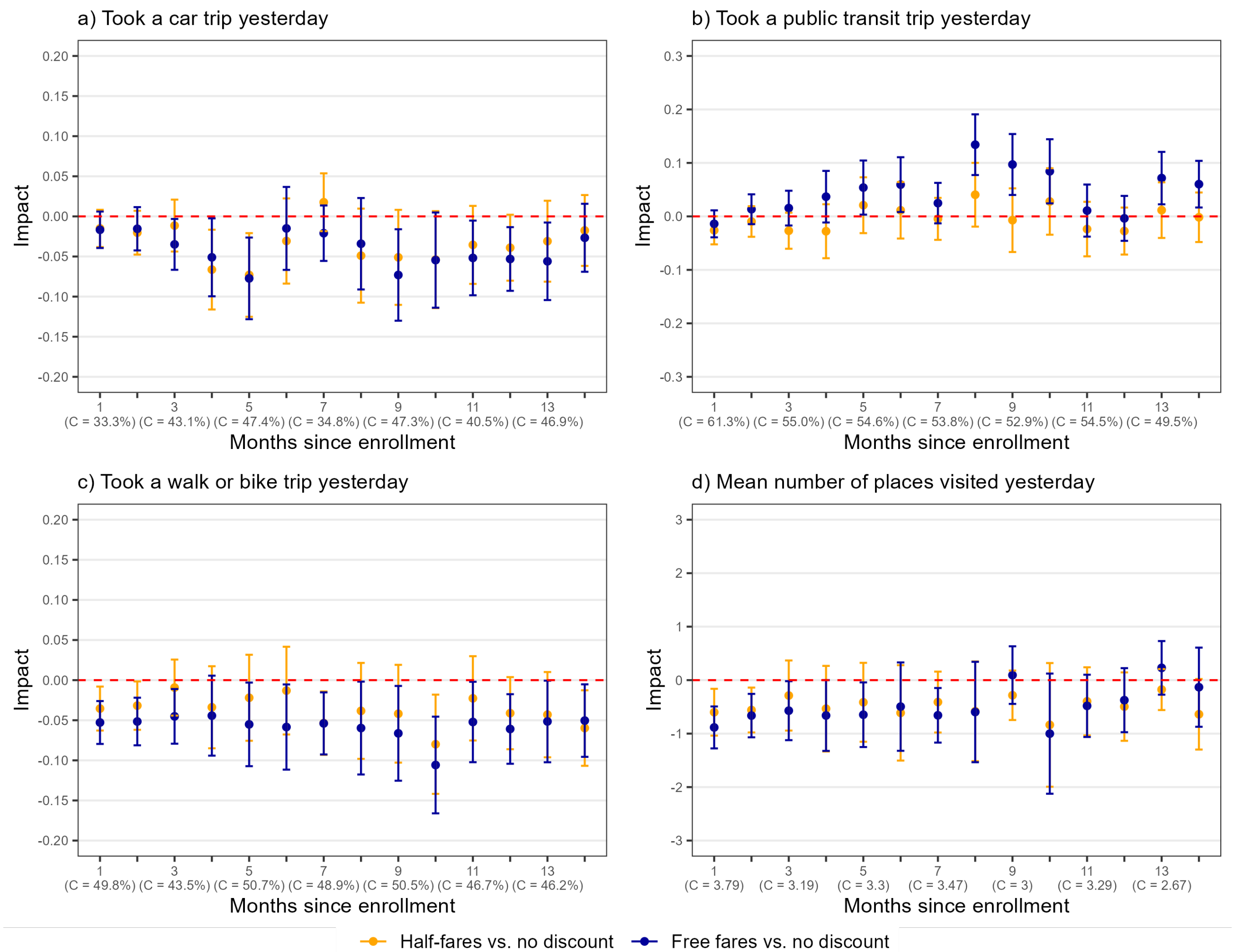
The Role of the ‘Fare’ in Welfare: Public Transportation Subsidies and their Effects on Low-Income Households

Online Appendix

Seth Chizeck and Oluchi Mbonu

A Additional figures and tables

Figure A1: Impacts of fare discounts on self-reported outcomes from travel diaries, by month



Notes: Figure presents estimates of the effect of being assigned to each discount level relative to no discount on the travel behavior of the adult sample, as reported in the text-message travel diaries. Each diary asked the respondent to describe their travels yesterday. The diaries were sent to participants once every three days in the first two months after enrollment, then once a month for the next 10 months, then once a week for the next two months. Treatment effects are estimated by running repeated cross-sectional regressions by month, where the outcome for each participant is their mean response to the given diary question across all of their responses in the month. We regress the outcome on an indicators for treatment assignment, 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). Error bars represent 95% confidence intervals using robust standard errors.

Figure A2: Impact of fare discounts on mobility outcomes measured from smartphone GPS data, by month

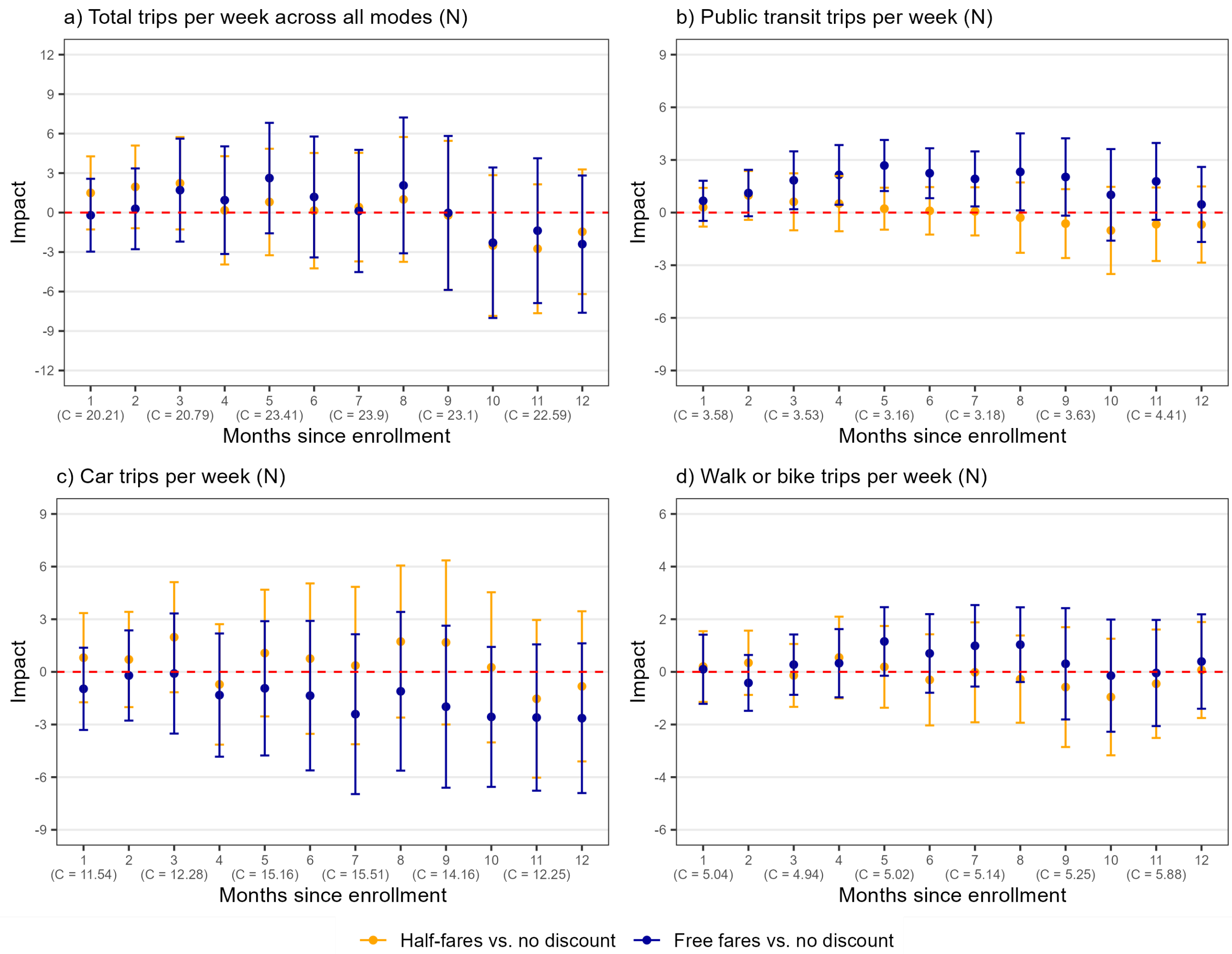


Figure A2: Impact of fare discounts on mobility outcomes measured from smartphone GPS data, by month *(continued)*

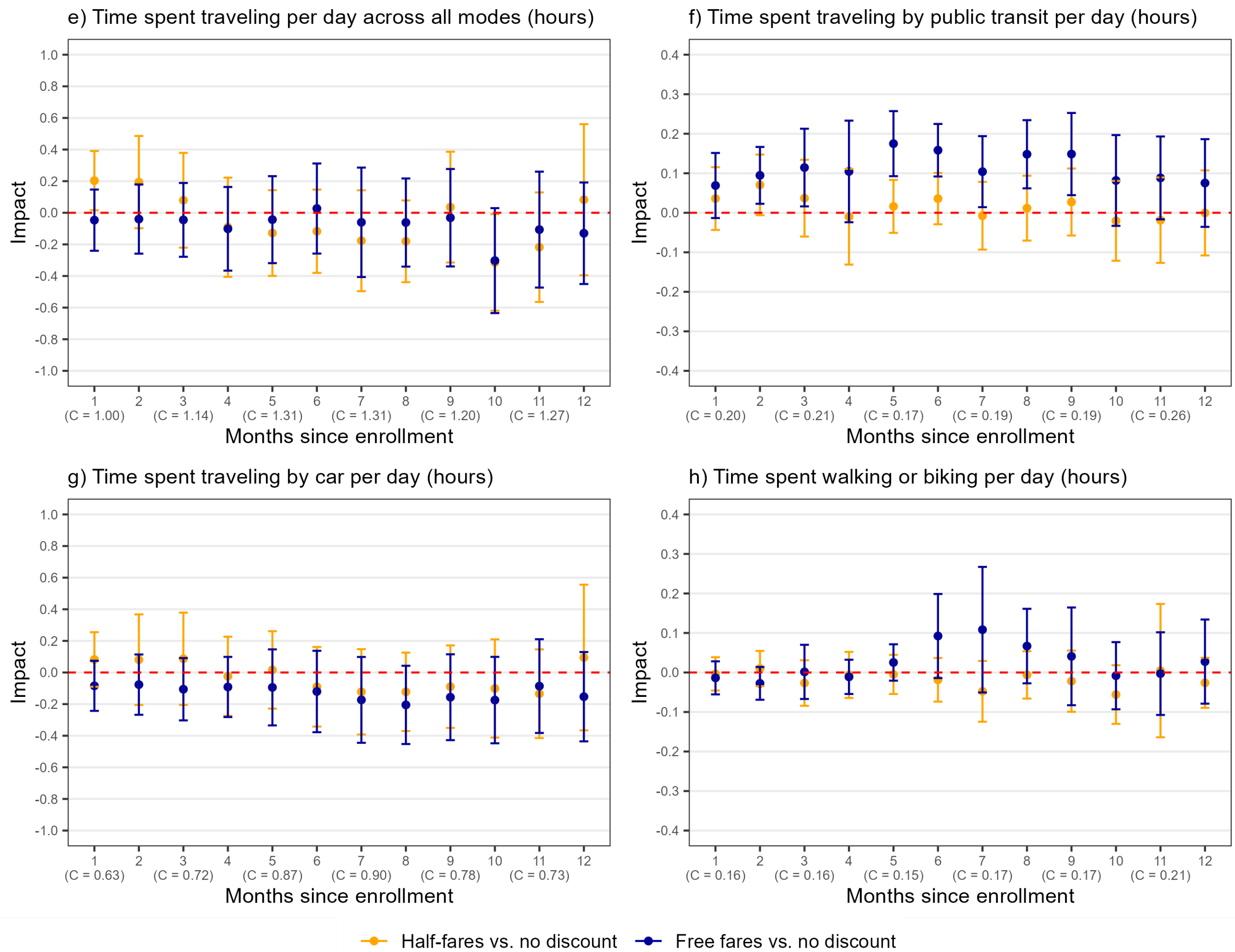


Figure A2: Impact of fare discounts on mobility outcomes measured from smartphone GPS data, by month *(continued)*

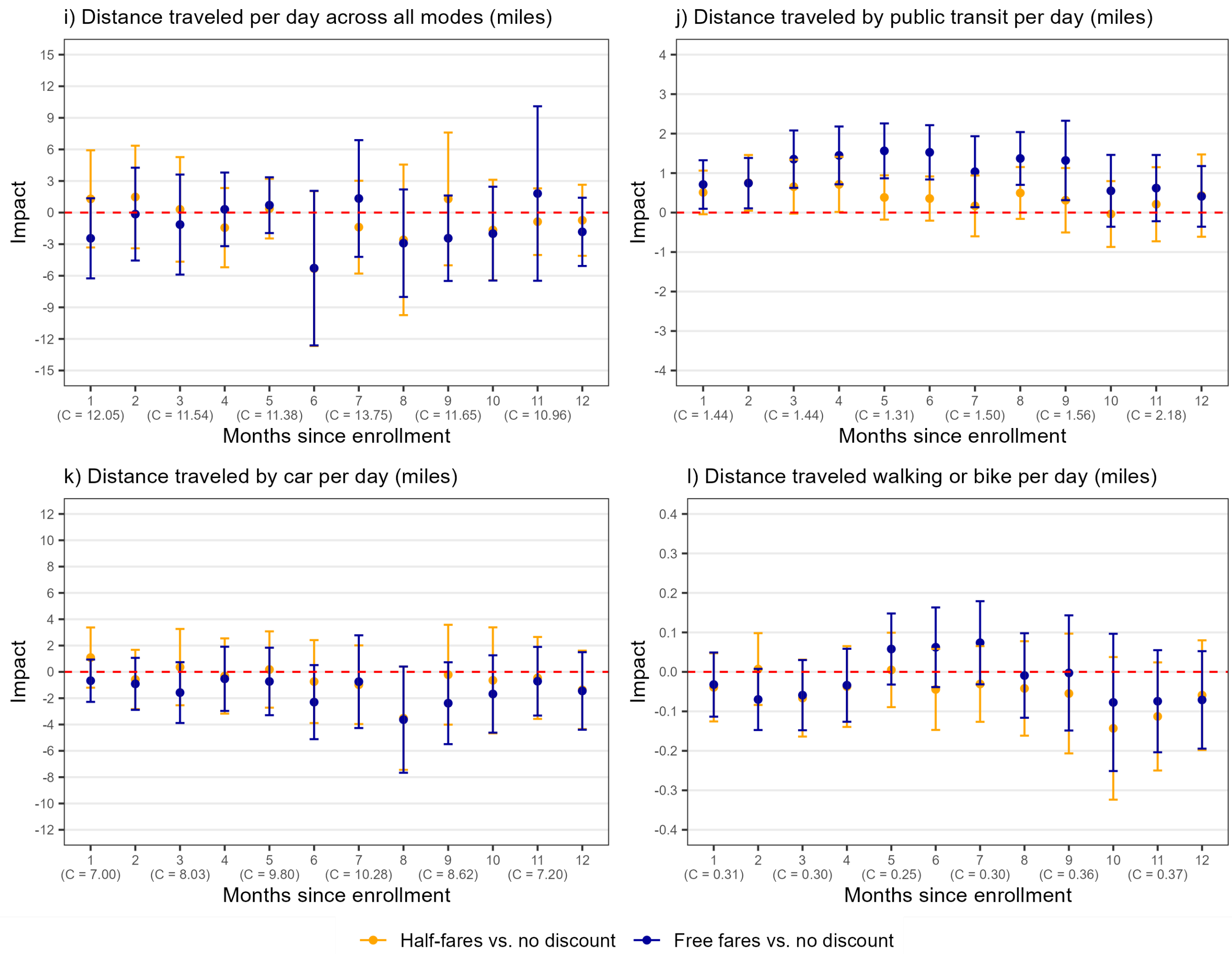
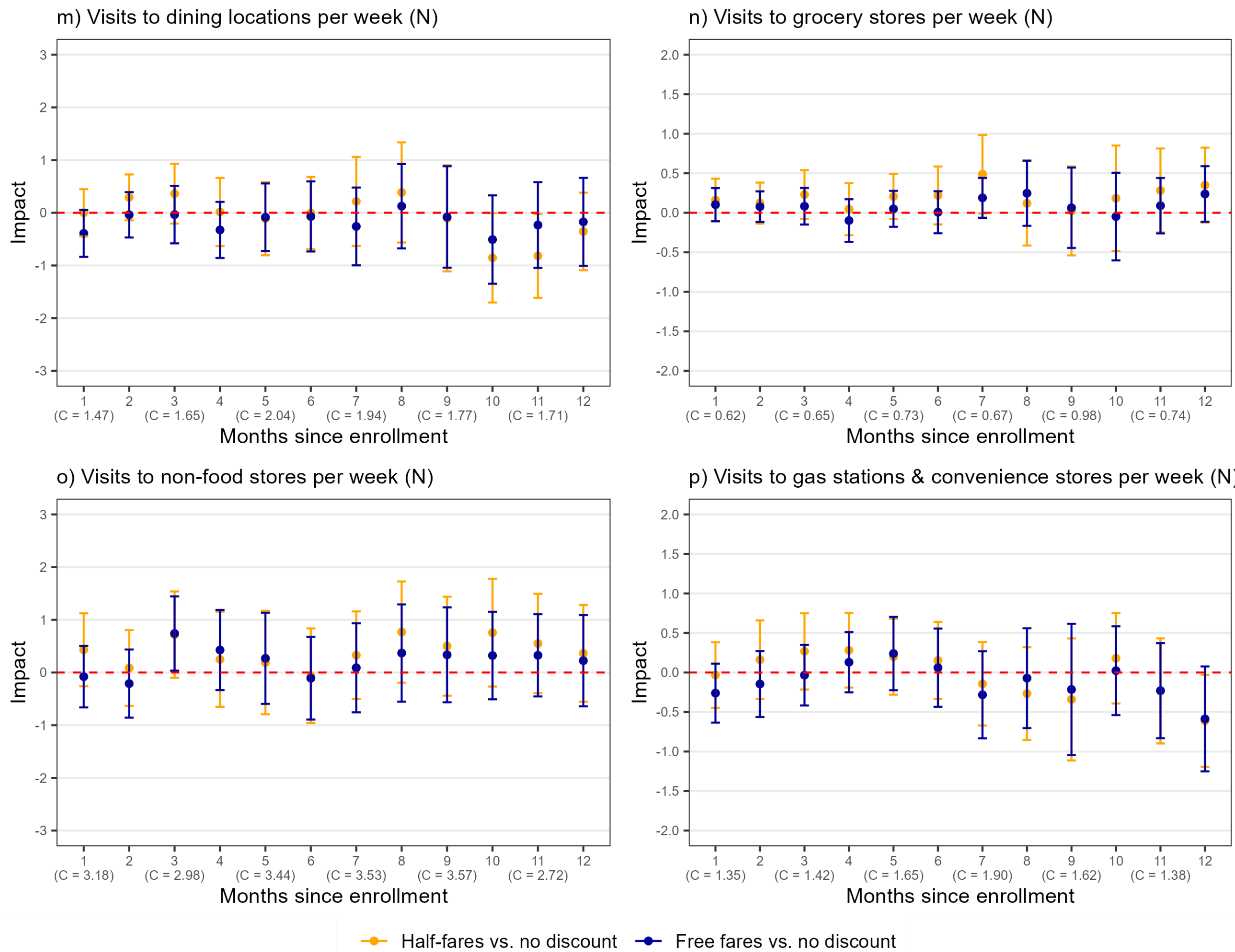
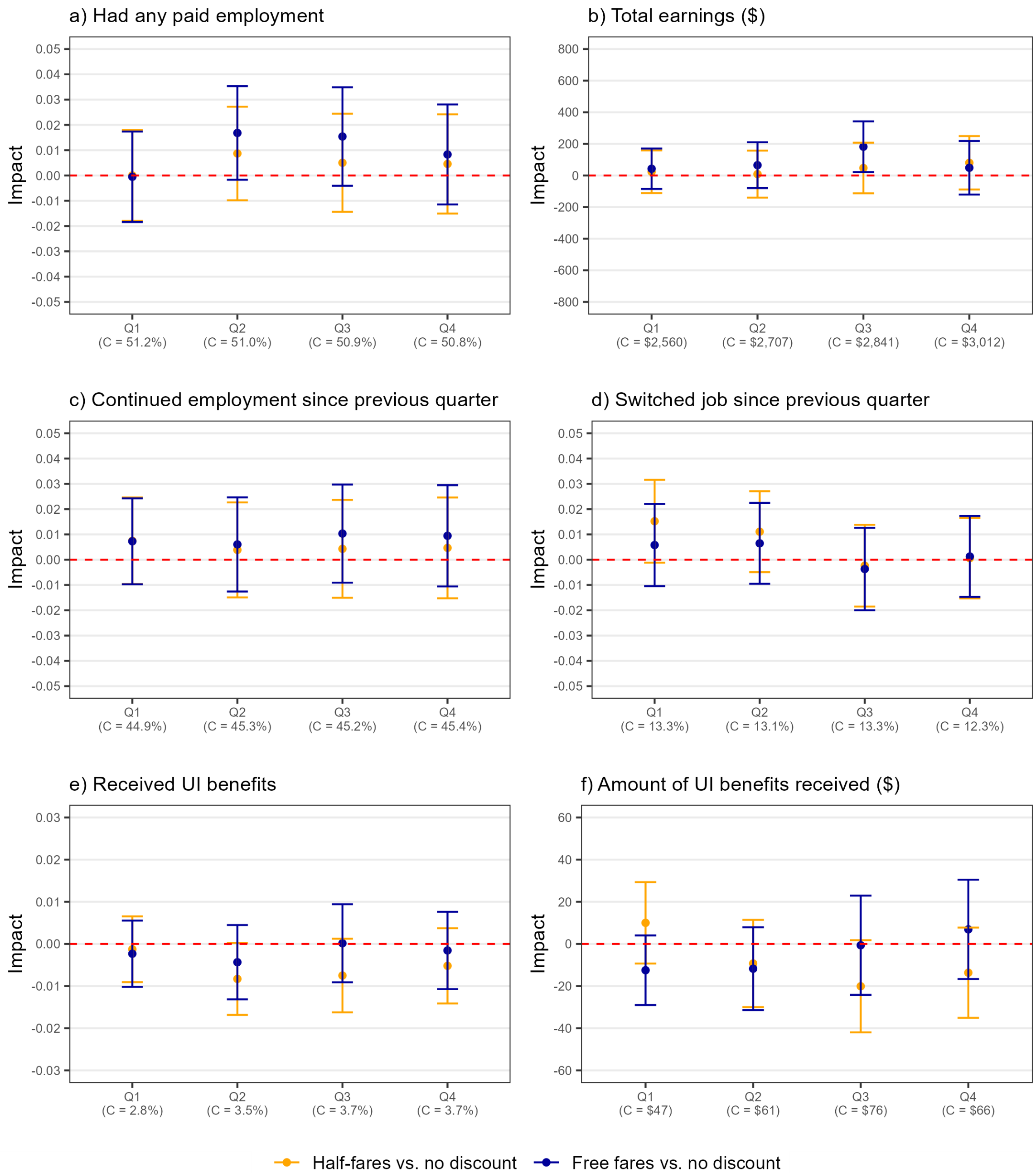


Figure A2: Impact of fare discounts on mobility outcomes measured from smartphone GPS data, by month *(continued)*



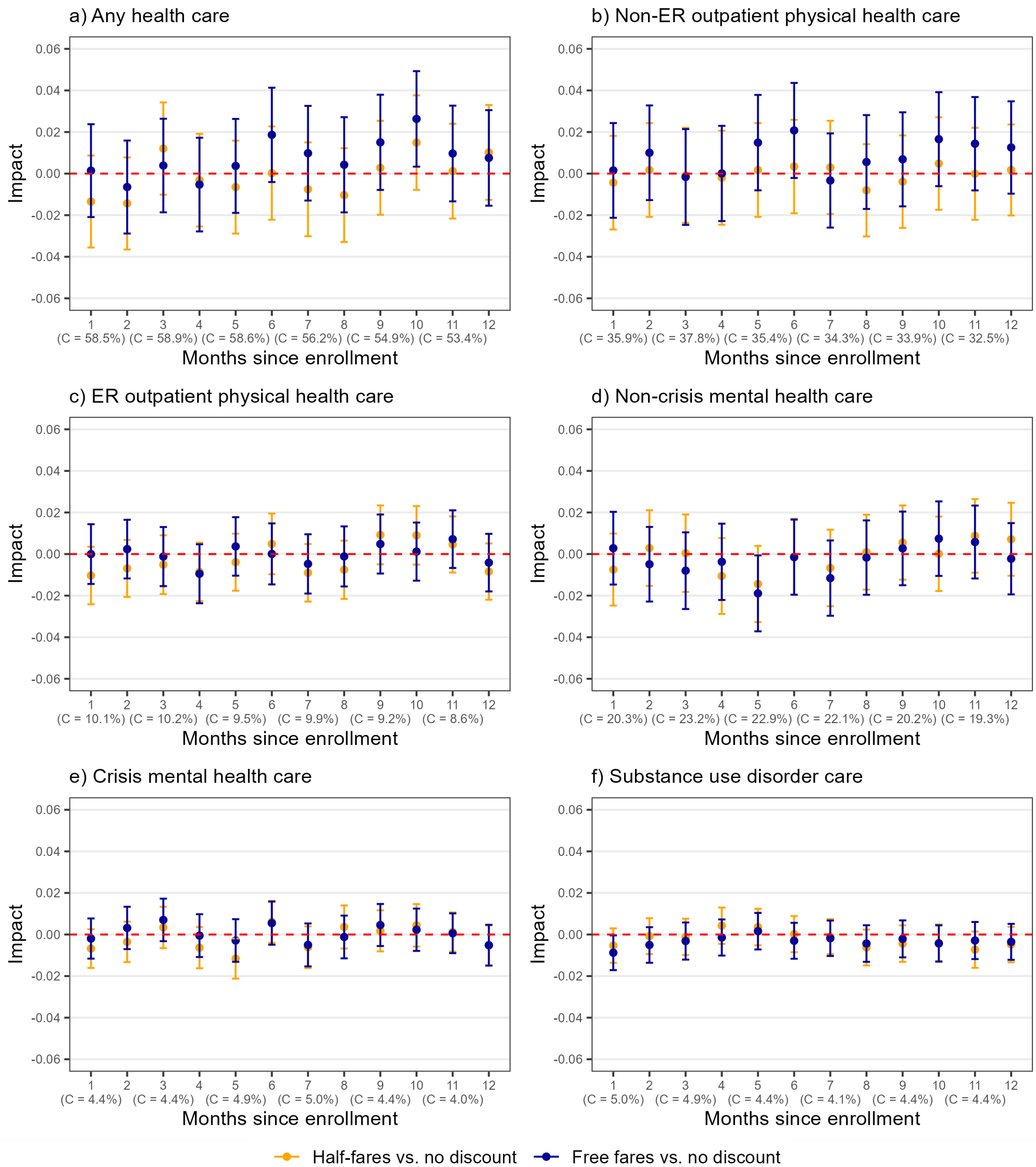
Notes: Figure presents estimates of the effect of fare discounts on various mobility and travel outcomes measured using smartphone Google Maps location history (GPS) data. Treatment effects are estimated by running repeated cross-sectional regressions by month. We regress the outcome on indicators for 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 365 days before the person enrolled in the study. Error bars represent 95% confidence intervals using robust standard errors.

Figure A3: Effect of fare discounts on employment outcomes by calendar quarter



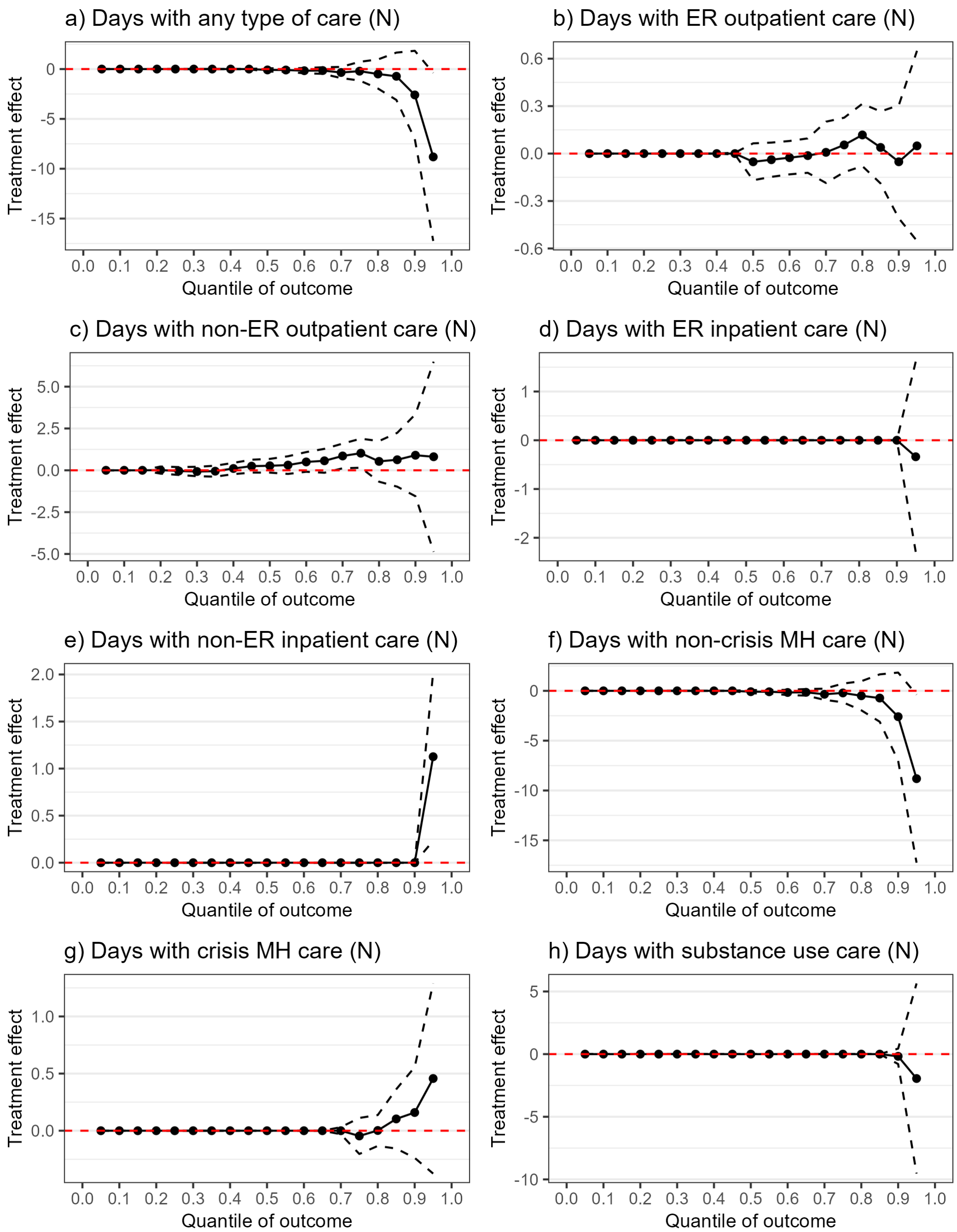
Notes: Figure presents the effect of being assigned to each fare discount level, relative to no discount, on quarterly employment outcomes in each of the first four calendar quarters after the quarter in which the participant enrolled in the study. Outcomes are measured from Pennsylvania unemployment insurance (UI) administrative records. The 'Total earnings ($)' and 'Amount of UI benefits received ($)' outcomes include individuals with zero earnings or zero benefits in the quarter. 'Continued employment since previous quarter' is a binary outcome that equals 1 if the person was employed in the current quarter and in the previous quarter. 'Switched job since previous quarter' is a binary outcome that equals 1 if the person was employed in both the current and previous quarter, and they worked for an employer in the current quarter that they did not work for in the previous quarter. The treatment effect in Panel B Q3 is a pre-specified confirmatory study 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), lives within the PRT 7-day frequent service walkshed (y/n), and the outcome measured in the four quarters prior to the quarter in which the person enrolled in the study. Error bars represent 95% confidence intervals using robust standard errors.

Figure A4: Impacts on the likelihood of receiving health care, by month



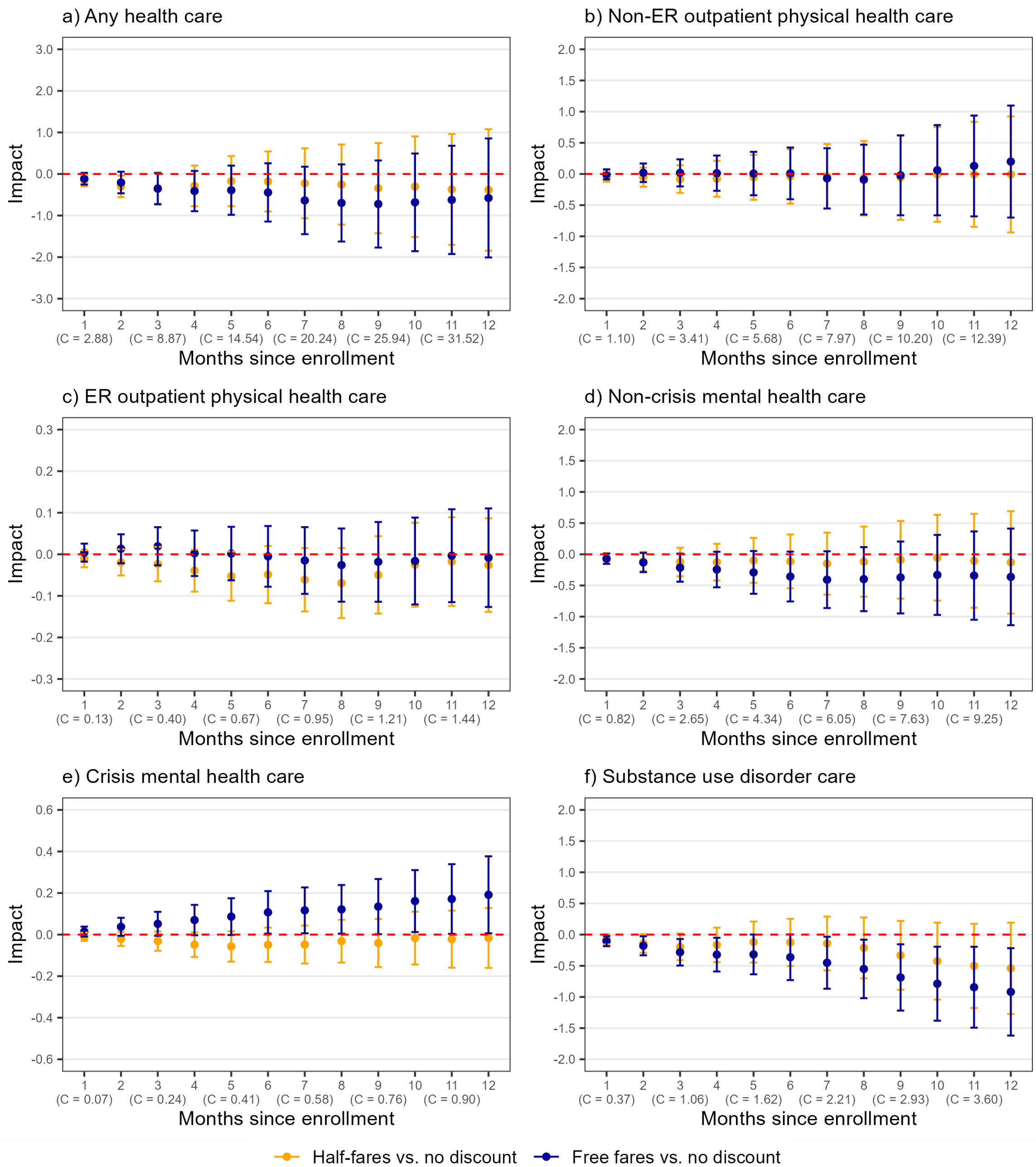
Notes: Figure presents estimates of the effect of being assigned to each discount on the monthly likelihood than an adult participant received Medicaid-funded health care. Data comes from Medicaid claims records. The outcome is a binary indicator for whether the participant received any health care in the given month. 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: Impacts on quantiles of the distribution of number of days with a health care claim in the first 365 days after enrollment, for free fares versus no discount



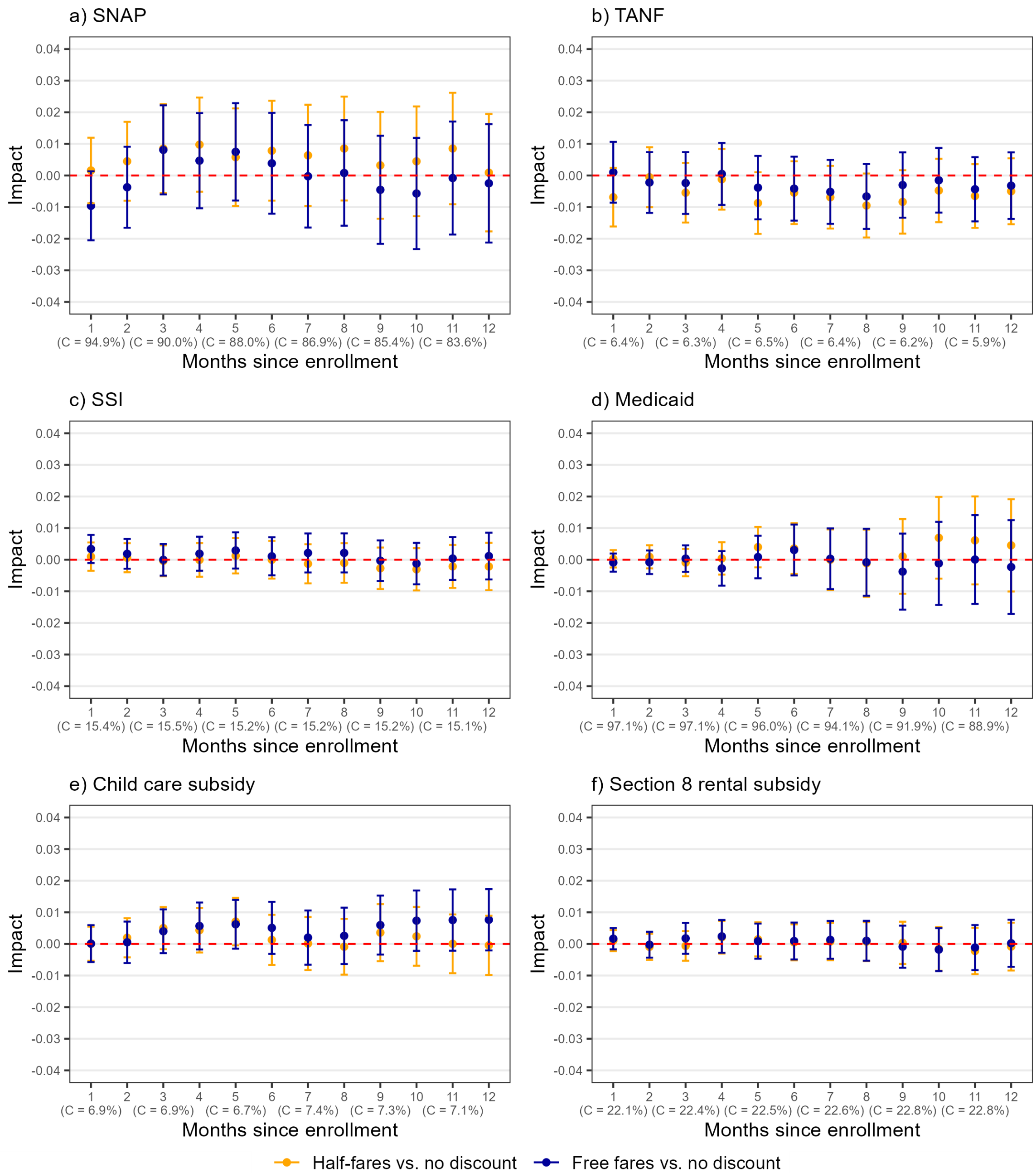
Notes: Figure presents estimates of the effect of being assigned to free fares relative to no discount on quantiles of the number of days that a person received health care in the first 365 days after enrolling in the study. Data comes from Medicaid claims records. Estimates come from a quantile regression 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 A6: Impacts on the cumulative number of days with a health care claim over first 12 months



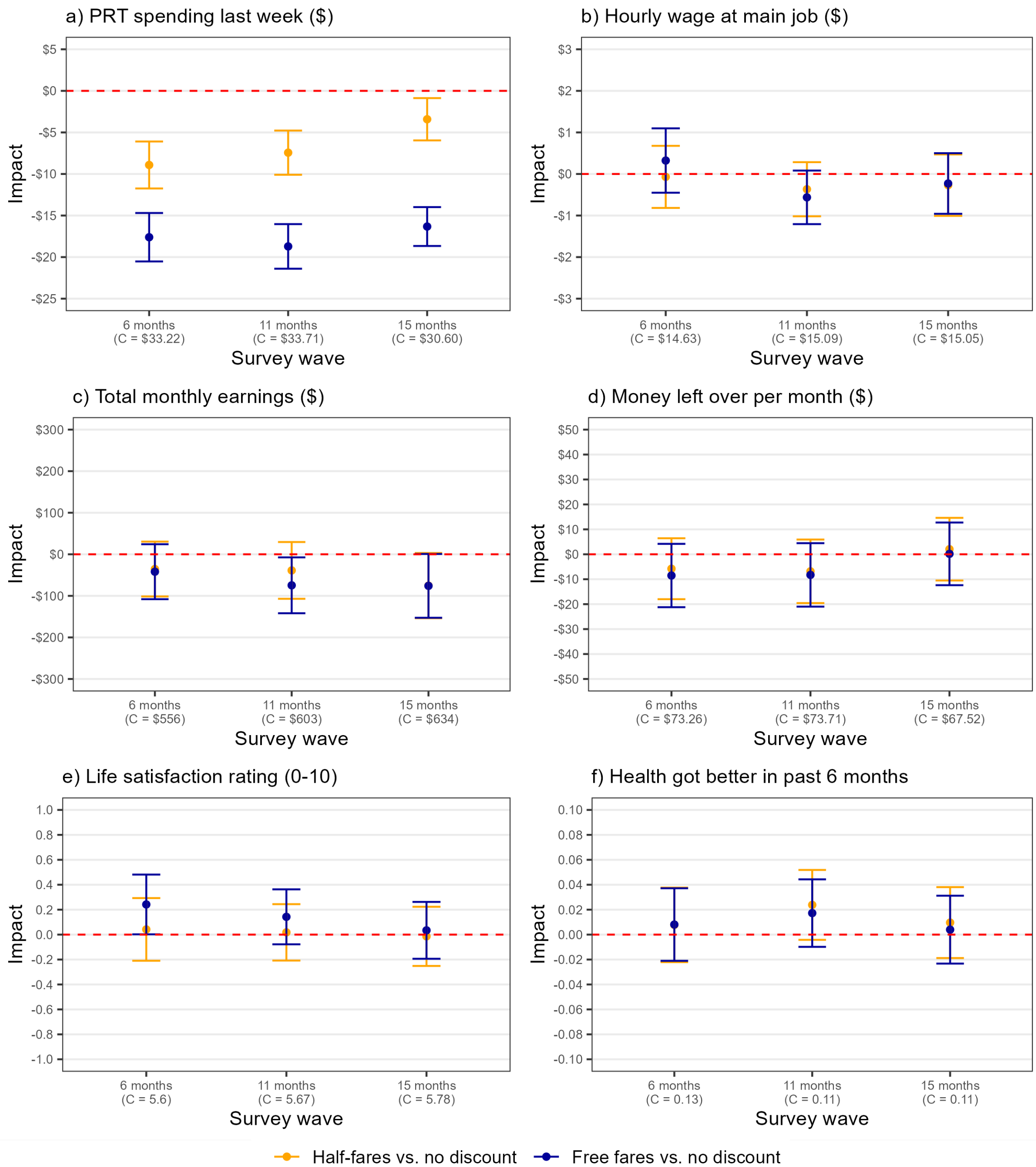
Notes: Figure presents estimates of the effect of being assigned to each discount on the cumulative number of distinct days with at least one Medicaid-funded health care claim in each of the first 12 months after enrollment. Data comes from Medicaid claims records. The outcome is the number of days on 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 A7: Impacts on the likelihood of receiving public benefits, by month



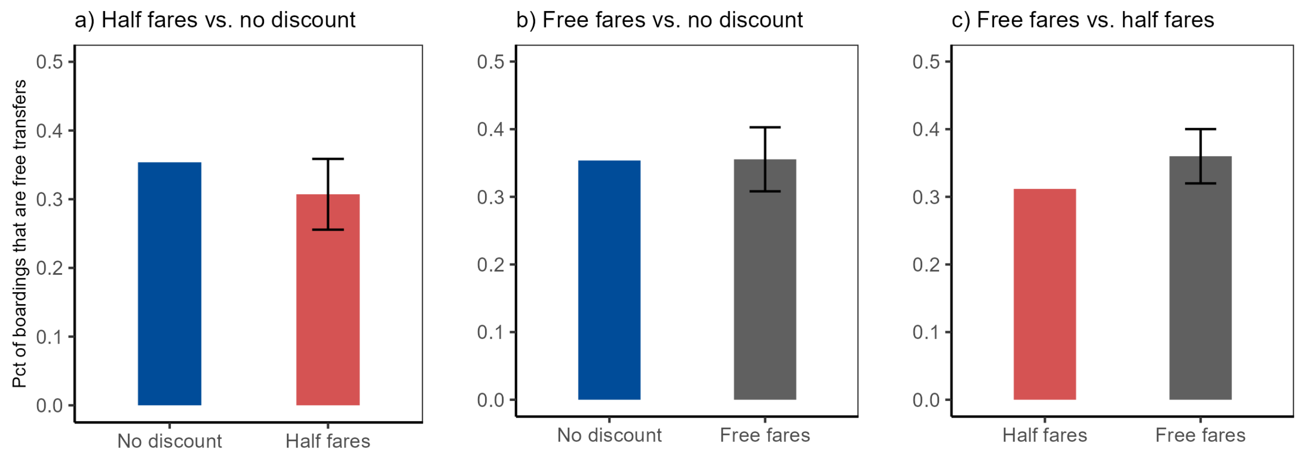
Notes: Figure presents estimates of the effect of being assigned to each discount relative to no discount on the likelihood than an adult participant was receiving public benefits at some point in the month, over the first 12 months of their study enrollment. Data comes from administrative records from the Allegheny County Department of Human Services (ACDHS) and the Pennsylvania Department of Human Services (PADHS). The outcome is a binary indicator for whether the participant received the given benefit in the given month. Estimates come from a regression of the outcome on an indicator for being in the 100% discount group versus the no-discount group, 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 A8: Effect of fare discounts on select outcomes from follow-up surveys, by survey wave



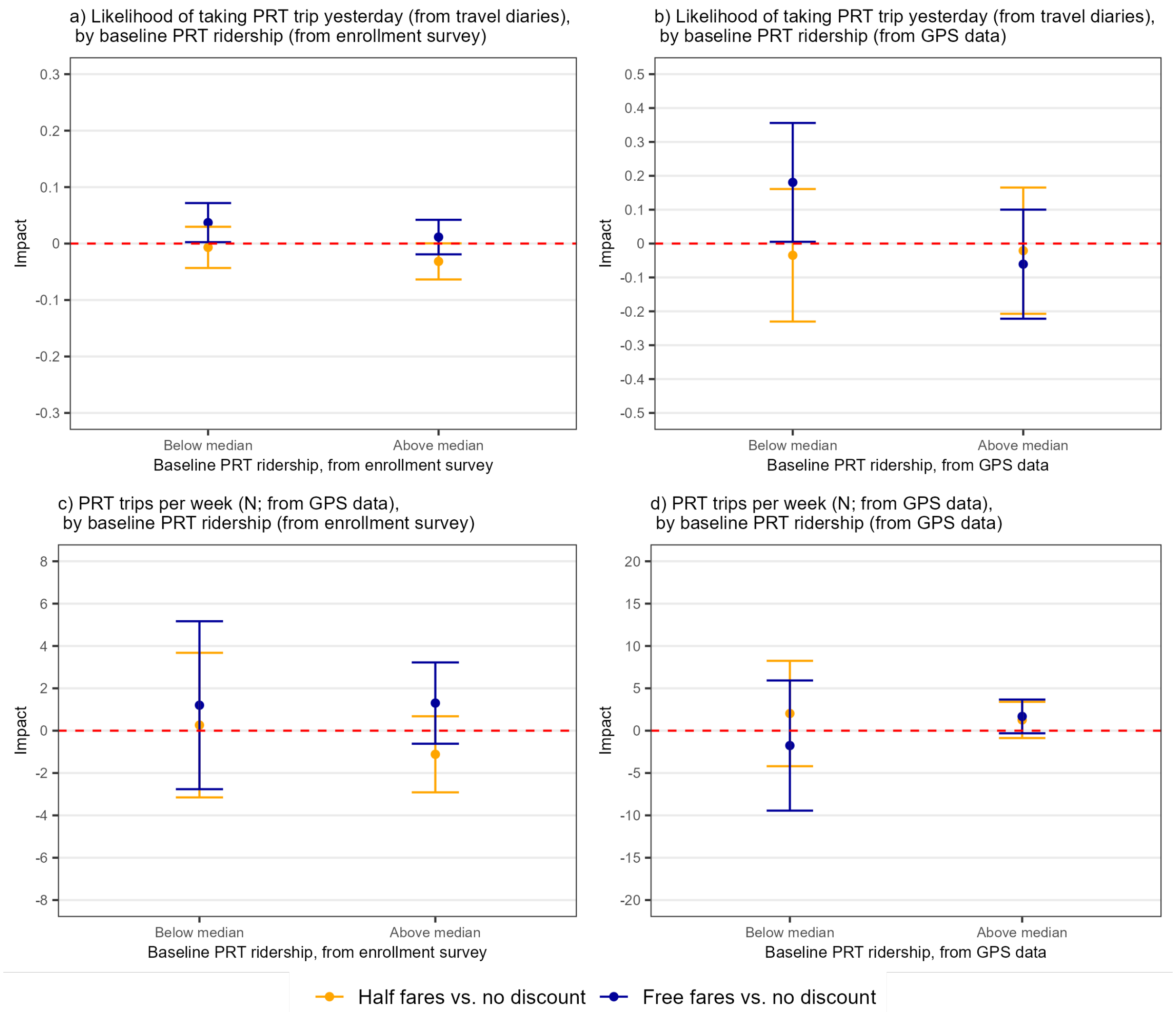
Notes: Figure presents estimates of the effect of each fare discount level on select outcome measures that were collected in all three follow-up survey waves (6 months, 11 months, and 15 months post-enrollment). We regress the outcome on indicators for treatment status, adjusting for the following baseline 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), and lives within the PRT 7-day frequent service walkshed (y/n). Error bars represent 95% confidence intervals using robust standard errors.

Figure A9: Impact of fare discounts on rates of "free transfer" transit boardings, among adult participants with at least 10 boardings



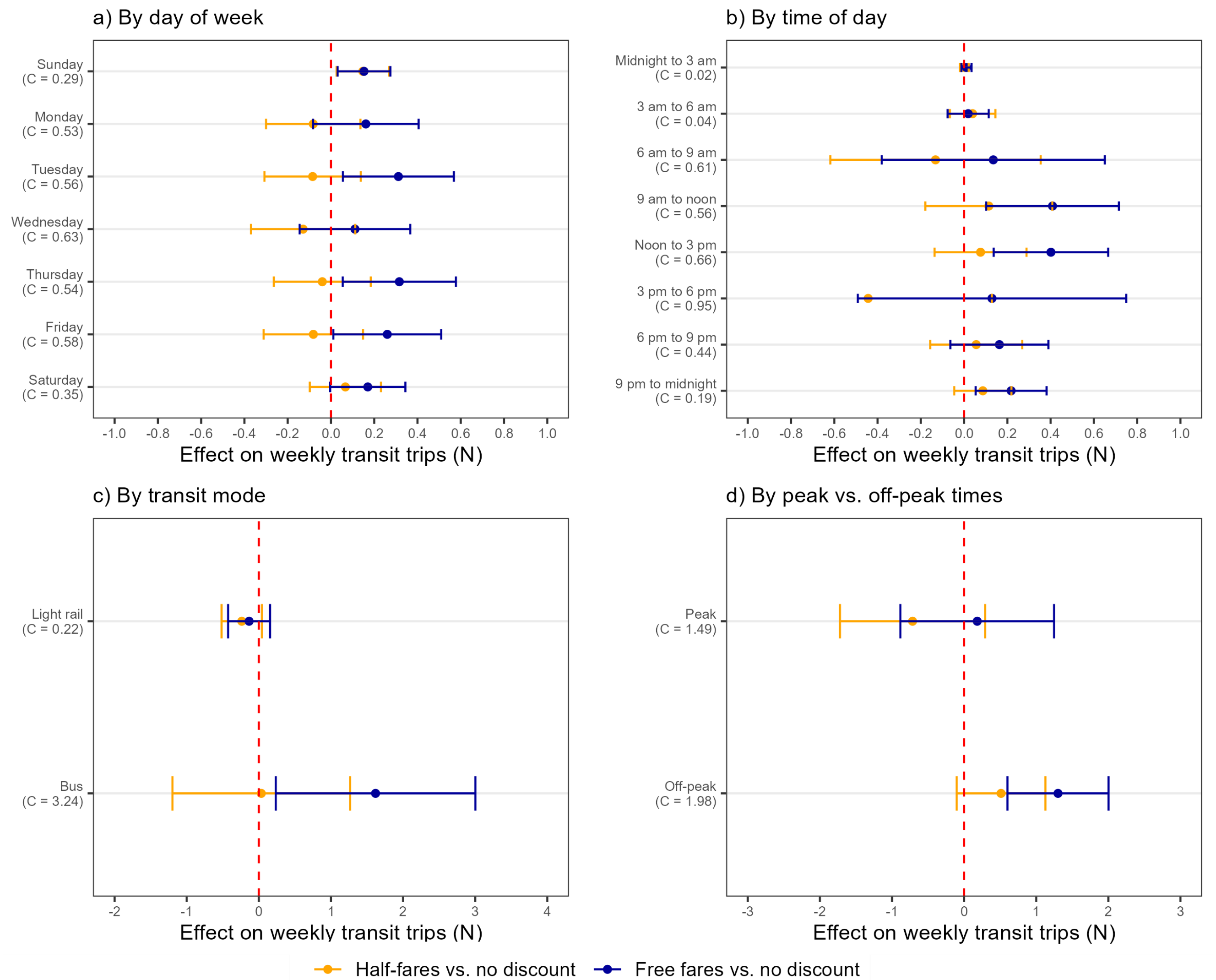
Notes: Figure presents estimates of the effect of being assigned to each discount level on the proportion of an adult participant's public transit boardings that would be categorized as free transfers. The analysis is based on smartphone Google Maps location history data, and only includes the participants who had at least 10 boardings during the study. A free transfer is a boarding for which the rider does not need to pay. Pittsburgh Regional Transit (PRT) categorizes boardings as free transfers using the following logic: Riders are always required to pay for the first boarding on a given day, where the day is defined to start at 3 am. Any boardings that take place within three hours of the first boarding of the day are considered free transfers. Riders are then required to pay for the next boarding after the end of this 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. Estimates come from a regression of the outcome on an indicator 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). Error bars represent the 95% confidence interval of the treatment effect using robust standard errors.

Figure A10: Effect of fare discounts on public transit ridership, by baseline level of ridership



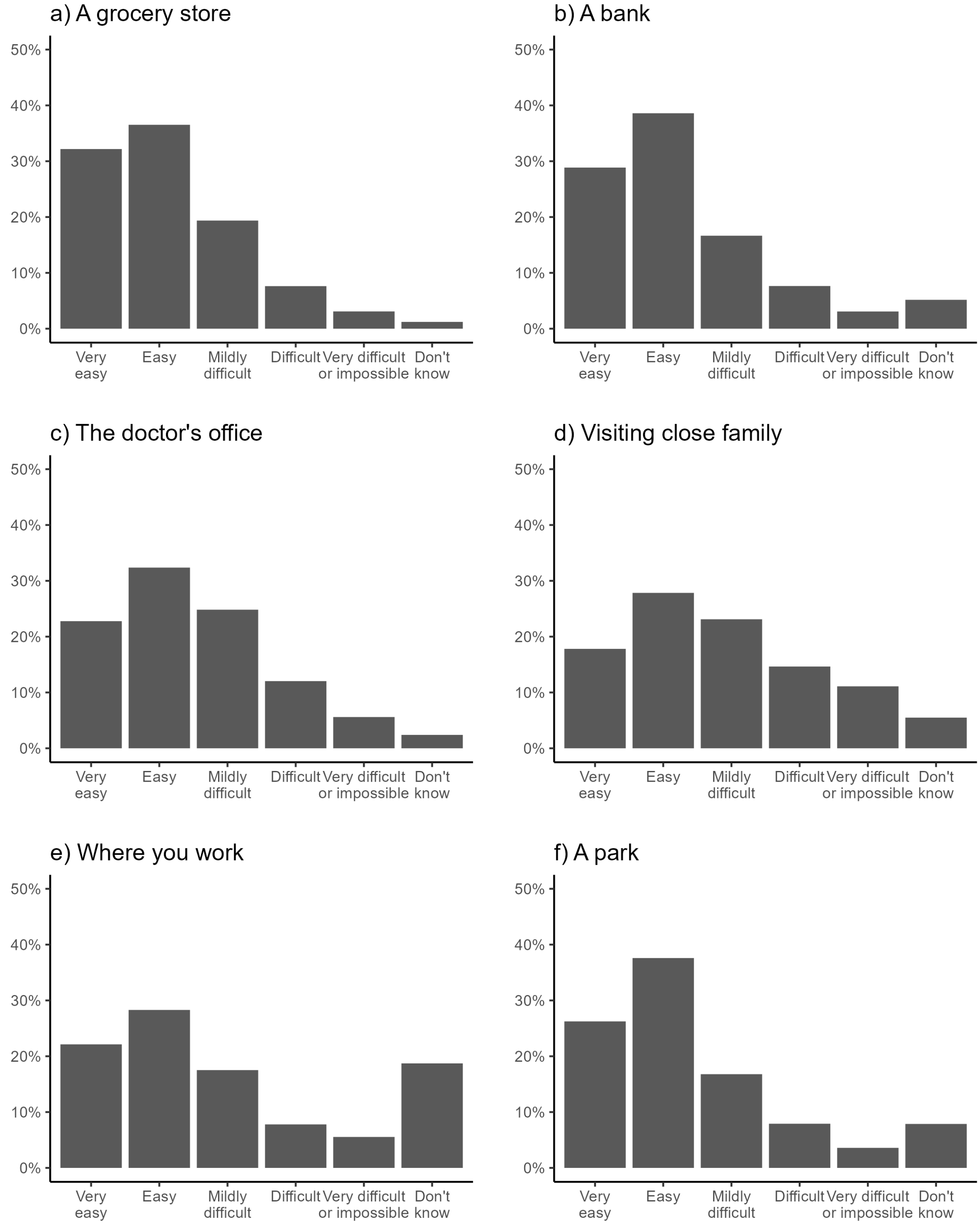
Notes: Figure presents estimates of each fare discount level on various measures of public transit ridership among the adult sample. The effects are disaggregated by the person's level of public transit ridership before enrolling in the study. The outcomes in panels A and B are measured from the travel 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 A11: Impacts on number of public transit trips per week according to smartphone GPS data, grouped by mode and timing of trip



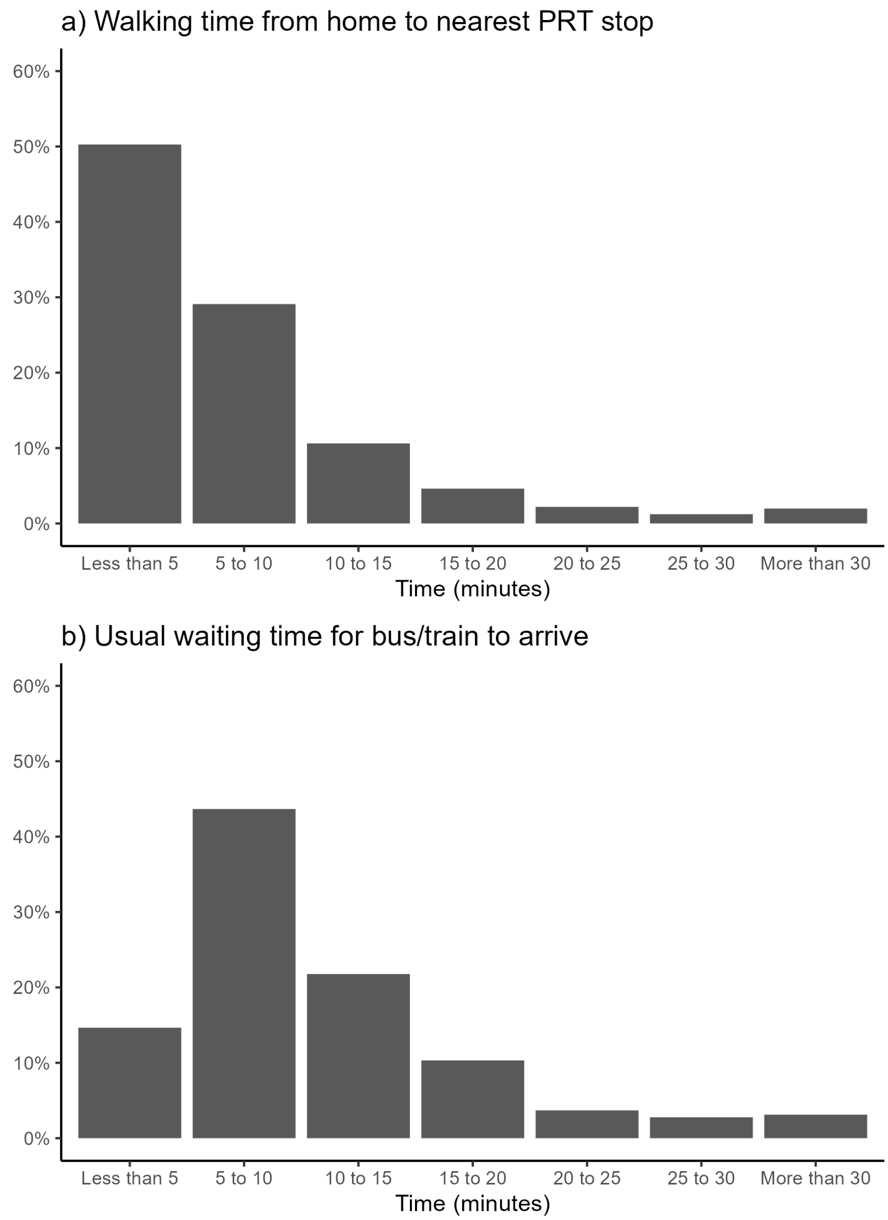
Notes: Figure presents estimates of the effect of being assigned to each treatment status (50% discount or 100% discount) on the number of public transit trips per week among the adult sample. Data comes from smartphone Google Maps location history records. Peak hours are defined as 6 am to 9 am and 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 A12: Responses to post-endline survey question "How easy is it for you to get to the following places by public transportation?"



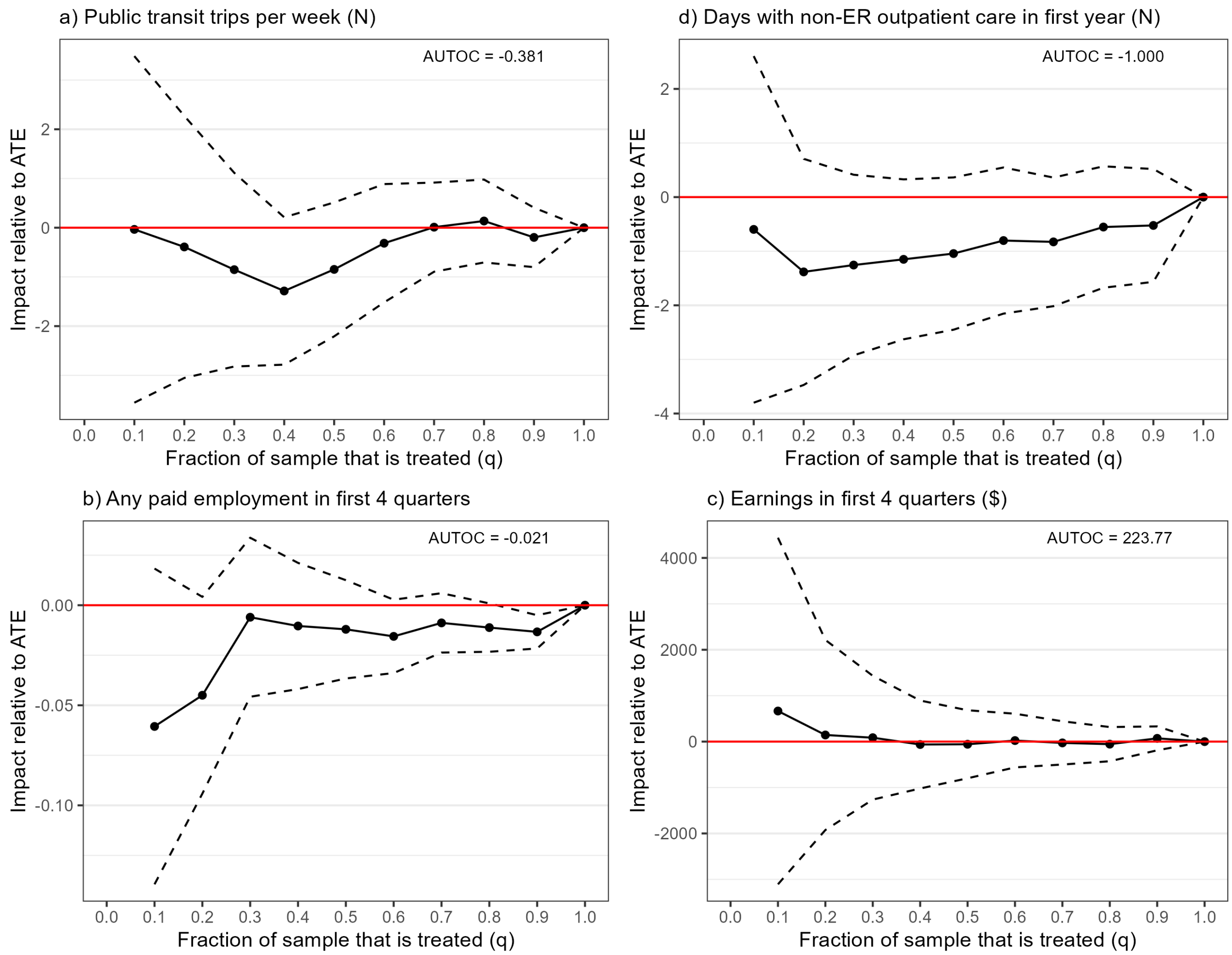
Notes: Figure presents the distribution of responses to the post-endline (i.e. 15-month follow-up) survey question that asked "How easy is it for you to get to the following places by public transportation?"

Figure A13: Responses to post-endline survey questions about walking time to nearest Pittsburgh Regional Transit (PRT) stop, and usual waiting time for the bus or train to arrive



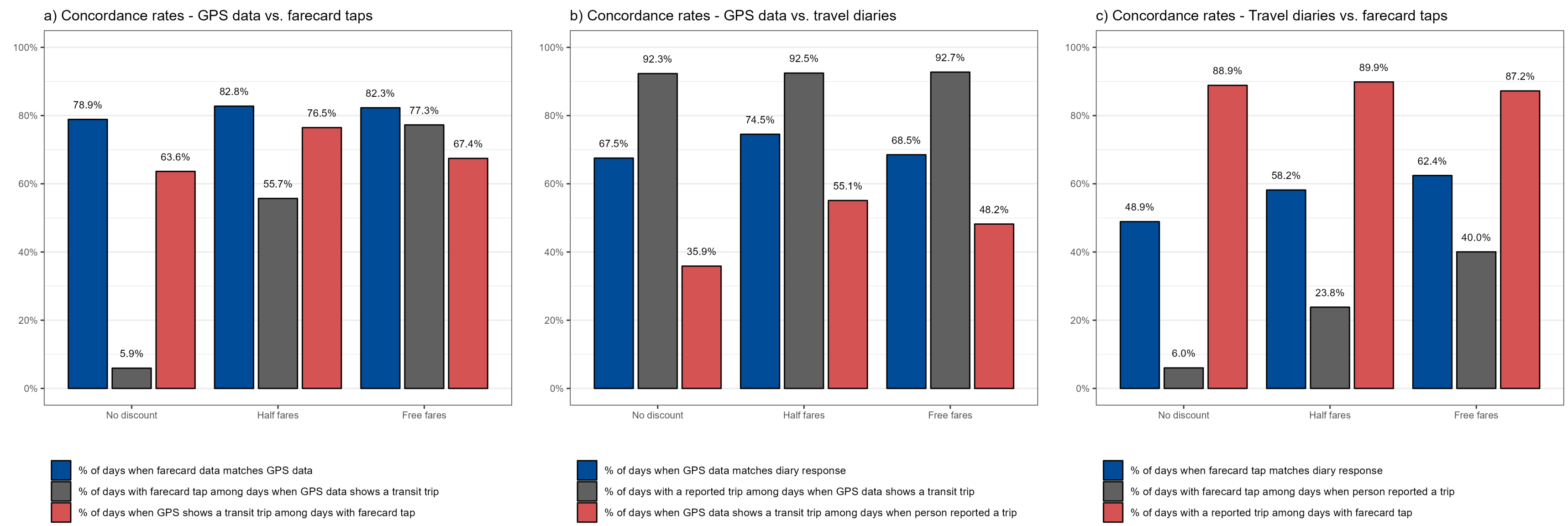
Notes: The top panel presents the distribution of responses to the post-endline (15-month follow-up) survey question that asked "How long does it take you to walk from your home to the nearest bus or T stop? Provide your best estimate even if you don't walk to this stop regularly." The bottom panel presents the distribution of responses to the post-endline survey question that asked "Think about the PRT stop that you use most often to go somewhere from home. How long do you usually wait at this stop for the bus or the T to arrive?"

Figure A14: Targeting operator characteristic curves for effect of free fares relative to no discount on select outcomes



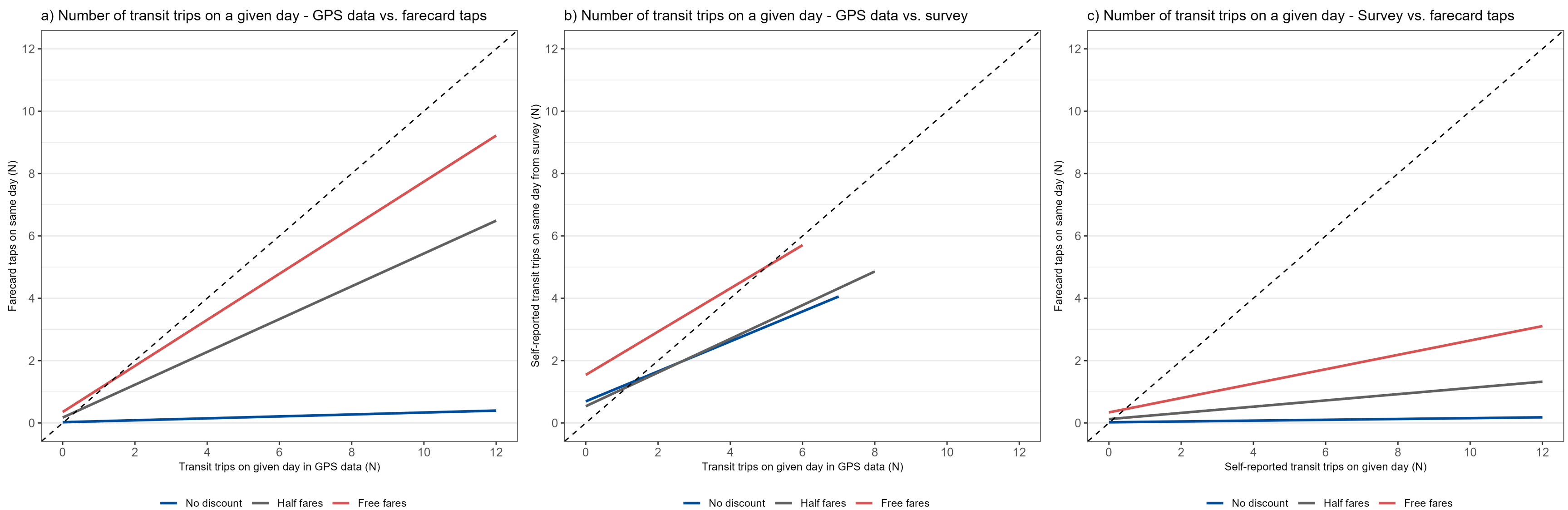
Notes: Figure presents targeting operator characteristic (TOC) curves for the effect on select outcomes of being assigned to the 100% discount relative to no discount. The data for panel a) comes from smartphone GPS data; panels b) and c) come from Pennsylvania unemployment insurance (UI) records; panel d) comes from Medicaid claims records. The TOC curves are based on conditional average treatment effects (CATE's) estimated for each sample member using generalized random forests via the 'grf' package in R. The TOC curve plots the benefit of treating only the fraction q of the study sample that is in the top qth percentile of CATE's among the study sample. This benefit is quantified as the treatment effect relative to the average treatment effect (ATE) for the full sample. Dotted lines represent 95% confidence intervals using robust standard errors. The area under the TOC (AUTOC) summarizes the ability of the estimated CATE's to identify individuals that have particularly large benefits to treatment.

Figure A15: Cross-validation of having at least one public transit trip on a given day; comparing farecard tap data, travel diary data, and smartphone GPS data



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 A16: Cross-validation of the number of transit trips on a given day; comparing farecard tap data, travel diary data, and smartphone GPS data



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 people to report the number of public 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 ordinary least squares regression.

Table A1: Impacts 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 trips last week (N)	4,048	11.95	-2.58 (2.00)	-0.696 (2.11)	1.88**† (0.919)
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)
Method of transportation used most often last week					
Public transportation	4,062	0.629	0.030 (0.019)	0.124***††† (0.018)	0.094***††† (0.016)
Car (yours or someone else's)	4,062	0.197	-0.005 (0.015)	-0.060***††† (0.014)	-0.055***††† (0.013)
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)
I have access to a car	4,059	0.356	0.004 (0.019)	-0.011 (0.018)	-0.014 (0.017)
Have shared study ConnectCard with someone else	2,796	0.042	0.004 (0.014)	0.009 (0.013)	0.005 (0.009)
Trips taken with children yesterday across all modes (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)
Still have study ConnectCard in possession	2,677	0.693	0.165***††† (0.030)	0.242***††† (0.028)	0.077***††† (0.015)
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: Impacts on self-reported employment outcomes at 15 months after enrollment

Outcome	N	Control mean	Treatment effect: Half fares	Treatment effect: Free fares	Free vs. half fares
Employment situation					
Employed	3,871	0.523	-0.022 (0.018)	-0.020 (0.018)	0.002 (0.017)
Unemployed and seeking work	3,871	0.177	0.013 (0.016)	-0.005 (0.015)	-0.017 (0.015)
In school or training program	3,871	0.038	0.011 (0.007)	0.012* (0.007)	0.002 (0.007)
Unable to work due to illness/injury	3,871	0.182	<0.001 (0.015)	0.018 (0.015)	0.017 (0.014)
Homemaker	3,871	0.057	<0.001 (0.009)	-0.006 (0.008)	-0.006 (0.008)
Retired	3,871	0.029	-0.008 (0.008)	-0.011 (0.007)	-0.003 (0.006)
Hourly wage at main job ($; excludes zeroes)	1,787	15.05	-0.269 (0.377)	-0.229 (0.372)	0.040 (0.364)
Weekly work hours (N)	3,871	17.13	-1.13 (0.821)	-1.77** (0.792)	-0.638 (0.706)
Total monthly earnings ($)	3,871	633.8	-75.38* (39.99)	-75.97* (39.17)	-0.587 (33.32)
Total jobs held (N)	3,871	0.559	-0.061** (0.026)	-0.069*** (0.025)	-0.007 (0.023)
Rating of aspects of main job (1-10)					
Fit with your experience and skills	1,951	7.02	0.245 (0.182)	-0.075 (0.178)	-0.320* (0.172)
Opportunities for promotion over next 3 yrs	1,948	5.41	-0.202 (0.209)	-0.407** (0.201)	-0.206 (0.197)
Satisfied with aspects of main job					
Pay	1,949	0.344	-0.017 (0.033)	-0.030 (0.032)	-0.012 (0.030)
Other aspects of main job besides pay	1,940	0.350	0.023 (0.033)	0.022 (0.032)	-0.001 (0.031)
All aspects of job overall	1,950	0.464	0.007 (0.035)	-0.014 (0.034)	-0.021 (0.032)
Do you work from home for main job?					
No	1,950	0.830	0.025 (0.026)	0.015 (0.025)	-0.009 (0.023)
Yes	1,950	0.088	-0.005 (0.021)	-0.026 (0.019)	-0.022 (0.017)
Sometimes	1,950	0.083	-0.020 (0.018)	0.011 (0.019)	0.031* (0.017)
Primary commute mode to main job last week					
Bus	1,789	0.580	0.028 (0.035)	0.089*** (0.033)	0.061* (0.031)
Light rail	1,789	0.031	-0.002 (0.011)	0.004 (0.011)	0.006 (0.010)
Personal car	1,789	0.170	-0.027 (0.024)	-0.039* (0.022)	-0.012 (0.020)
Carpool	1,789	0.031	0.005 (0.014)	-0.003 (0.013)	-0.007 (0.013)
Walk or bike	1,789	0.107	-0.040* (0.022)	-0.054** (0.022)	-0.014 (0.018)
Ridesharing app (e.g. Uber or Lyft)	1,789	0.043	0.026 (0.017)	<0.001 (0.016)	-0.025 (0.016)
Round-trip commute time on typical day (minutes)	1,380	73.89	16.38 (13.63)	15.93 (13.06)	-0.451 (13.66)
Actively searched for job in past 4 weeks	3,067	0.468	-0.019 (0.024)	-0.015 (0.023)	0.004 (0.022)
Job search activities among active searchers					
Jobs applied to in past 4 weeks (N)	1,296	10.90	-2.32** (1.00)	-0.878 (1.10)	1.44* (0.873)
Time spent searching for a job last week (hours)	1,290	10.72	-0.654 (1.02)	-0.672 (0.888)	-0.018 (0.899)

Table A2: Impacts on self-reported employment outcomes at 15 months after enrollment *(continued)*

Outcome	N	Control mean	Treatment effect: Half fares	Treatment effect: Free fares	Free vs. half fares
Applied to a job posting	1,297	0.685	0.012 (0.038)	0.029 (0.037)	0.017 (0.035)
Looked at job postings	1,297	0.736	0.016 (0.036)	-0.029 (0.035)	-0.045 (0.033)
Traveled around to search in person	1,297	0.209	-0.057* (0.032)	<0.001 (0.033)	0.058** (0.028)
Posted or updated resume or other info	1,297	0.377	-0.027 (0.038)	0.039 (0.038)	0.066* (0.035)
Contacted an employer in person	1,297	0.243	-0.017 (0.033)	-0.021 (0.032)	-0.004 (0.030)
Contacted an employer online	1,297	0.328	-0.014 (0.036)	0.013 (0.036)	0.026 (0.033)

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. Data comes from the post-endline survey, which took place 15 months after the participant enrolled in the study. The hourly wage, weekly work hours, and monthly earnings numbers only include the respondents who reported being currently employed or on a temporary leave from work. The questions about job search activities include respondents who are not currently employed and those who are currently employed but reported looking for a new or additional job. 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 A3: Impacts 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)
Rating of current health					
Poor	3,807	0.109	-0.014	-0.009	0.005
			(0.013)	(0.013)	(0.012)
Fair	3,807	0.340	0.029	0.051***	0.022
			(0.020)	(0.020)	(0.019)
Good	3,807	0.370	-0.004	-0.032	-0.028
			(0.021)	(0.020)	(0.019)
Very good	3,807	0.124	-0.005	<0.001	0.005
			(0.013)	(0.013)	(0.012)
Excellent	3,807	0.058	-0.006	-0.010	-0.004
			(0.010)	(0.010)	(0.009)
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 chronic health condition(s)	3,783	0.391	0.003	0.041**	0.038**
			(0.019)	(0.019)	(0.018)
Which chronic conditions have you been diagnosed with?					
Hypertension/high blood pressure	2,410	0.391	0.030	-0.005	-0.036
			(0.026)	(0.024)	(0.024)
High cholesterol	2,410	0.190	0.011	0.033*	0.021
			(0.019)	(0.019)	(0.018)
Coronary heart disease	2,410	0.051	-0.005	-0.017*	-0.011
			(0.011)	(0.010)	(0.009)
Asthma	2,410	0.399	-0.005	-0.002	0.003
			(0.027)	(0.026)	(0.025)
Cancer or malignancy of any kind	2,410	0.057	0.001	0.007	0.006
			(0.011)	(0.011)	(0.011)
Diabetes/prediabetes/borderline diabetes	2,410	0.240	0.013	0.032	0.019
			(0.023)	(0.022)	(0.021)
C.O.P.D., emphysema, or chronic bronchitis	2,410	0.109	-0.004	-0.003	0.001
			(0.014)	(0.014)	(0.013)
Hepatitis	2,410	0.049	-0.019*	-0.017	0.002
			(0.011)	(0.010)	(0.009)
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)

Table A3: Impacts on self-reported health outcomes at 15 months after enrollment *(continued)*

			Treatment effect		
Outcome	N	Control mean	Half fares	Free fares	Free vs. half fares
ER visits in past 6 months (N)	3,571	0.935	0.002 (0.071)	0.021 (0.066)	0.019 (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 (0.017)	-0.016 (0.017)	-0.008 (0.016)
Skipped doses	738	0.443	0.021 (0.053)	-0.019 (0.052)	-0.040 (0.048)
Took less medication	738	0.434	-0.032 (0.051)	-0.020 (0.050)	0.012 (0.047)
Delayed filling a prescription	738	0.605	0.043 (0.052)	0.048 (0.051)	0.006 (0.048)
Primary mode of travel to last doctor's appt					
Bus or light rail	3,697	0.546	0.006 (0.021)	0.087***††† (0.020)	0.081***††† (0.019)
Walk or bike	3,697	0.082	-0.001 (0.012)	-0.023** (0.011)	-0.022** (0.010)
Personal car	3,697	0.169	-0.017 (0.015)	-0.035** (0.014)	-0.018 (0.013)
Ridesharing app	3,697	0.096	0.016 (0.013)	-0.025** (0.012)	-0.042***†† (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 (0.018)	0.004 (0.017)	0.016 (0.016)
Feeling down, depressed, or hopeless	3,648	0.253	-0.017 (0.018)	-0.017 (0.018)	<0.001 (0.017)
Feeling tired or having little energy	3,657	0.324	-0.003 (0.020)	0.007 (0.019)	0.010 (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)	-0.018 (0.018)	0.019 (0.016)
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)

Table A3: Impacts on self-reported health outcomes at 15 months after enrollment *(continued)*

			Treatment effect		
Outcome	N	Control mean	Half fares	Free fares	Free vs. half fares
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: Impacts 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: Impacts on health care utilization among the child sample within the first 365 days after enrollment

Outcome (N = 4,928)	Control mean	Treatment effect: 50% discount	Treatment effect: 100% discount	100% vs. 50% effects
Received any health care	0.835	0.001 (0.013)	0.019 (0.013)	0.018 (0.013)
A. Physical health care				
Has at least one claim				
Any physical health care	0.818	<0.001 (0.014)	0.019 (0.013)	0.019 (0.013)
Non-ER outpatient	0.790	-0.009 (0.014)	0.014 (0.014)	0.023* (0.014)
ER outpatient	0.295	<0.001 (0.016)	-0.006 (0.016)	-0.006 (0.016)
Non-ER inpatient	0.011	-0.004 (0.003)	-0.004 (0.003)	<0.001 (0.003)
ER inpatient	0.015	-0.005 (0.004)	-0.005 (0.004)	<0.001 (0.003)
Days with at least one claim (N)				
Any physical health care	5.62	0.235 (0.374)	0.152 (0.328)	-0.084 (0.362)
Non-ER outpatient	3.21	0.213 (0.263)	0.059 (0.187)	-0.154 (0.254)
ER outpatient	0.500	-0.016 (0.036)	0.034 (0.039)	0.049 (0.037)
Non-ER inpatient	0.045	-0.028* (0.017)	0.013 (0.034)	0.042 (0.030)
ER inpatient	0.069	-0.020 (0.024)	-0.025 (0.022)	-0.005 (0.021)
Prescription fills (N)	3.38	-0.028 (0.236)	0.064 (0.236)	0.092 (0.225)
Days covered by a prescription (N)	55.10	0.316 (3.27)	3.91 (3.26)	3.59 (3.29)
B. Behavioral health care				
Has at least one claim				
Any behavioral health care	0.295	-0.001 (0.016)	0.032** (0.016)	0.033** (0.016)
Non-crisis	0.281	0.002 (0.016)	0.031* (0.016)	0.029* (0.016)
Crisis	0.072	-0.001 (0.009)	0.007 (0.009)	0.008 (0.009)
Substance use treatment	0.003	0.004* (0.002)	0.003 (0.002)	<0.001 (0.003)
Days with at least one claim (N)				
Any behavioral health care	5.99	0.108 (0.705)	1.21* (0.725)	1.10 (0.717)
Non-crisis	5.26	0.090 (0.662)	1.04 (0.679)	0.951 (0.673)
Crisis	0.215	-0.063 (0.041)	-0.026 (0.043)	0.038 (0.032)
Substance use treatment	0.021	0.042 (0.032)	0.044 (0.035)	0.002 (0.044)
Prescription fills (N)	0.813	0.032 (0.119)	0.190 (0.120)	0.158 (0.126)
Days covered by a prescription (N)	19.02	-0.588 (2.33)	3.42 (2.47)	4.01* (2.41)
Cost of care to managed care org. ($)	961.7	-74.53 (167.9)	153.5 (171.4)	228.0 (174.1)

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 365 days after enrollment. Data comes from Medicaid claims. The ‘received any health care’ outcome in the first row represents the likelihood that the child received any type of Medicaid-funded health care in the first 365 days post-enrollment. The ‘days with at least one claim’ outcome counts the cumulative number of days on which the child had at least one claim in the first 365 days post-enrollment. The ‘days covered by a prescription’ outcome counts the cumulative number of days in the first 365 days post-enrollment for which the child had a remaining dose from a filled prescription. The ‘cost of care to managed care org’ outcome measures the cumulative dollar amount of claims for the child that providers have billed to the Allegheny County Medicaid behavioral health managed care organization. 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

Table A6: Impacts 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)	2,550	11.91	0.585 (0.774)	2.11*** (0.783)	1.53* (0.788)
Absences - Excused (N)	2,550	2.57	0.160 (0.214)	0.342 (0.220)	0.182 (0.232)
Absences - Unexcused (N)	2,550	9.34	0.426 (0.703)	1.77** (0.712)	1.35* (0.718)
Out-of-school suspensions (N)	2,550	0.589	-0.048 (0.116)	0.055 (0.115)	0.103 (0.100)
2023-2024 school year					
Absences - Any (N)	2,533	18.55	-1.55 (1.15)	2.04* (1.20)	3.59*** (1.14)
Absences - Excused (N)	2,533	3.71	-0.126 (0.298)	0.310 (0.291)	0.436 (0.296)
Absences - Unexcused (N)	2,533	14.84	-1.43 (1.06)	1.73 (1.11)	3.15*** (1.04)
Out-of-school suspensions (N)	2,533	0.872	-0.041 (0.137)	-0.014 (0.123)	0.027 (0.131)
B. Pennsylvania System of School Assessment (PSSA) test scores					
2022-2023 school year					
English Language Arts score (SD)	652	-0.164	0.083 (0.056)	0.090 (0.056)	0.007 (0.058)
Math score (SD)	657	-0.527	0.105* (0.054)	0.065 (0.054)	-0.041 (0.056)
Science score (SD)	211	1.76	0.009 (0.173)	0.120 (0.181)	0.111 (0.183)
Mean score across all subjects (SD)	662	-0.114	0.093 (0.061)	0.058 (0.061)	-0.035 (0.063)
2023-2024 school year					
English Language Arts score (SD)	697	-0.241	0.103* (0.054)	0.106** (0.054)	0.003 (0.056)
Math score (SD)	700	-0.467	0.059 (0.049)	0.086 (0.052)	0.026 (0.053)
Science score (SD)	217	1.77	0.089 (0.168)	0.279* (0.165)	0.190 (0.166)
Mean score across all subjects (SD)	708	-0.153	0.095* (0.057)	0.149** (0.060)	0.054 (0.062)

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

Table A7: Impacts on cumulative employment outcomes for older youth in the first four full calendar quarters after enrollment

		Treatment effect		
Outcome (N = 697)	Control mean	Half fares	Free fares	Free vs. half fares
Had any paid employment	0.668	0.049 (0.043)	0.017 (0.043)	-0.033 (0.042)
Number of quarters with employment (N)	1.88	0.109 (0.150)	0.034 (0.150)	-0.075 (0.149)
Earnings ($)	3,804	401.9 (487.8)	-30.26 (473.6)	-432.1 (485.3)
Number of employers worked for (N)	1.29	0.155 (0.132)	0.027 (0.129)	-0.128 (0.125)
Number of 2-digit NAICS sectors worked for (N)	0.961	0.165* (0.090)	0.065 (0.086)	-0.101 (0.089)
Received any UI benefits	0.004	-0.004 (0.004)	-0.004 (0.004)	0 (<0.001)
Amount of UI benefits received ($)	22.25	-22.25 (22.25)	-22.25 (22.25)	0 (<0.001)

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 four full calendar quarters after the quarter in which the person enrolled in the study. Data comes from Pennsylvania unemployment insurance (UI) administrative records. The 'Earnings ($)' and 'Amount of UI benefits ($)' outcomes include individuals with zero earnings or zero benefits in the first four quarters. Estimates are from a regression of the outcome on indicators for each treatment status, with no covariate adjustment. Column N indicates the number of individuals 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

Table A8: Impacts on criminal justice outcomes in first 365 days after enrollment

Outcome (N = 9,544)	Control mean	Treatment effect: Half fares	Treatment effect: Free fares	Free vs. half fares
A. Likelihood of having a criminal charge in Allegheny County				
Any criminal charge	0.079	0.012* (0.007)	0.006 (0.006)	-0.005 (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)	0.006 (0.006)	-0.007 (0.006)
Felony	0.033	-0.002 (0.004)	0.001 (0.004)	0.004 (0.004)
By type of crime				
Person	0.017	0.009** (0.004)	0.006* (0.004)	-0.002 (0.004)
Property	0.028	0.004 (0.004)	<0.001 (0.004)	-0.004 (0.004)
Public Order	0.015	-0.003 (0.003)	-0.003 (0.003)	<0.001 (0.003)
Domestic violence	0.020	-0.002 (0.003)	-0.005 (0.003)	-0.003 (0.003)
Drugs	0.015	-0.002 (0.003)	<0.001 (0.003)	0.001 (0.003)
Weapons	0.003	<0.001 (0.001)	0.001 (0.001)	<0.001 (0.002)
Motor vehicle - DUI	0.003	<0.001 (0.001)	<0.001 (0.001)	<0.001 (0.001)
Motor vehicle - Non-DUI	<0.001	<0.001 (<0.001)	<0.001 (<0.001)	<0.001 (<0.001)
Other crime type	0.001	<0.001 (<0.001)	<0.001 (<0.001)	<0.001 (<0.001)
B. Likelihood of failing to appear for an Allegheny County criminal court hearing				
Any hearing	0.050	-0.018 (0.011)	-0.003 (0.013)	0.014 (0.010)
First pretrial hearing	0.071	-0.026 (0.021)	0.006 (0.027)	0.032 (0.023)
Any pretrial hearing	0.042	-0.001 (0.014)	0.003 (0.014)	0.004 (0.014)
Any posttrial hearing	0.040	-0.084* (0.045)	-0.092* (0.045)	-0.008 (0.013)
C. Incarcerations in Allegheny County Jail				
Spent any time in jail	0.043	0.002 (0.005)	<0.001 (0.005)	-0.002 (0.005)
Days spent in jail (N)	2.51	-0.355 (0.412)	-0.110 (0.457)	0.245 (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 A9: Impacts 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 365 days after enrollment				
Stayed at homeless shelter	0.018	<0.001	-0.001	-0.002
		(0.003)	(0.003)	(0.003)
Days spent in homeless shelter (N)	1.43	-0.243	-0.486	-0.243
		(0.336)	(0.298)	(0.279)
B. Involvement with child welfare services in first 365 days after enrollment				
Had a child welfare referral	0.147	0.005	0.012	0.007
		(0.008)	(0.008)	(0.008)
Child welfare referrals (N)	0.612	0.045	0.037	-0.008
		(0.047)	(0.044)	(0.045)
C. Likelihood of receiving public benefits in 12th month after enrollment				
SNAP	0.837	<0.001	-0.002	-0.003
		(0.009)	(0.010)	(0.010)
TANF	0.059	-0.005	-0.003	0.002
		(0.005)	(0.005)	(0.005)
Medicaid	0.880	0.005	-0.002	-0.007
		(0.007)	(0.008)	(0.007)
SSI	0.150	-0.002	0.001	0.003
		(0.004)	(0.004)	(0.004)
Section 8 rental subsidy	0.223	<0.001	<0.001	0.001
		(0.004)	(0.004)	(0.004)
Child care subsidy	0.070	<0.001	0.008	0.008
		(0.005)	(0.005)	(0.005)
D. Mean monthly benefit allotment, among benefit recipients ($)				
In November 2023				
SNAP	436.44	4.11	21.07**	16.96*
		(8.73)	(8.98)	(8.87)
TANF	177.67	-4.67	-7.13	-2.46
		(6.49)	(6.52)	(6.31)
In April 2024				
SNAP	423.98	8.24	23.15**	14.91
		(9.00)	(9.14)	(9.07)
TANF	176.30	-6.30	-8.95	-2.65
		(6.88)	(6.95)	(6.79)

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. The estimates in panel D are from t-test comparisons of mean differences that were calculated by PADHS based on data that was not available to the authors. 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: Impacts on number of Medical Assistance Transportation Program (MATP) trips taken per month

MATP trips per month (N = 9,544)	Control mean	Treatment effect		
		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 A11: Robustness of effect 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 impact of free fares relative to no discount on self-reported outcomes from travel diaries

Outcome	Control mean	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Number of places visited yesterday (N)	3.69	-0.648***	-0.553***	-0.563***	-0.605***	-0.570***	-0.551***	-0.489***
		(0.176)	(0.148)	(0.149)	(0.131)	(0.100)	(0.148)	(0.167)
Likelihood of taking at least one trip yesterday								
Car trip	0.346	-0.005	-0.029***	-0.031***	-0.019**	-0.033***	-0.029***	-0.031**
		(0.009)	(0.011)	(0.011)	(0.008)	(0.008)	(0.011)	(0.014)
Walk or bike trip	0.469	-0.060***	-0.046***	-0.046***	-0.051***	-0.049***	-0.046***	-0.043**
		(0.011)	(0.013)	(0.013)	(0.008)	(0.010)	(0.013)	(0.017)
PRT trip	0.576	0.006	0.025**	0.026**	0.011	0.028***	0.026**	0.032**
		(0.010)	(0.012)	(0.012)	(0.009)	(0.008)	(0.012)	(0.016)
Likelihood of leaving house yesterday								
For work	0.406	-0.019**	-0.025**	-0.026**	-0.023***	-0.026***	-0.024**	-0.029**
		(0.010)	(0.011)	(0.011)	(0.008)	(0.008)	(0.011)	(0.014)
For school	0.131	-0.017**	-0.012*	-0.012*	-0.018***	-0.012**	-0.011	-0.010
		(0.007)	(0.007)	(0.007)	(0.006)	(0.005)	(0.007)	(0.009)
For groceries	0.508	-0.045***	-0.029***	-0.030***	-0.040***	-0.028***	-0.028***	-0.024*
		(0.010)	(0.011)	(0.011)	(0.009)	(0.007)	(0.011)	(0.014)
For leisure	0.238	-0.016*	-0.024**	-0.025***	-0.016**	-0.026***	-0.023**	-0.029**
		(0.008)	(0.010)	(0.010)	(0.008)	(0.008)	(0.010)	(0.012)
For health care	0.170	-0.024***	-0.010	-0.011	-0.017***	-0.008*	-0.009	-0.006
		(0.007)	(0.007)	(0.007)	(0.007)	(0.005)	(0.007)	(0.009)
For social services	0.084	-0.030***	-0.019***	-0.020***	-0.027***	-0.019***	-0.018***	-0.019***
		(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	(0.006)
For other reason	0.281	-0.023***	-0.013	-0.011	-0.027***	-0.011	-0.013	-0.008
		(0.009)	(0.010)	(0.010)	(0.008)	(0.008)	(0.010)	(0.012)
Did not leave house yesterday	0.134	0.025***	0.022***	0.023***	0.026***	0.021***	0.021***	0.018*
		(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.007)	(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		
Only uses diaries from follow-up surveys								
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 impact of free fares relative to no discount on mobility outcomes from smartphone GPS data

Outcome	Control mean	(1)	(2)	(3)	(4)	(5)	(6)
Likelihood of taking at least one trip on a given day (%)							
Public transportation	0.205	0.073*** (0.027)	0.069** (0.031)	0.052** (0.026)	0.088** (0.036)	0.062** (0.026)	0.003 (0.060)
Private vehicle	0.520	-0.050 (0.032)	-0.049 (0.034)	-0.056* (0.032)	-0.043 (0.044)	-0.069** (0.029)	0.025 (0.064)
Walk or bike	0.298	0.022 (0.029)	0.019 (0.031)	0.022 (0.025)	0.056 (0.041)	0.028 (0.028)	0.028 (0.060)
All travel modes	0.702	-0.040 (0.029)	-0.041 (0.032)	-0.039 (0.027)	-0.013 (0.042)	-0.031 (0.023)	-0.008 (0.061)
Number of trips per week (N)							
Public transportation	3.47	1.56** (0.624)	0.999 (0.844)	1.48** (0.716)	1.88** (0.872)	1.36* (0.790)	0.846 (1.44)
Private vehicle	13.39	-2.18 (1.35)	-1.79 (1.42)	-1.67 (1.44)	-0.035 (1.51)	-1.99 (1.36)	-1.22 (2.52)
Walk or bike	4.94	0.017 (0.621)	-0.012 (0.637)	0.385 (0.513)	0.787 (0.875)	0.308 (0.548)	0.403 (1.38)
All travel modes	21.86	-0.622 (1.50)	-0.832 (1.70)	-0.108 (1.65)	1.38 (1.95)	-0.671 (1.59)	0.263 (3.43)
Time spent traveling per day (hours)							
By public transportation	0.202	0.079** (0.038)	0.038 (0.049)	0.093*** (0.035)	0.110** (0.055)	0.102*** (0.032)	0.084 (0.080)
By private vehicle	0.830	-0.095 (0.087)	-0.100 (0.106)	-0.180** (0.088)	0.037 (0.115)	-0.203** (0.089)	0.136 (0.182)
By walking or biking	0.185	0.016 (0.029)	0.019 (0.030)	-0.003 (0.034)	0.045 (0.037)	-0.015 (0.036)	0.070 (0.071)
All travel modes	1.30	-0.051 (0.101)	-0.103 (0.120)	-0.182* (0.101)	0.123 (0.137)	-0.201** (0.093)	0.231 (0.212)
Total distance traveled per day (miles)							
By public transportation	1.57	0.628** (0.306)	0.466 (0.413)	0.974*** (0.259)	0.575 (0.462)	1.03*** (0.243)	0.825 (0.634)
By private vehicle	8.65	-2.03* (1.15)	-1.13 (1.19)	-1.45* (0.874)	-2.20 (1.98)	-1.25 (0.884)	-0.687 (2.01)
By walking or biking	0.310	-0.087* (0.051)	-0.051 (0.039)	-0.020 (0.036)	-0.065 (0.073)	-0.038 (0.033)	0.052 (0.142)
All travel modes	12.03	-1.72 (1.46)	-0.644 (1.50)	-1.26 (1.36)	-0.834 (2.12)	-1.04 (1.20)	-6.84 (4.83)
Mean daily maximum distance from home (miles)	21.63	-9.50 (9.93)	-3.31 (7.70)	-1.52 (2.67)	-9.04 (10.77)	-0.133 (2.19)	-11.49 (10.25)
Likelihood of leaving house on a given day (%)	0.461	-0.068* (0.038)	-0.054 (0.047)	-0.069 (0.045)	-0.046 (0.036)	-0.038 (0.049)	-0.002 (0.095)
Number of times left house per day (N)	0.703	-0.148** (0.069)	-0.118 (0.076)	-0.133* (0.073)	-0.126 (0.091)	-0.087 (0.076)	-0.081 (0.156)

Table A13: Robustness of impact of 100% discount relative to no discount on mobility outcomes from smartphone GPS data *(continued)*

Outcome	Control mean	(1)	(2)	(3)	(4)	(5)	(6)
Time spent at home per day (hours)	11.91	-0.806 (0.923)	-0.408 (1.11)	-0.746 (1.22)	-0.132 (0.745)	0.194 (1.28)	-0.251 (2.35)
Number of visits per week (N)							
Places to eat or drink	1.72	-0.121 (0.230)	0.034 (0.223)	-0.101 (0.246)	-0.076 (0.299)	-0.221 (0.256)	-0.235 (0.529)
Grocery stores	0.717	0.081 (0.101)	0.115 (0.125)	0.089 (0.106)	0.124 (0.137)	0.027 (0.107)	0.234 (0.223)
Health care	0.289	0.050 (0.070)	-0.049 (0.136)	0.043 (0.054)	0.136*** (0.052)	0.053 (0.056)	0.098 (0.196)
School	0.511	-0.144 (0.095)	-0.138 (0.104)	-0.122 (0.113)	0.033 (0.125)	-0.148 (0.109)	0.371 (0.264)
Shopping (non-food)	3.04	-0.048 (0.305)	0.041 (0.329)	0.058 (0.286)	0.533 (0.430)	0.092 (0.247)	-1.29* (0.701)
Gas stations and convenience stores	1.48	-0.375* (0.207)	-0.265 (0.169)	-0.196 (0.168)	-0.133 (0.277)	-0.184 (0.173)	0.482 (0.506)
Transportation facilities	1.62	0.307 (0.288)	0.054 (0.420)	0.184 (0.351)	0.451 (0.447)	0.061 (0.438)	0.902 (0.777)
Private residences besides own home	<0.001	0.002 (0.002)	0.001 (<0.001)	0.002 (0.002)	0.002 (0.002)	0.002 (0.001)	-0.003 (0.002)
Other types of locations	1.71	0.040 (0.199)	-0.154 (0.210)	0.075 (0.186)	0.275 (0.238)	0.005 (0.202)	0.077 (0.520)
Pooled mean outcome		X	X	X	X	X	
Day-level panel data with day, month, & year FE's							X
Includes benchmark covariates			X	X		X	X
Includes pre-enrollment outcome as covariate				X		X	X
Post-double LASSO covariate selection					X		
Includes weights for GPS day coverage						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 (5) 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) 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 effect of free fares relative to no discount on employment outcomes

	Control mean	(1)	(2)	(3)	(4)	(5)	(6)
A. Cumulative outcomes in first 4 calendar quarters after enrollment, from UI administrative records							
Had any paid employment	0.632	0.013	0.013	0.014	0.013		0.013
		(0.012)	(0.010)	(0.009)	(0.010)		(0.010)
Number of quarters with employment (N)	2.04	0.046	0.051	0.054*	0.060*		0.051
		(0.045)	(0.036)	(0.031)	(0.035)		(0.036)
Earnings ($)	11,120	333.9	358.4	338.4	471.0		255.8
		(382.9)	(332.2)	(268.4)	(299.0)		(313.6)
Number of employers worked for (N)	1.31	0.056	0.054	0.021	0.059*		0.054
		(0.039)	(0.035)	(0.030)	(0.033)		(0.035)
Number of 2-digit NAICS sectors worked in (N)	0.986	0.027	0.026	0.023	0.030		0.026
		(0.025)	(0.022)	(0.020)	(0.022)		(0.022)
Received any UI benefits	0.068	<0.001	<0.001	-0.001	-0.003		<0.001
		(0.006)	(0.006)	(0.006)	(0.006)		(0.006)
Amount of UI benefits received ($)	249.4	-10.80	-9.78	-21.44	-25.28		-14.09
		(30.47)	(30.17)	(29.31)	(30.51)		(25.69)
B. Outcomes in 4th calendar quarter after enrollment, from UI administrative records							
Had any paid employment	0.508	0.012	0.012	0.013	0.014		0.012
		(0.013)	(0.011)	(0.010)	(0.012)		(0.011)
Earnings ($)	3,012	54.61	57.01	52.53	112.2		23.74
		(110.7)	(99.85)	(87.87)	(95.55)		(94.73)
Earnings if employed ($; excludes zeroes)	5,923	-28.34	141.3	-75.72	-44.26		81.50
		(158.6)	(178.1)	(164.7)	(154.8)		(169.9)
C. Self-reported outcomes from 11-month follow-up survey							
Currently employed	0.524	-0.018	-0.013		0.004	-0.019	-0.013
		(0.020)	(0.018)		(0.022)	(0.019)	(0.018)
Hourly wage at main job ($; excludes zeroes)	15.33	0.152	0.443		0.160	0.199	-0.562*
		(0.688)	(0.695)		(0.692)	(0.599)	(0.329)
Total jobs held (N)	0.589	-0.043	-0.038		-0.035	-0.043	-0.054**
		(0.062)	(0.076)		(0.063)	(0.081)	(0.025)
Weekly work hours (N)	16.78	-1.60**	-1.38*		-1.05	-1.60**	-1.38*
		(0.799)	(0.737)		(0.889)	(0.805)	(0.737)
Monthly earnings ($)	927.5	-266.7*	-179.6		-223.9*	-225.2*	-74.71**
		(139.1)	(119.3)		(132.0)	(119.6)	(34.34)
Quarterly earnings ($)	2,782	-800.0*	-538.7		-671.6*	-675.5*	-224.1**
		(417.4)	(358.0)		(395.9)	(370.7)	(103.0)
Quarterly earnings if employed ($; excludes zeroes)	6,161	-1,206	225.1		-1,372	-417.0	232.2
		(928.5)	(965.3)		(876.1)	(924.0)	(655.0)
Jobs applied to in past 4 weeks (N), among active job seekers	11.04	0.944	2.47		0.722	1.55	-0.775
		(3.25)	(4.26)		(3.30)	(3.59)	(0.889)
No covariates		X					
Includes benchmark covariates			X	X		X	X
Includes outcome in quarter 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 outcomes in panels A and B come from Pennsylvania unemployment insurance (UI) administrative records. The outcomes in panel C are self-reported and come from the endline survey, which took place 11 months after random assignment. 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 effect of free fares vs. no discount on health care utilization among the adult sample within the first 365 days after enrollment

Outcome (N = 9,544)	Control mean	(1)	(2)	(3)	(4)	(5)
Received any health care	0.889	0.004 (0.008)	0.003 (0.008)	0.003 (0.008)		-0.004 (0.008)
A. Physical health care						
Has at least one claim						
Any physical health care	0.871	0.002 (0.008)	0.001 (0.008)	<0.001 (0.008)		-0.004 (0.009)
Non-ER outpatient	0.835	0.005 (0.009)	0.005 (0.009)	0.004 (0.009)		<0.001 (0.010)
ER outpatient	0.534	-0.013 (0.013)	-0.013 (0.012)	-0.011 (0.012)		-0.010 (0.014)
Non-ER inpatient	0.056	0.015** (0.006)	0.014** (0.006)	0.015** (0.006)		0.009 (0.007)
ER inpatient	0.058	-0.003 (0.006)	-0.003 (0.006)	-0.001 (0.006)		-0.002 (0.007)
Days with at least one claim (N)						
Any physical health care	22.79	0.739 (1.08)	0.792 (1.05)	0.461 (0.519)	0.446 (0.504)	0.605 (0.556)
Non-ER outpatient	13.60	0.481 (0.993)	0.506 (0.978)	0.200 (0.466)	0.189 (0.445)	-0.006 (0.484)
ER outpatient	1.58	-0.035 (0.076)	-0.036 (0.075)	-0.009 (0.061)	-0.003 (0.050)	0.109 (0.080)
Non-ER inpatient	0.244	0.184** (0.076)	0.185** (0.077)	0.210** (0.093)	0.062** (0.026)	0.146* (0.081)
ER inpatient	0.438	-0.001 (0.069)	0.001 (0.068)	0.027 (0.065)	0.016 (0.037)	0.213 (0.140)
Prescription fills (N)	12.53	<0.001 (0.434)	0.027 (0.418)	-0.054 (0.404)	0.041 (0.377)	0.401 (0.268)
Days covered by a prescription (N)	155.7	2.88 (3.66)	3.19 (3.55)	0.833 (2.24)	0.833 (2.24)	2.65 (2.45)
B. Behavioral health care						
Has at least one claim						
Any behavioral health care	0.601	-0.003 (0.012)	-0.004 (0.012)	-0.002 (0.012)		-0.014 (0.012)
Non-crisis	0.542	-0.011 (0.013)	-0.011 (0.012)	-0.009 (0.012)		-0.019 (0.012)
Crisis	0.294	-0.011 (0.011)	-0.011 (0.011)	-0.005 (0.011)		-0.008 (0.012)
Substance use treatment	0.103	-0.003 (0.008)	-0.003 (0.007)	-0.003 (0.007)		0.005 (0.007)
Days with at least one claim (N)						
Any behavioral health care	16.13	-1.53 (0.959)	-1.52 (0.937)	-1.02* (0.568)	-1.26** (0.509)	0.911 (0.575)
Non-crisis	10.15	-0.860 (0.785)	-0.844 (0.777)	-0.367 (0.401)	-0.735** (0.338)	0.619 (0.411)
Crisis	0.974	0.120 (0.097)	0.122 (0.098)	0.198** (0.096)	0.098* (0.056)	0.248** (0.103)
Substance use treatment	3.93	-0.856* (0.458)	-0.858* (0.452)	-0.913** (0.362)	-0.459* (0.265)	-0.018 (0.390)
Prescription fills (N)	2.63	0.026 (0.152)	0.021 (0.148)	-0.029 (0.143)	-0.009 (0.133)	0.117 (0.115)
Days covered by a prescription (N)	62.90	1.89 (2.96)	1.91 (2.86)	1.95 (1.73)	1.95 (1.73)	4.17** (1.78)
Cost of care to managed care org. ($)	2,288	-303.6 (207.4)	-305.9 (204.0)	-42.82 (169.2)	-48.54 (118.1)	526.3** (259.3)
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 the 100% discount relative to no discount on health care utilization for the adult sample, as measured in the first 365 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 365 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 365 days post-enrollment. The 'days covered by a prescription' outcome counts the cumulative number of days in the first 365 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: Heterogeneity in impact of free fares relative to no discount on select outcomes, by assorted baseline subgroups (pt. 1)

	Children enrolled		Sex		Race	
	No	Yes	Male	Female	Non-White	White
A. Public transit trips per week (N; from GPS data)						
Control mean	3.96	2.29	3.84	3.31	3.63	3.33
Treatment effect	0.161	1.84	1.50	0.762	0.275	1.87**
SE	(1.04)	(2.04)	(1.13)	(1.06)	(1.39)	(0.746)
P-value of diff.	[0.109]		[0.501]		[0.735]	
B. PRT spending last week ($; from post-endline survey)						
Control mean	29.68	32.43	27.50	31.46	32.27	27.49
Treatment effect	-16.73***	-13.87***	-12.95***	-16.93***	-15.47***	-17.78***
SE	(1.48)	(3.04)	(2.58)	(1.34)	(1.47)	(1.91)
P-value of diff.	[0.629]		[0.227]		[0.518]	
C. Had any paid employment in Q1 - Q4 after enrollment (from UI data)						
Control mean	0.588	0.741	0.539	0.668	0.689	0.525
Treatment effect	0.014	0.016	0.015	0.012	0.010	0.011
SE	(0.012)	(0.029)	(0.021)	(0.012)	(0.013)	(0.017)
P-value of diff.	[0.842]		[0.927]		[0.914]	
D. Total earnings in Q1 - Q4 after enrollment ($; from UI data)						
Control mean	9,141	16,018	8,323	12,213	12,186	9,118
Treatment effect	495.8	-485.7	69.23	582.7	260.8	202.8
SE	(377.7)	(983.0)	(686.8)	(385.3)	(408.8)	(579.5)
P-value of diff.	[0.370]		[0.329]		[0.922]	
E. Number of days with a non-ER outpatient claim in first 365 days after enrollment (N; from Medicaid claims)						
Control mean	15.21	9.58	13.04	13.82	14.22	12.43
Treatment effect	0.781	-1.74	1.52	0.505	-0.208	1.41
SE	(1.27)	(3.16)	(1.58)	(1.28)	(1.46)	(1.17)
P-value of diff.	[0.620]		[0.849]		[0.351]	
N - Control	2,248	901	890	2,259	2,059	1,090
N - Treatment	2,204	950	880	2,274	2,099	1,055

Notes: This table reports heterogeneity in the effect of free fares versus no discount on select outcomes across sample subgroups 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 'children enrolled' subgroup 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 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

Table A17: Heterogeneity in impact of free fares relative to no discount on select outcomes, by assorted baseline subgroups (pt. 2)

	Has access to a car		Employed at baseline		Above 75p earnings	
	No	Yes	No	Yes	No	Yes
A. Public transit trips per week (N; from GPS data)						
Control mean	4.03	1.71	3.15	3.91	2.70	5.71
Treatment effect	0.960	-0.418	1.60**	-0.169	1.63***	-4.10**
SE	(0.942)	(2.03)	(0.753)	(1.52)	(0.621)	(1.71)
P-value of diff.	[0.498]		[0.947]		[0.620]	
B. PRT spending last week ($; from post-endline survey)						
Control mean	32.05	24.57	29.88	31.45	30.20	31.72
Treatment effect	-17.20***	-10.92***	-16.48***	-15.19***	-16.29***	-19.26***
SE	(1.31)	(3.96)	(1.71)	(1.78)	(1.44)	(3.53)
P-value of diff.	[0.053]		[0.860]		[0.752]	
C. Had any paid employment in Q1 - Q4 after enrollment (from UI data)						
Control mean	0.623	0.671	0.419	0.910	0.520	0.962
Treatment effect	0.016	-0.029	0.019	<0.001	0.010	0.046**
SE	(0.011)	(0.027)	(0.016)	(0.013)	(0.012)	(0.020)
P-value of diff.	[0.413]		[0.290]		[0.323]	
D. Total earnings in Q1 - Q4 after enrollment ($; from UI data)						
Control mean	10,496	13,923	4,838	19,344	6,085	26,075
Treatment effect	-152.9	867.2	532.4	332.3	317.8	2,367*
SE	(350.3)	(1,214)	(377.0)	(643.4)	(314.8)	(1,297)
P-value of diff.	[0.017]		[0.667]		[0.453]	
E. Number of days with a non-ER outpatient claim in first 365 days after enrollment (N; from Medicaid claims)						
Control mean	13.63	13.49	17.96	7.87	15.58	7.72
Treatment effect	0.566	0.501	0.347	1.25	0.687	0.628
SE	(1.06)	(2.79)	(1.48)	(0.837)	(1.13)	(1.90)
P-value of diff.	[0.942]		[0.638]		[0.803]	
N - Control	2,580	569	1,788	1,361	2,331	781
N - Treatment	2,579	575	1,814	1,340	2,340	766

Notes: This table reports heterogeneity in the effect of free fares versus no discount on select outcomes across sample subgroups 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 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

Table A18: Heterogeneity in impact of free fares relative to no discount on GPS outcomes, by assorted baseline subgroups (pt. 1)

	Children enrolled		Race		Sex	
	No	Yes	Non-White	White	Male	Female
A. Number of public transit trips per week (N)						
Control mean	3.96	2.29	3.63	3.33	3.84	3.31
Treatment effect	0.161	1.84	0.275	1.87**	1.50	0.762
SE	(1.04)	(2.04)	(1.39)	(0.746)	(1.13)	(1.06)
P-value of diff.	[0.109]		[0.735]		[0.501]	
B. Number of private vehicle trips per week (N)						
Control mean	12.28	16.02	12.42	14.22	13.49	13.35
Treatment effect	0.297	-15.19***	-0.111	-2.29	-1.27	-1.57
SE	(1.70)	(2.86)	(1.85)	(1.96)	(2.43)	(1.76)
P-value of diff.	[0.057]		[0.813]		[0.606]	
C. Number of walk or bike trips per week (N)						
Control mean	5.84	2.78	4.25	5.53	7.82	3.73
Treatment effect	-0.893	5.14***	0.037	0.079	-0.915	0.253
SE	(0.822)	(1.70)	(1.05)	(0.811)	(1.55)	(0.686)
P-value of diff.	[0.018]		[0.731]		[0.105]	
D. Number of trips per week across all travel modes (N)						
Control mean	22.16	21.13	20.35	23.15	25.24	20.44
Treatment effect	-0.456	-8.23**	0.212	-0.400	-0.736	-0.571
SE	(2.14)	(3.98)	(2.51)	(2.00)	(3.02)	(1.97)
P-value of diff.	[0.820]		[0.832]		[0.361]	
N - Control	93	39	61	71	39	93
N - Treatment	131	50	85	96	63	118

Notes: This table reports the variation in treatment effects on smartphone GPS outcomes across certain sample subgroups defined by baseline characteristics. The 'children enrolled' subgroup 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 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

Table A19: Heterogeneity in impact of free fares relative to no discount on GPS outcomes, by assorted baseline subgroups (pt. 2)

	Has access to a car		Employed at baseline		In PRT 7-day freq. svc. walkshed	
	No	Yes	No	Yes	No	Yes
A. Number of public transit trips per week (N)						
Control mean	4.03	1.71	3.15	3.91	3.36	3.68
Treatment effect	0.960	-0.418	1.60**	-0.169	1.08	0.631
SE	(0.942)	(2.03)	(0.753)	(1.52)	(1.02)	(1.37)
P-value of diff.	[0.498]		[0.947]		[0.636]	
B. Number of private vehicle trips per week (N)						
Control mean	10.10	23.68	12.33	14.86	15.34	9.62
Treatment effect	-0.356	-4.01	-1.31	-1.65	-3.54**	1.73
SE	(1.25)	(6.29)	(2.06)	(2.00)	(1.74)	(2.31)
P-value of diff.	[0.515]		[0.625]		[0.028]	
C. Number of walk or bike trips per week (N)						
Control mean	5.67	2.67	4.65	5.35	4.42	5.95
Treatment effect	0.002	-4.07*	-0.016	-0.453	0.092	-0.694
SE	(0.709)	(2.24)	(0.651)	(1.25)	(0.707)	(1.22)
P-value of diff.	[0.927]		[0.965]		[0.814]	
D. Number of trips per week across all travel modes (N)						
Control mean	19.84	28.14	20.19	24.18	23.19	19.27
Treatment effect	0.593	-8.68	0.241	-2.30	-2.41	1.67
SE	(1.72)	(5.65)	(2.21)	(2.60)	(2.06)	(2.93)
P-value of diff.	[0.353]		[0.699]		[0.049]	
N - Control	100	32	77	55	87	45
N - Treatment	150	31	108	73	117	64

Notes: This table reports the variation in treatment effects on smartphone GPS outcomes across certain sample subgroups defined by baseline characteristics. The 'in PRT 7-day freq. svc. walkshed' subgroup indicates whether the participant lived within the Pittsburgh Regional Transit (PRT) 7-day frequent service walkshed at baseline. 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 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

Table A20: Heterogeneity in impact 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. The treatment effect in Panel D differs significantly between these two sub-samples. The effect is positive when limiting the control group to those who live with a higher-discount participant, but negative when limiting the control group to those who do not live with a higher-discount participant. This difference is not necessarily what we would expect to see if control members gain access to some discounted transit trips when living with a higher-discount participant. The results in this table thus do not provide clear evidence on the extent of treatment spillovers or the direction in which such spillovers might bias the treatment effects. Robust standard errors are in parentheses. ***p <0.01, **p <0.05, *p <0.1

Table A21: Heterogeneity in impact of fare discounts on adults' health care utilization within the first 365 days after enrollment, by baseline receipt of health care

	Half fares vs. no discount				Free fares vs. no discount			
	Full sample	No care in year before enrollment		Recv'd care in year before enrollment	Full sample	No care in year before enrollment		Recv'd care in year before enrollment
A. Days with any health care claim (N)								
N	9,544	1,033		8,511	9,544	1,033		8,511
Control mean	34.60	2.78		38.35	34.60	2.78		38.35
Treatment effect	-0.370	0.629		-1.16	-0.565	1.28		-0.811
SE	(0.757)	(0.778)		(1.44)	(0.740)	(0.881)		(1.47)
P-value of diff.			[0.994]				[0.266]	
B. Days with an ER outpatient physical health claim (N)								
N	9,544	4,545		4,999	9,544	4,545		4,999
Control mean	1.58	0.670		2.40	1.58	0.670		2.40
Treatment effect	-0.024	-0.037		-0.013	-0.009	-0.003		0.006
SE	(0.058)	(0.048)		(0.137)	(0.061)	(0.050)		(0.138)
P-value of diff.			[0.886]				[0.979]	
C. Days with a non-ER outpatient physical health claim (N)								
N	9,544	1,538		8,006	9,544	1,538		8,006
Control mean	13.60	2.12		15.78	13.60	2.12		15.78
Treatment effect	-0.007	-0.200		0.249	0.200	0.054		0.616
SE	(0.482)	(0.328)		(1.11)	(0.466)	(0.388)		(1.14)
P-value of diff.			[0.305]				[0.893]	
D. Days with a non-crisis behavioral health claim (N)								
N	9,544	4,612		4,932	9,544	4,612		4,932
Control mean	10.15	1.14		18.80	10.15	1.14		18.80
Treatment effect	-0.126	0.324		-3.03**	-0.367	-0.044		-1.57
SE	(0.425)	(0.255)		(1.37)	(0.401)	(0.197)		(1.46)
P-value of diff.			[0.014]				[0.272]	
E. Days with a crisis behavioral health claim (N)								
N	9,544	6,849		2,695	9,544	6,849		2,695
Control mean	0.974	0.439		2.32	0.974	0.439		2.32
Treatment effect	-0.011	-0.022		0.080	0.198**	0.108*		0.250
SE	(0.074)	(0.044)		(0.261)	(0.096)	(0.060)		(0.299)
P-value of diff.			[0.700]				[0.764]	

Notes: Table presents the effect of being assigned to each fare discount level on adult participants' utilization of various types of health care. Effects are shown for the full sample and by whether the participant received the given type of care in the 365 days before they enrolled in the study. Data comes from Medicaid claims. The care utilization outcomes are defined as the cumulative number of days in which the participant had at least one claim for the given type of care, as measured in the first 365 days after enrollment. Estimates come from a regression of the outcome on treatment indicators, 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 p-value of the difference between subgroup effects is calculated by regressing the outcome on a treatment indicator, an indicator for having received the given type of health care in the 365 days prior to study enrollment, and the interaction of these two variables. The p-value of the interaction term is reported in row 'P-value of diff.'. Robust standard errors are in parentheses. ***p <0.01, **p <0.05, *p <0.1

Table A22: Local average treatment effects (LATE) of free fares relative to no discount on travel behavior

Outcome	N	Control mean	Effect	First-stage F stat	First-stage R-squared
A. Outcomes from PRT farecard tap data					
PRT farecard taps per week (N)	6,130	0.298	5.17*** (0.104)	34,440	0.849
Proportion of days with > 0 taps	6,130	0.018	0.271*** (0.004)	34,440	0.849
B. Outcomes from post-endline survey					
PRT trips last week (N)	2,696	11.95	-0.735 (2.20)	19,210	0.881
PRT spending last week ($)	2,313	33.53	-17.99*** (2.78)	19,149	0.896
6-item Transportation Security Index (TSI) score category					
No insecurity/secure	2,615	0.182	0.089*** (0.017)	19,274	0.885
Marginal/Low insecurity	2,615	0.288	0.032 (0.020)	19,274	0.885
Moderate/High insecurity	2,615	0.531	-0.121*** (0.021)	19,274	0.885
Still have study ConnectCard in possession	1,743	0.693	0.226*** (0.026)	8,467	0.832
C. Outcomes from travel diaries					
Number of places visited yesterday (N)	4,597	3.69	-0.668*** (0.181)	27,532	0.861
Likelihood of taking at least one trip yesterday					
Car trip	4,642	0.346	-0.008 (0.010)	27,731	0.861
Public transportation trip	4,635	0.576	0.009 (0.011)	27,643	0.860
Walk or bike trip	4,631	0.469	-0.066*** (0.012)	27,592	0.860
D. Outcomes from smartphone Google Maps location history data					
Number of trips taken per week					
Car trips	298	13.66	-2.04 (1.48)	3,960	0.934
Public transportation trips	298	3.38	1.25** (0.628)	3,960	0.934
Walk or bike trips	298	4.98	-0.440 (0.616)	3,960	0.934
Total trips across all modes	298	22.09	-1.26 (1.61)	3,960	0.934

Notes: Table presents estimates of the local average treatment effect (LATE) of the 100% discount relative to no discount on various travel-related outcomes for the adult sample. Outcome data is winsorized at the 99th percentile if it comes from a survey question that permitted an unbounded numeric response. Estimates are from a two-stage least squares regression that 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), 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. N indicates the number of participants across the free-fares and no-discount 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

Table A23: P-values for sharp null hypothesis tests, assorted outcomes

Outcome	Test stat	Treatment contrast: Half-fares vs control	Treatment contrast: Free-fares vs control
Public transit trips per week (N)	Mean difference	0.083	0.109
	Normalized rank	0.070	0.001
	Kolmogorov-Smirnov	0.366	0.010
Hours worked per week (N)	Mean difference	0.789	0.869
	Normalized rank	0.635	0.609
	Kolmogorov-Smirnov	0.833	0.949
Had any paid employment in Q1 - Q4 after enrollment	Mean difference	0.293	0.196
	Normalized rank	0.539	0.314
	Kolmogorov-Smirnov	0.539	0.314
Total earnings in Q1 - Q4 after enrollment ($)	Mean difference	0.424	0.304
	Normalized rank	0.514	0.495
	Kolmogorov-Smirnov	0.371	0.758
Days with non-ER outpatient claim in 365 days after enrollment (N)	Mean difference	0.991	0.591
	Normalized rank	0.890	0.279
	Kolmogorov-Smirnov	0.899	0.187

Notes: Table presents p-values for the sharp null hypothesis that the treatment effect is zero for every adult participant. P-values are calculated using Fisher's exact test with 1,000 treatment assignment permutations. The 'Public transit trips per week' outcome is measured from smartphone GPS data. The 'Hours worked per week' outcome comes from the endline survey. The 'Had any paid employment in Q1 - Q4 after enrollment' and 'Total earnings in Q1 - Q4 after enrollment' outcomes come from Pennsylvania unemployment insurance (UI) records. The 'Days with non-ER outpatient claim in 365 days after enrollment' outcome comes from Medicaid claims data. We use three different test statistics as robustness checks: 1. The regression-adjusted difference in mean outcome for the treatment versus control group, using the benchmark set of covariates used throughout the paper, 2. The difference in the mean normalized rank of the outcome for the treatment versus control group ($T^{\text{rank}} = |\bar{R}_T - \bar{R}_C|$, where $R_i = \sum_{i'=1}^{N} 1(Y_{i'}^{\text{obs}} < Y_i^{\text{obs}}) + \frac{1}{2}\left(1 + \sum_{i'=1}^{N} 1(Y_{i'}^{\text{obs}} = Y_i^{\text{obs}})\right) - \frac{N+1}{2}$), and 3. The Kolmogorov-Smirnov statistic, which measures the maximum distance between the cumulative distribution function $\hat{F}$ of the outcome for the treatment group versus the control group ($T^{\text{KS}} = \max|\hat{F}_T(Y_i) - \hat{F}_C(Y_i)|$)

B Survey response rates and nonresponse bias

B.1 Midline survey

All adult study participants were invited to complete the midline survey, which took place six months after the participant enrolled in the study. The vast majority of questions in the survey 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.

Table B1 presents the midline survey completion rates by fare discount and survey incentive amount. Overall, 34.5% of study participants completed the survey. Across the three discount arms, the $20 incentive group was 4.1 percentage points more likely than the $10 incentive group to complete the survey.

Table B1: Midline survey completion rates, by incentive amount

Discount group	Total	$20 incentive	$10 incentive	$20 versus $10 diff.
0%	0.304	0.320	0.289	0.031* (0.016)
50%	0.347	0.368	0.328	0.040** (0.017)
100%	0.384	0.410	0.358	0.052*** (0.017)
Total	0.345	0.366	0.325	0.041*** (0.010)

Notes: This table presents the midline (6-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 B2 presents the differential response rates to certain questions within the survey. Across all questions 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. Only 14.5% of the control group responded to the question about total monthly earnings, while 34.8% responded to the question that asked for a rating of your current health.

Table B2: Midline survey response rates, by discount group

Survey question	Total respondents	Control group response rate	Response rate differences: Half fares vs. control	Free fares vs. control	Free vs. half fares
A. Transportation questions					
PRT trips in past week (N)	3,819	0.346	0.056***	0.106***	0.050***
			(0.012)	(0.012)	(0.012)
PRT spending in past week ($)	3,366	0.301	0.053***	0.100***	0.047***
			(0.012)	(0.012)	(0.012)
B. Employment questions					
Currently employed	3,601	0.326	0.056***	0.099***	0.043***
			(0.012)	(0.012)	(0.012)
Hourly wage at main job ($)	1,621	0.153	0.015	0.035***	0.020**
			(0.009)	(0.009)	(0.010)
Weekly work hours (N)	3,601	0.326	0.056***	0.099***	0.043***
			(0.012)	(0.012)	(0.012)
Total monthly earnings ($)	3,601	0.326	0.056***	0.099***	0.043***
			(0.012)	(0.012)	(0.012)
C. Financial questions					
Cannot afford $400 expense	3,434	0.312	0.053***	0.088***	0.035***
			(0.012)	(0.012)	(0.012)
Behind with finances	3,346	0.309	0.047***	0.077***	0.030**
			(0.012)	(0.012)	(0.012)
Monthly savings ($)	3,348	0.305	0.051***	0.087***	0.036***
			(0.012)	(0.012)	(0.012)
D. Health and well-being questions					
Current health good or better	3,519	0.324	0.048***	0.087***	0.039***
			(0.012)	(0.012)	(0.012)
Life satisfaction rating (0-10)	3,511	0.323	0.049***	0.086***	0.038***
			(0.012)	(0.012)	(0.012)
Feeling anxious last 2 weeks	3,317	0.307	0.044***	0.078***	0.035***
			(0.012)	(0.012)	(0.012)
I have finished the survey	3,296	0.304	0.043***	0.080***	0.037***
			(0.012)	(0.012)	(0.012)

Notes: Table presents the response rates to various midline (6-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 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. Robust standard errors are in parentheses. ***p <0.01, **p <0.05, *p <0.1

Table B3 explores the extent of selection into midline survey completion on observable baseline characteristics. Survey completers were 7.8 percentage points more likely to be female than the non-completers, 10 percentage points more likely to be White, and 14 percentage points more likely to have more than a high school degree.

Table B3: Selection into midline survey completion on baseline characteristics

	Completers	Non-completers	Difference
Panel A. Demographics			
Female	0.772	0.695	0.078*** (0.009)
Age group			
18 - 29	0.203	0.239	-0.037*** (0.009)
30 - 39	0.304	0.271	0.032*** (0.010)
40 - 49	0.206	0.171	0.035*** (0.009)
50 - 59	0.143	0.142	0.001 (0.008)
60 - 64	0.054	0.072	-0.018*** (0.005)
Race			
Black	0.518	0.626	-0.108*** (0.011)
White	0.403	0.303	0.100*** (0.010)
Other	0.057	0.046	0.011** (0.005)
Hispanic	0.035	0.032	0.003 (0.004)
Children in household (N)	1.13	1.13	<0.001 (0.030)
Highest education			
Less than high school	0.061	0.092	-0.031*** (0.006)
High school	0.474	0.587	-0.113*** (0.011)
More than high school	0.458	0.317	0.141*** (0.010)
Panel B. Transportation			
Owns a car	0.074	0.048	0.025*** (0.005)
PRT trips last week (N)	9.35	10.40	-1.05*** (0.267)
PRT spending last week ($)	27.18	31.34	-4.17*** (0.650)
Panel C. Employment (from baseline survey)			
Employed past 12 months	0.612	0.600	0.013 (0.011)
Currently employed	0.434	0.423	0.010 (0.011)
Hours worked per week at main job (N)	30.21	31.05	-0.845** (0.362)
Hourly wage at main job ($)	13.73	13.34	0.389*** (0.120)
Panel D. Employment in quarter prior to enrollment (from UI records)			
Total earnings ($)	2,342.53	2,241.46	101.07 (70.99)
Received nonzero UI benefits	0.034	0.030	0.004 (0.004)
N	**3,296**	**6,248**	

Notes: This table compares the mean baseline characteristics between the adult participants who completed the midline survey and those who did not. 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 B4 explores whether the sample of midline survey respondents remains balanced across randomization arms on certain relevant baseline characteristics. The midline respondent sample does not demonstrate worse balance than the full study sample on most characteristics shown in the table.

Table B5 reports intent-to-treat impacts on outcomes derived from the midline 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 B4: Randomization balance among midline survey respondents

	No discount		Half fares		Free fares		
	N	Mean	N	Mean	N	Mean	Free fares vs. no discount diff.
A. Demographics							
Female	958	0.770	1,126	0.780	1,212	0.767	-0.004 (0.018)
Age group							
18 - 29	958	0.212	1,126	0.194	1,212	0.204	-0.008 (0.018)
30 - 39	958	0.305	1,126	0.313	1,212	0.294	-0.011 (0.020)
40 - 49	958	0.198	1,126	0.202	1,212	0.216	0.018 (0.017)
50 - 59	958	0.145	1,126	0.139	1,212	0.146	0.001 (0.015)
60 - 64	958	0.051	1,126	0.061	1,212	0.050	-0.002 (0.009)
Race							
Black	958	0.511	1,126	0.509	1,212	0.532	0.021 (0.022)
White	958	0.412	1,126	0.411	1,212	0.388	-0.025 (0.021)
Other	958	0.059	1,126	0.053	1,212	0.059	<-0.001 (0.010)
Hispanic	958	0.033	1,126	0.028	1,212	0.044	0.010 (0.008)
Children in household (N)	958	1.07	1,126	1.11	1,212	1.20	0.129** (0.059)
Highest education							
Less than high school	958	0.040	1,126	0.067	1,212	0.072	0.032*** (0.010)
High school	958	0.467	1,126	0.481	1,212	0.474	0.007 (0.022)
More than high school	958	0.487	1,126	0.446	1,212	0.446	-0.042* (0.022)
B. Transportation							
Owns a car	958	0.081	1,126	0.065	1,212	0.076	-0.006 (0.012)
PRT trips last week (N)	958	8.86	1,126	8.90	1,212	9.11	0.249 (0.402)
PRT spending last week ($)	958	25.41	1,126	27.60	1,212	26.95	1.54 (1.11)
C. Employment							
Employed past 12 months	958	0.640	1,126	0.607	1,212	0.595	-0.045** (0.021)
Currently employed	958	0.459	1,126	0.429	1,212	0.417	-0.042* (0.021)
Hours worked per week at main job (N)	440	28.77	483	30.35	506	31.33	2.57*** (0.722)
Hourly wage at main job ($)	440	13.77	483	13.65	505	13.78	0.008 (0.241)
D. Employment in quarter prior to enrollment (from UI records)							
Total earnings ($)	949	2,333.26	1,117	2,334.65	1,204	2,355.36	22.10 (143.80)
Received nonzero UI benefits	949	0.032	1,117	0.038	1,204	0.032	<-0.001 (0.008)
Total midline respondents	**958**		**1,126**		**1,212**		

Notes: Table presents mean baseline characteristics across study groups among the adult participants who completed the midline (6-month follow-up) 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. 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 B5: Impacts of fare discounts on various midline survey outcomes, with extreme value bounds

			Treatment effect		
Outcome	N	Control mean	Half fares	Free fares	Free vs. half fares
Panel A. Transportation outcomes					
PRT trips last week (N)	3,819	11.52	-2.06 [-653; 597]	-0.869 [-652; 550]	1.19** [-148; 138]
PRT spending last week ($)	3,366	50.32	-25.75* [-5,240; 4,832]	-30.76* [-6,986; 5,985]	-5.01 [-6,449; 5,989]
Could not get to work or appointment	3,829	0.595	-0.100*** [-0.658; 0.590]	-0.262*** [-0.706; 0.494]	-0.162*** [-0.644; 0.501]
Panel B. Employment outcomes					
Employed	3,601	0.506	-0.007 [-0.652; 0.640]	-0.011 [-0.633; 0.617]	-0.004 [-0.599; 0.595]
Unemployed and seeking work	3,601	0.179	0.039** [-0.649; 0.643]	0.008 [-0.653; 0.598]	-0.031* [-0.621; 0.573]
Hourly wage at main job ($)	1,621	16.30	-0.225 [-591; 580]	2.55 [-591; 567]	2.77 [-402; 394]
Weekly work hours (N)	1,617	33.93	-0.966 [-142; 140]	0.009 [-141; 138]	0.975 [-139; 137]
Total monthly earnings ($)	1,526	1,674.06	-358.90 [-42,799; 41,861]	49.24 [-136,819; 132,480]	408.14 [-133,863; 132,489]
Panel C. Financial outcomes					
Cannot afford $400 expense	3,434	0.567	0.016 [-0.652; 0.668]	-0.014 [-0.641; 0.646]	-0.030 [-0.622; 0.612]
Behind with finances	3,346	0.460	0.008 [-0.667; 0.667]	-0.005 [-0.659; 0.646]	-0.013 [-0.635; 0.623]
Monthly savings ($)	3,348	125.45	-47.76 [-33,111; 30,740]	-22.81 [-33,074; 29,115]	24.95 [-22,832; 21,655]
Panel D. Health and well-being outcomes					
Current health good or better	3,519	0.562	-0.025 [-0.664; 0.640]	-0.030 [-0.645; 0.620]	-0.005 [-0.610; 0.608]
Life satisfaction rating (0-10)	3,511	5.60	0.042 [-6; 7]	0.242** [-6; 6]	0.200* [-6; 6]
Feeling anxious last 2 weeks	3,317	0.312	-0.007 [-0.683; 0.658]	-0.008 [-0.675; 0.633]	-0.001 [-0.641; 0.624]

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 midline survey incentive payments enable us to test for these 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 B6. The differences in item-level response rates ranged from 2.7 percentage points (total monthly earnings) to 4.7 percentage points (monthly savings). These significant differences in response rates raise the potential for selection bias in the survey results on the dimension of the incentive amount.

Table B6: Midline 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. $10 diff.
Panel A. Transportation questions					
PRT trips last week (N)	4,771	0.419	4,773	0.381	0.039*** (0.010)
PRT spending last week ($)	4,771	0.372	4,773	0.333	0.040*** (0.010)
Could not get to work or appointment	4,771	0.420	4,773	0.383	0.037*** (0.010)
Panel B. Employment questions					
Employed	4,771	0.395	4,773	0.360	0.036*** (0.010)
Unemployed and seeking work	4,771	0.395	4,773	0.360	0.036*** (0.010)
Hourly wage at main job ($)	4,771	0.184	4,773	0.155	0.029*** (0.008)
Weekly work hours (N)	4,771	0.184	4,773	0.155	0.028*** (0.008)
Total monthly earnings ($)	4,771	0.173	4,773	0.146	0.027*** (0.007)
Panel C. Financial questions					
Cannot afford $400 expense	4,771	0.381	4,773	0.338	0.043*** (0.010)
Behind with finances	4,771	0.372	4,773	0.330	0.042*** (0.010)
Monthly savings ($)	4,771	0.374	4,773	0.327	0.047*** (0.010)
Panel D. Health and well-being questions					
Current health good or better	4,771	0.389	4,773	0.349	0.040*** (0.010)
Life satisfaction rating (0-10)	4,771	0.388	4,773	0.348	0.040*** (0.010)
Feeling anxious last 2 weeks	4,771	0.369	4,773	0.326	0.043*** (0.010)
I have finished the survey	4,771	0.366	4,773	0.325	0.041*** (0.010)

Notes: This table compares midline (6-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 midline 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 B7 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 $2.41 (14.5%) higher hourly wage than the respondents in the low incentive group. The high incentive respondents were also 2.9 percentage points (6.1%)

more likely to report being behind on their finances, and 2.7 percentage points (8.6%) more likely to report feeling anxious in the last two weeks.

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 B7. 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 several of the survey questions in Table B7. For example, the 95% confidence interval for the mean difference in hours worked per week rules out differences that are more than +/- 5% of the control mean. 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 small differences in item-level response rates shown in Table B6 provide some reassurance that selection bias is limited: Doubling the $10 incentive to $20 increased response rates by roughly two to five 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 B7: Comparing midline 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. $10 difference	Marginal responders vs. always-responders difference
A. Transportation questions						
PRT trips last week (N)	2,001	10.33	1,818	11.32	-0.990 (0.746)	-10.78 (10.00)
PRT spending last week ($)	1,777	32.48	1,589	37.59	-5.11 (9.34)	-48.09 (163.7)
Could not get to work or appointment	2,003	0.473	1,826	0.461	0.012 (0.016)	0.132 (0.223)
B. Employment questions						
Employed	1,885	0.503	1,716	0.478	0.024 (0.017)	0.272 (0.263)
Unemployed and seeking work	1,885	0.198	1,716	0.194	0.004 (0.013)	0.048 (0.190)
Hourly wage at main job ($)	880	16.65	741	14.23	2.41** (1.12)	15.25** (9.68)
Weekly work hours (N)	1,885	15.78	1,716	14.61	1.17* (0.680)	12.95* (95.01)
Total monthly earnings ($)	1,885	791.8	1,716	663.5	128.3 (144.2)	1,425 (2,145)
C. Financial questions						
Cannot afford $400 expense	1,820	0.569	1,614	0.571	-0.002 (0.017)	-0.017 (0.158)
Behind with finances	1,773	0.473	1,573	0.444	0.029* (0.017)	0.255* (0.182)
Monthly savings ($)	1,785	120.3	1,563	68.10	52.18 (33.26)	418.3 (330.9)
D. Health and well-being questions						
Current health good or better	1,854	0.540	1,665	0.524	0.016 (0.017)	0.158 (0.188)
Life satisfaction rating (0-10)	1,851	5.70	1,660	5.66	0.041 (0.096)	0.401 (1.10)
Feeling anxious last 2 weeks	1,761	0.314	1,556	0.287	0.027* (0.016)	0.229* (0.164)

Notes: This table compares respondents' answers to certain midline (6-month follow-up) survey questions between the high ($20) and low ($10) incentive groups. The vast majority of questions in the midline 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

B.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 B8 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 B8: 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 B9 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.

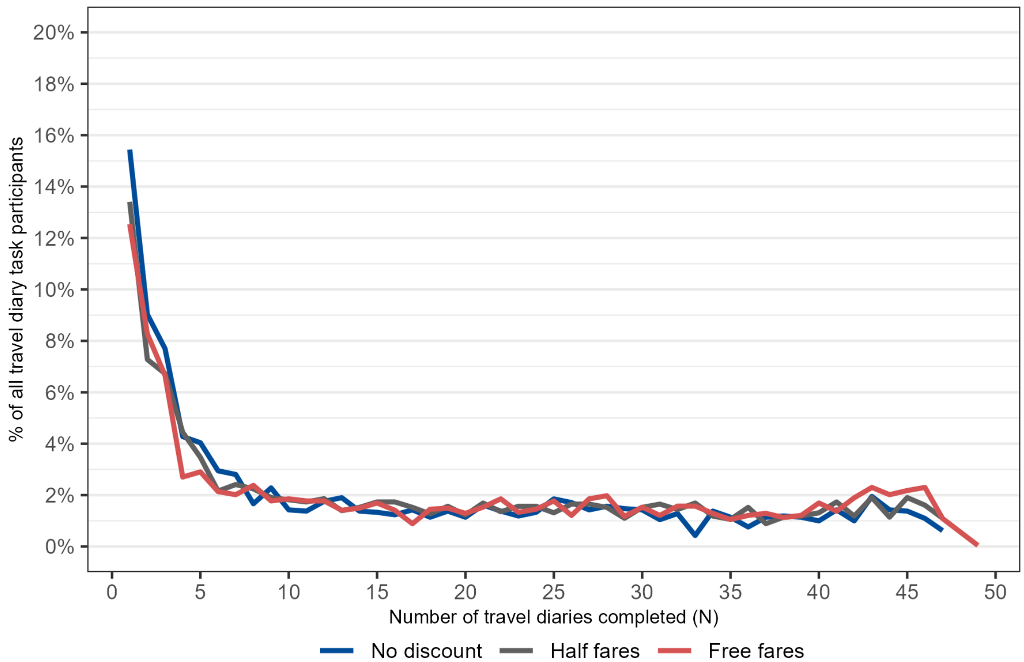
Table B9: Travel diary participation by incentive amount

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 B1 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 B1: 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 B10 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 B11 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 B10: Selection into travel diary surveys on baseline characteristics

	Completed a diary	Did not complete a diary	Difference
Panel A. Demographics			
Female	0.766	0.657	0.109*** (0.010)
Age group			
18 - 29	0.219	0.240	-0.020** (0.009)
30 - 39	0.299	0.257	0.042*** (0.009)
40 - 49	0.191	0.172	0.019** (0.008)
50 - 59	0.138	0.148	-0.010 (0.007)
60 - 64	0.056	0.079	-0.023*** (0.005)
Race			
Black	0.568	0.625	-0.057*** (0.010)
White	0.356	0.305	0.051*** (0.010)
Other	0.052	0.046	0.007 (0.005)
Hispanic	0.037	0.027	0.009** (0.004)
Children in household (N)	1.19	1.06	0.126*** (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	0.302	0.107*** (0.010)
Panel B. Transportation			
Owns a car	0.062	0.050	0.012*** (0.005)
PRT trips last week (N)	9.99	10.03	-0.038 (0.281)
PRT spending last week ($)	28.94	31.33	-2.39*** (0.692)
Panel C. Employment (from baseline survey)			
Employed past 12 months	0.629	0.570	0.059*** (0.010)
Currently employed	0.447	0.400	0.047*** (0.010)
Hours worked per week at main job (N)	30.63	31.01	-0.385 (0.361)
Hourly wage at main job ($)	13.62	13.25	0.378*** (0.119)
Panel D. Employment in quarter prior to enrollment (from UI records)			
Total earnings ($)	2,393.08	2,127.28	265.80*** (68.84)
Received nonzero UI benefits	0.031	0.031	<0.001 (0.004)
N	**5,780**	**3,675**	

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. ***p <0.01, **p <0.05, *p <0.1

Table B11: Randomization balance among participants who completed at least one travel diary

	No discount		Half fares		Free fares		
	N	Mean	N	Mean	N	Mean	Free fares vs. no discount diff.
A. Demographics							
Female	1,724	0.766	1,997	0.771	2,071	0.760	-0.007 (0.014)
Age group							
18 - 29	1,724	0.233	1,997	0.208	2,071	0.219	-0.014 (0.014)
30 - 39	1,724	0.284	1,997	0.317	2,071	0.294	0.010 (0.015)
40 - 49	1,724	0.183	1,997	0.189	2,071	0.201	0.019 (0.013)
50 - 59	1,724	0.138	1,997	0.135	2,071	0.142	0.004 (0.011)
60 - 64	1,724	0.055	1,997	0.061	2,071	0.054	<-0.001 (0.007)
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 ($)	1,724	29.60	1,997	28.44	2,071	28.59	-1.01 (0.993)
C. Employment							
Employed past 12 months	1,724	0.642	1,997	0.625	2,071	0.621	-0.021 (0.016)
Currently employed	1,724	0.448	1,997	0.447	2,071	0.446	-0.002 (0.016)
Hours worked per week at main job (N)	773	30.09	892	30.77	924	30.93	0.840 (0.536)
Hourly wage at main job ($)	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	2,438	68.64 (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 B12 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 B12 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 B12.

Table B12: 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

B.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 B13 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.

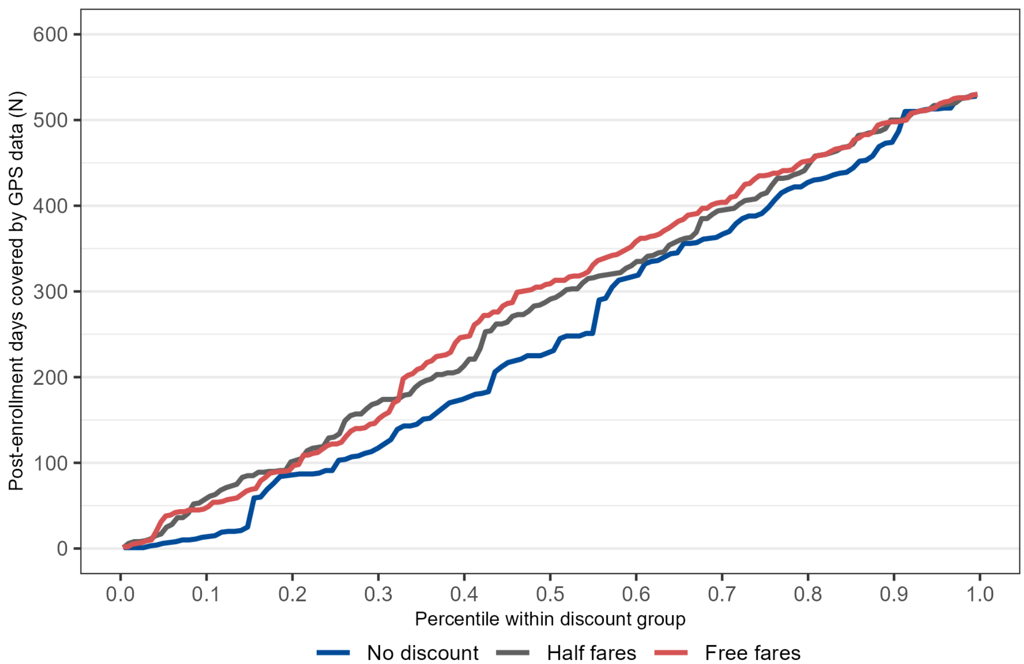
Table B13: GPS data sharing participation, by discount group

					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 B2 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 B2: 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 B14 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 B14: 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 group			
18 - 29	0.163	0.230	-0.067*** (0.018)
30 - 39	0.341	0.279	0.062*** (0.022)
40 - 49	0.261	0.179	0.081*** (0.021)
50 - 59	0.117	0.144	-0.027* (0.015)
60 - 64	0.013	0.068	-0.056*** (0.006)
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 ($)	2,088.56	2,284.94	-196.38 (148.80)
Received nonzero UI benefits	0.019	0.032	-0.012* (0.007)
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. ***p <0.01, **p <0.05, *p <0.1

Table B15 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 B15: 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 group							
18 - 29	132	0.212	159	0.138	181	0.149	-0.063 (0.044)
30 - 39	132	0.356	159	0.340	181	0.331	-0.025 (0.055)
40 - 49	132	0.235	159	0.270	181	0.271	0.036 (0.050)
50 - 59	132	0.114	159	0.138	181	0.099	-0.014 (0.036)
60 - 64	132	0.015	159	0.006	181	0.017	0.001 (0.014)
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 ($)	132	22.54	159	26.29	181	28.80	6.26** (2.73)
C. Employment							
Employed past 12 months	132	0.621	159	0.579	181	0.569	-0.052 (0.056)
Currently employed	132	0.417	159	0.453	181	0.403	-0.013 (0.056)
Hours worked per week at main job (N)	55	27.62	72	29.54	73	27.88	0.259 (1.98)
Hourly wage at main job ($)	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	156	2,114	180	1,966	-304 (370)
Received nonzero UI benefits	130	0.031	156	0.019	180	0.011	-0.020 (0.017)
Total midline respondents	**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 B16 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 B16: 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

C Study materials

C.1 Study recruitment flyer

Figure C1: Flyer 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.

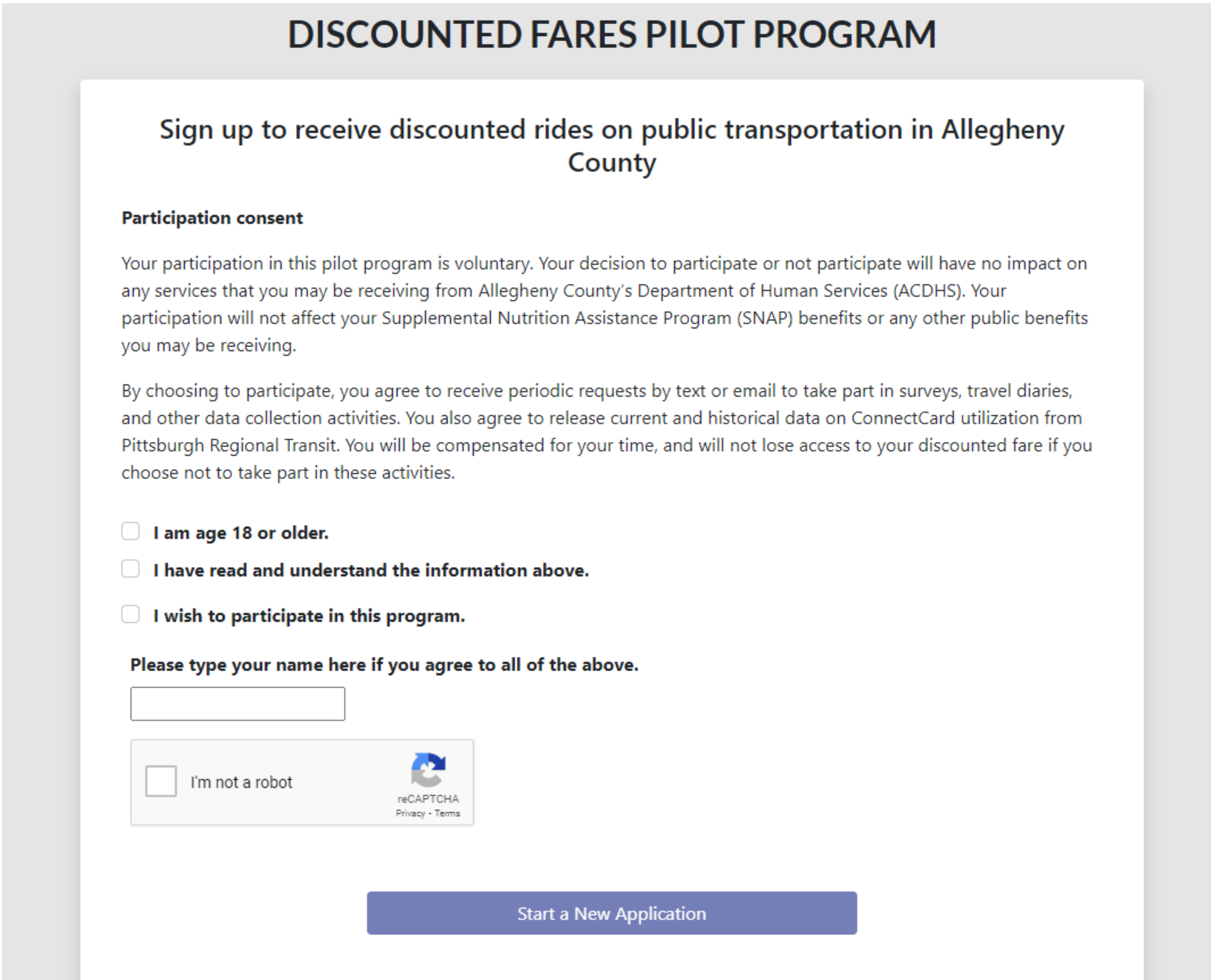
DHS wants to understand how local residents may benefit from lowering the cost of public transit. This will include examining the impact on ridership and whether there is increased access to jobs, services and other resident needs.

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

Allegheny County Discounted Fares Pilot Program

C.2 Study application

Figure C2: 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 C3: First section of study application form

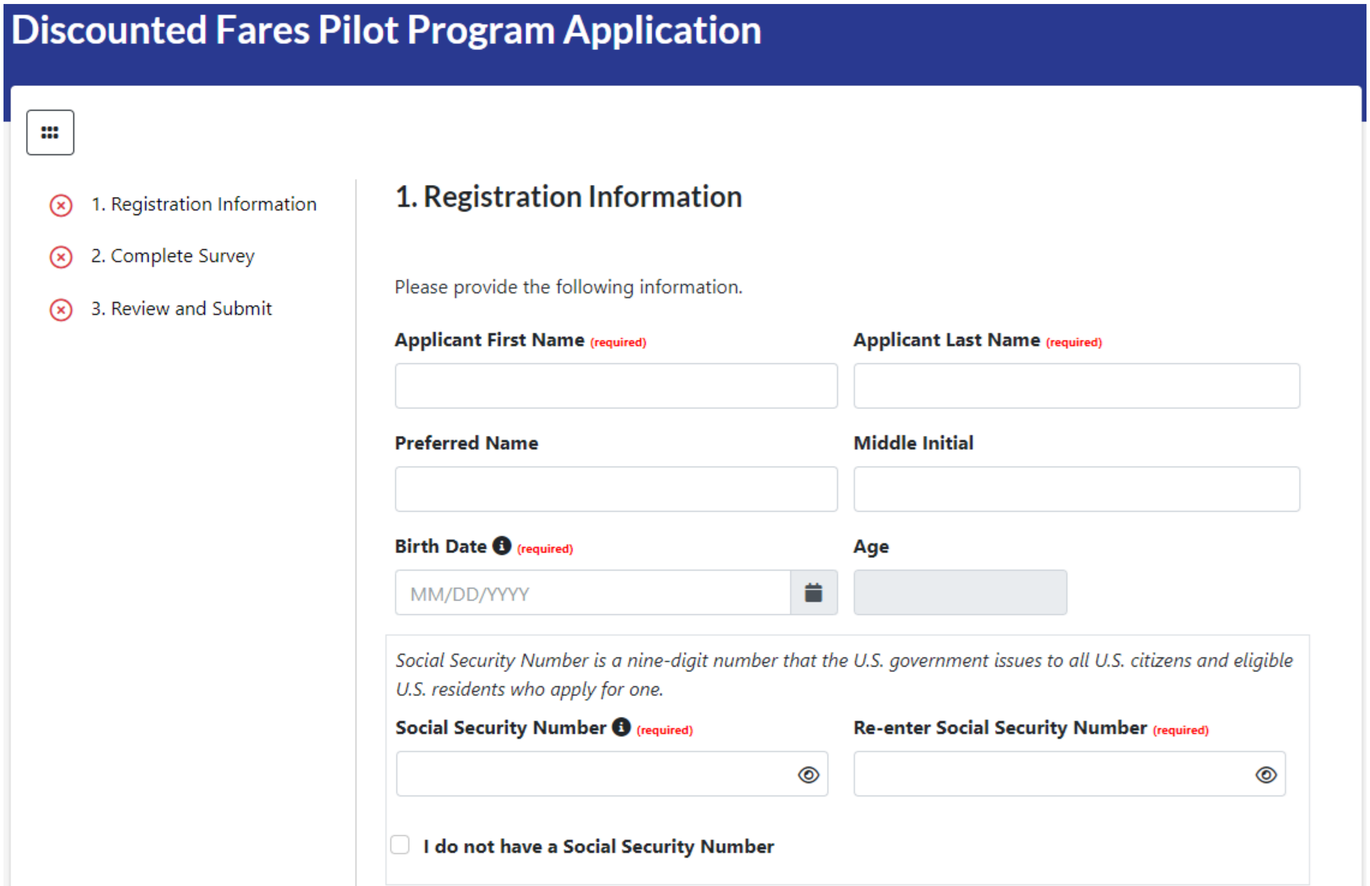
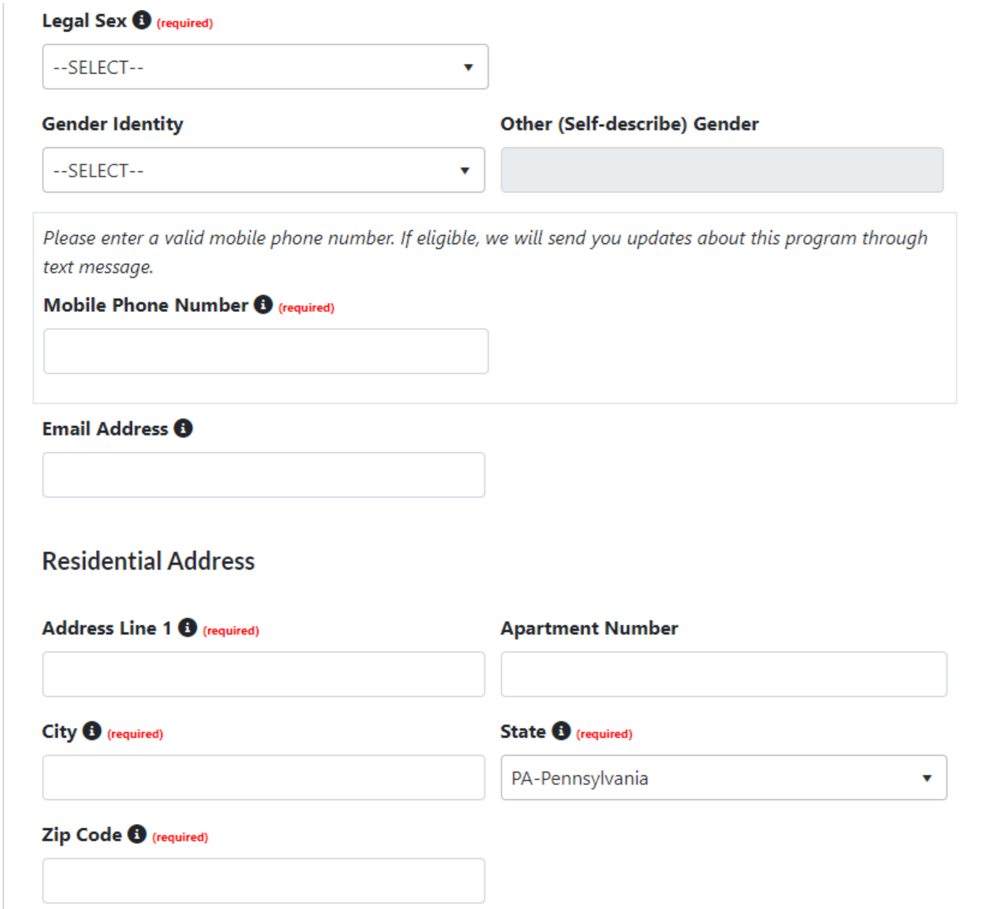


Figure C4: Second section of study application form


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

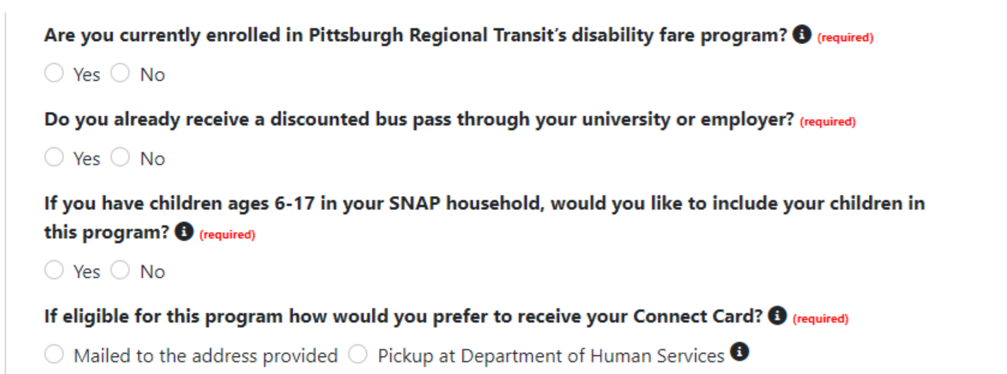
City (required)

State (required)

PA-Pennsylvania

Zip Code (required)

Figure C5: 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

C.3 Baseline survey

Figure C6: First section of baseline survey

The following survey is for research purposes only. Your responses to this survey will not impact your eligibility or your assigned discount group for this program.

Including yourself, how many adults between age 18 and 64 currently live in your household? Please include people who are not related to you and people who are temporarily away. (required)

How many children under age 18 live in your household at least half the time? Please include biological and adopted children, as well as foster-, step-, and grandchildren. (required)

What is your race? (required)

- Black, African American, or African
- Asian or Asian American
- American Indian, Alaska Native, or Indigenous
- White
- Native Hawaiian or Pacific Islander
- Other
- Prefer not to say

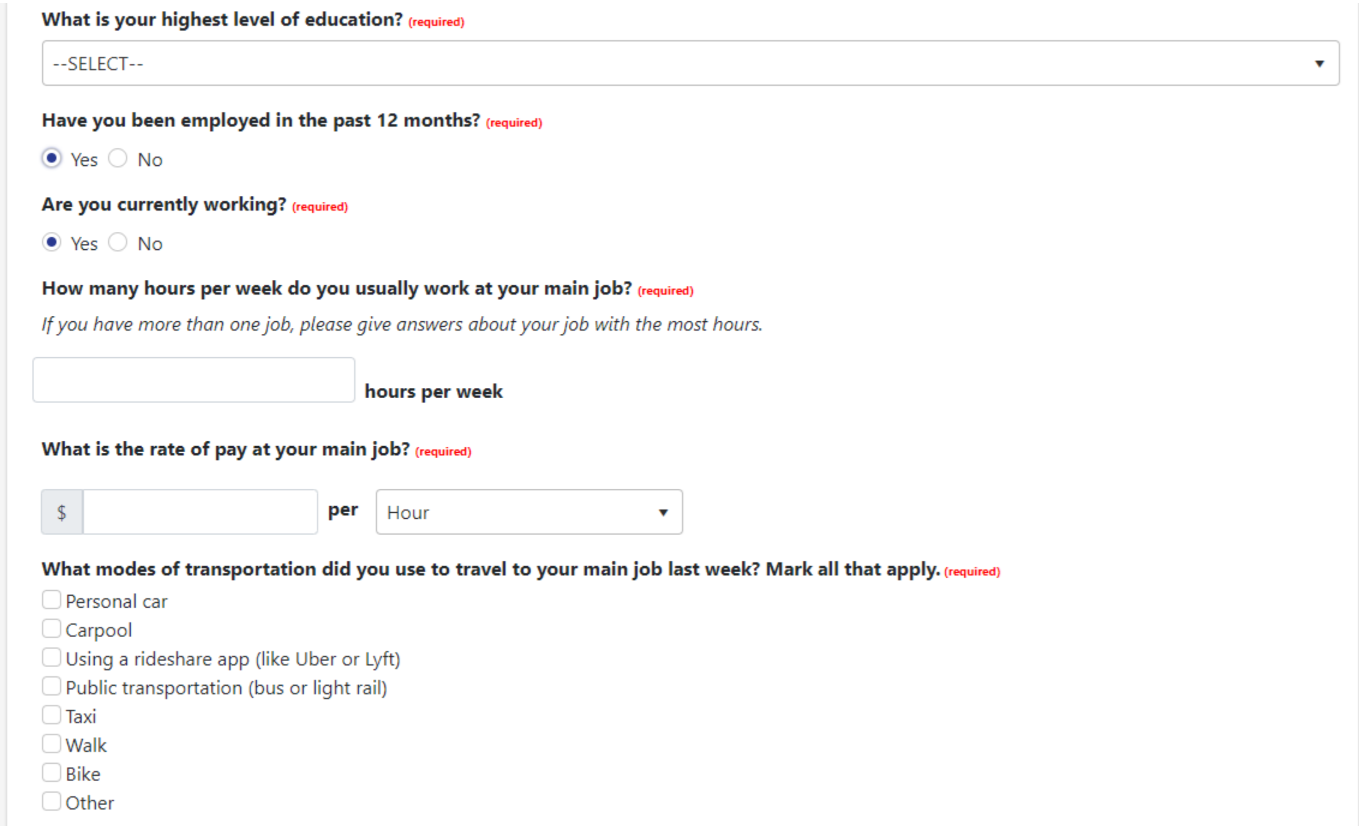
Ethnicity (required)

--SELECT--

What is your primary language? (required)

--SELECT--

Figure C7: Second section of baseline survey


What is your highest level of education? (required)

--SELECT--

Have you been employed in the past 12 months? (required)

Yes No

Are you currently working? (required)

Yes No

How many hours per week do you usually work at your main job? (required)

If you have more than one job, please give answers about your job with the most hours.

hours per week

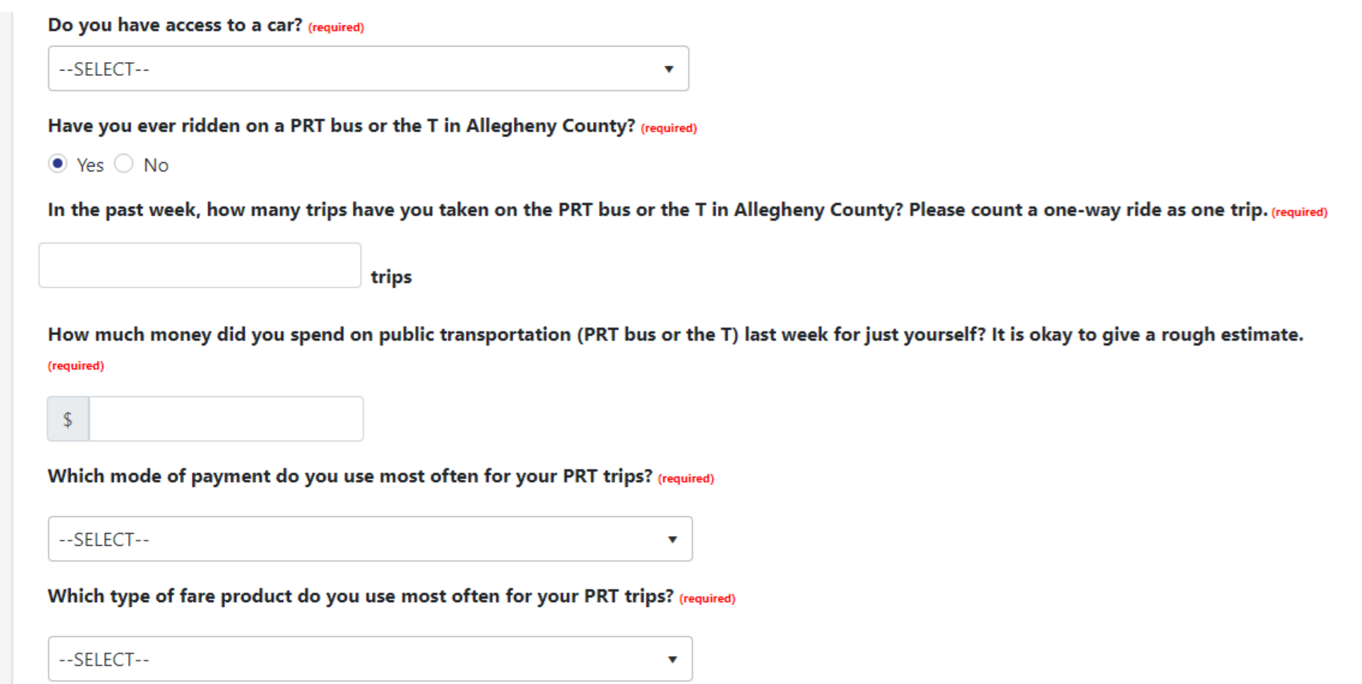
What is the rate of pay at your main job? (required)

$ per Hour

What modes of transportation did you use to travel to your main job last week? Mark all that apply. (required)

- Personal car
- Carpool
- Using a rideshare app (like Uber or Lyft)
- Public transportation (bus or light rail)
- Taxi
- Walk
- Bike
- Other

Figure C8: Third section of baseline survey


Do you have access to a car? (required)

--SELECT--

Have you ever ridden on a PRT bus or the T in Allegheny County? (required)

Yes No

In the past week, how many trips have you taken on the PRT bus or the T in Allegheny County? Please count a one-way ride as one trip. (required)

trips

How much money did you spend on public transportation (PRT bus or the T) last week for just yourself? It is okay to give a rough estimate. (required)

$

Which mode of payment do you use most often for your PRT trips? (required)

--SELECT--

Which type of fare product do you use most often for your PRT trips? (required)

--SELECT--

C.4 Text message travel diary survey

Each travel diary survey asked the following five questions:

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 to 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

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