Experimental Evidence on the Effects of Means-Tested Public Transportation Subsidies on Travel Behavior

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Abstract

Means-tested reduced transit fare programs are increasingly prevalent. This paper describes the results of a unique experiment in which a randomly selected group of low-income individuals in King County, Washington received up to six months of free public transportation. We leverage the experiment to explore how public transit's cost affects mobility. Using administrative data tracking transit card taps on King County's fleet of vehicles, we find that free fares sharply increase transit card use. Follow-up surveys corroborate an increase in travel by public transportation, but also indicate that some of the treatment effect on transit card use is driven by payment method substitution. Treatment effects on overall travel by any mode are less clear. Finally, we find little persistent impact of free fares on transit card use after the subsidy ends.

Keywords: public transportation, transit subsidies, reduced fares, habit formation, randomized controlled trial
JEL: R4, R5, H7

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1 Introduction

Governments around the world have recently moved to reduce or even eliminate fares on their public transportation systems. In the U.S., local governments have focused in particular on reducing cost barriers to using public transit for low-income individuals in an effort to increase access to jobs and amenities. For example, New York City, Seattle, San Francisco, Dallas, and Portland have rolled out large-scale means-tested reduced-fare programs in the past decade (Redden, 2018; Darling et al., 2021). Several cities, including Seattle, Boston, Los Angeles, Salt Lake City, and Denver, are considering reducing transit fares to zero at least for people with low income (Hess, 2020; Gellerman, 2021).

These policy initiatives have both equity and efficiency rationales. For families in the lowest income quintile in the U.S., transportation consumes a larger budget share than any other major spending category besides housing.[1] Individuals with low income also rely disproportionately on public transportation for their travel needs (Garrett and Taylor, 1999; Glaeser, Kahn and Rappaport, 2008; Heaps, Abramsohn and Skillen, 2021). Meanwhile, travel by transit may be inefficiently low because of scale economies in transit systems and negative externalities associated with other modes of transportation (Parry and Small, 2009). However, little is known about the extent to which means-tested transit subsidies stimulate transit use, much less whether they affect travel by other modes or overall mobility.

In this paper, we evaluate the effects of subsidized transit fares on travel behavior using a randomized controlled trial (RCT) in which a randomly selected group of public assistance clients in King County, Washington (home of Seattle) received transit cards that provided up to six months of free public transit. Taking advantage of the RCT together with rich administrative data from King County Metro, we track transit card use for individuals with free fares as well as for a counterfactual group of individuals with transit cards providing positive (but discounted) fares. We follow up with surveys of study participants that pro-

[1]According to the 2019 Consumer Expenditure Survey, among consumer units in the lowest income quintile, 40.2% of spending went to housing and 16.0% went to transportation. The next largest category was food at 15.3%.

vide visibility into transportation mode and payment method substitution as well as travel purposes and overall mobility. By tracking individuals' transit card use both during and after the subsidy period, we also use the experiment to shed light on whether short-term subsidization of alternative transportation modes can induce long-lasting behavioral changes.

Leveraging experimental variation in transit prices and King County Metro data on transit card "taps" on its fleet of vehicles, we find that providing fare-free public transit to low-income individuals quadruples average measured boardings relative to charging approximately \$1.50 per bus or train ride. The effects are similar across age, race, and ethnicity subgroups. The magnitudes of the response to the treatment are also comparable for individuals with different levels of baseline transit use. However, we observe some heterogeneity in the effects of free fares on card use along dimensions that may matter for transit system operations and efficiency. Treatment increases card taps most during off-peak hours of the workweek. While there is only limited evidence that treatment effects vary across neighborhoods with different degrees of public transit penetration, the additional card taps induced by free fares appear predominately on routes that are not crowded.

We also collect survey data on payment method, travel mode, and trip purpose to supplement our administrative data. Though suffering from smaller sample sizes, the survey data corroborate our findings based on administrative data that the treatment sharply increased transit card use during the subsidy period. The survey data also suggest that up to half of the treatment effect on travel by transit measured in the administrative records stems from transit payment method substitution (i.e., switching from untrackable cash payment and nonpayment to payment using a transit card), though the remainder represents a real increase in transit use. Whether new transit trips result from new travel or travel mode substitution (i.e., substituting transit trips for car trips) is less clear.

Finally, we examine the degree to which higher transit card use persists among individuals in the treatment group after the subsidy is removed. We find that after free transit is no longer available, transit card use among individuals in the treatment group quickly converges with that of individuals in the control group. We interpret this result as suggesting that any habit formation was not sufficiently strong to overcome other frictions or obstacles low-income individuals face in using public transit cards when faced with a positive price for transit rides.

This study makes several important contributions. First, our findings speak to well-known theories of urban location and spatial mismatch. Standard urban location theory posits that transportation costs loom large in decisions about employment and where to live (Fujita, 1991). Transportation costs may be particularly salient and consequential for low-income individuals. Wilson (1997) and Kain (1968) argue that geographic isolation of low-income people from job locations perpetuates neighborhood poverty. A large empirical literature tests these theories; however, these studies tend to focus on transit system expansions rather than changes in price (e.g., Holzer, Quigley and Raphael (2003)). Randomized controlled trials in this domain are also rare. The few experimental studies of transportation subsidies that do exist tend to examine relatively modest subsidies (Phillips, 2014; Gravert and Collentine, 2019; Bull, Munoz and Silva, 2021; Rosenblum, 2020) or focus on developing country contexts (Bryan, Chowdhury and Mobarak, 2014; Franklin, 2018; Abebe et al., 2021) quite different from those for which urban location and spatial mismatch theories were originally conceived. Our findings provide visibility into how the structure and cost of transit fares affect travel behavior among a broad set of people who have low income and live in a major U.S. metropolitan area.

Our paper also relates to a long line of research in urban and transportation economics on the elasticities of demand for different modes of transportation. A number of papers have estimated consumers' sensitivity to public transit prices (Webster and Bly, 1980; Goodwin, 1992; Davis, 2021). Recent work has also considered how heavily discounted or fare-free public transit affects individuals' transit use (Cats, Yusak and Reimal, 2017; Hall, Perl and Sawatzky, 2020; Bull, Munoz and Silva, 2021).[2] Much of this work has focused on the

[2] Keblowski (2020) discusses the prevalence of fare-free public transportation worldwide.

efficiency implications of subsidizing public transportation in light of the scale economies associated with transit use as well as the negative externalities that alternative modes of transportation, and in particular car travel, generate (Parry and Small, 2009; Basso and Silva, 2014). However, while it is well established that current, typically flat fare structures are regressive (Cervero, 1981; Pucher, 1982; Brown, 2018), few papers have considered the distributional implications of means-tested pricing of public transit. Indeed, there has been little work on transit price elasticities for low-income riders specifically. Therefore, our evaluation provides critical evidence on the impacts of means-tested reduced-fare programs on program participants and on transit systems overall.

Finally, we contribute to the literature in behavioral economics that documents the importance of habit formation and highlights barriers individuals might face in making everyday financial decisions. Becker and Murphy (1988) provide a theoretical framework for studying addictive behaviors, which can be generalized to studying habit formation. A small number of studies use experiments to test if short-run interventions in the transportation domain have long-run effects on socially beneficial behaviors.[3] Kristal and Whillans (2020) show in a series of experiments that small behavioral 'nudges' did not meaningfully affect carpooling at a large organization. Gravert and Collentine (2019) also show in three field experiments in Sweden that behavioral interventions designed to increase public transit use fail to influence travel behavior, but that economic incentives are effective in boosting short- and longer-term transit usage. Meanwhile, Yang and Lim (2017) find that providing a 10-week discount for traveling during off-peak hours on Singapore's subways shifted the timing of transit use beyond the treatment period.[4] Relative to this literature, we study a longer subsidy period and a lower income group of people. We find that providing fare-free public transit even for a relatively extended duration does not yield persistent effects on transit card use, which points to other barriers individuals may face in using fare cards to pay for public transit in

[3] Metcalfe and Dolan (2012) review the extant literature on behavioral interventions designed to influence travel behavior.

[4] In a non-experimental setting, Larcom, Rauch and Willems (2017) find that a short-lived transit strike in London led some individuals to permanently change their commuting habits.

the face of a positive price. Non-price interventions, for example making it easier to transfer money to transit cards, might instead provide benefits even without the free fare.

The remainder of this paper is organized as follows. Section 2 discusses the King County context. We describe the experimental design and empirical strategy in Section 3, then detail our data sources in Section 4. Section 5 describes the main RCT results, then Section 6 considers the persistence of the impacts after the subsidy period ends. We conclude with a discussion of the implications of our findings in Section 7.

2 The King County Context

King County has a population of over two million people, which makes it the largest county in the state of Washington and 13th largest in the U.S. by population. The county seat is the city of Seattle, but the county also includes 38 other cities and towns. About 30% of Washington's population, 40% of its jobs, and 50% of its payroll reside in King County.[5]

Figure 1 shows a map of the western portion King County, which is the location of Seattle and the area served by King County Metro Transit (Metro). Neighborhoods (census block groups) on the map are shaded according to their quartile of median household income. The map also shows the extant transit system at the time of our study. Bus routes are shown as gray lines. RapidRide routes, which are limited-stop bus routes similar to bus rapid transit lines, appear in red. The light rail, which at the time ran from the University of Washington through downtown Seattle to (just past) SeaTac Airport, is shown in blue. According to the 2019 American Community Survey, 15% of the total working population aged 18-64 in King County, and 20% of those with income at or below 200% of the federal poverty level, use public transit to commute to work.

Metro launched a means-tested public transportation fare program in 2015 called ORCA LIFT, which we refer to as LIFT. LIFT made reduced-fare ORCA transit cards available to

[5] Authors' calculations based on American Community Survey, Bureau of Labor Statistics, and Washington Employment Security Department data.

all people with income 200% or less of the federal poverty level.[6] The LIFT program provides cards that look the same as full-fare ORCA cards, but that allow users to pay roughly half the full fare for a transit ride. While the exact fare depends on the local agency and service, for the Metro buses that account for a large share of transit ridership in the region, the LIFT fare is $1.50 per ride instead of the standard $2.75. A LIFT card is re-loadable online, by phone, by mail, at certain retailers, and at stations throughout the county.

The process of signing up for and renewing LIFT cards affects the research design for our RCT. Low-income people can enroll in LIFT at one of a number of locations throughout King County. At each office, a government or non-profit agency verifies the applicant's income and issues a LIFT card. This subsidy lasts until an expiration date; this expiration date is hard-coded on the card at manufacture and can be up to two years from the time of issuance. At expiration, an individual can renew the card by repeating the original process of income verification at a participating office. If an individual cannot or does not renew their card, the card automatically reverts to a regular adult, full-fare ORCA card.

3 Transit Subsidy Experiment

3.1 Experimental design

We conducted a randomized controlled trial providing up to six months of free public transit to low-income residents of King County. The at-risk population consisted of individuals visiting Department of Social and Health Services (DSHS) Community Service Offices (CSOs) in King County. Washington's DSHS administers public assistance programs, including SNAP and TANF. DSHS offices in King County have also enrolled individuals in the LIFT program since 2015, although DSHS clients typically visit CSOs to enroll in or renew food and cash

[6] "ORCA" is an acronym for "One Regional Card for All," and ORCA cards are valid on most transit systems in the Seattle metropolitan area. As of early 2020, nearly 82,000 LIFT cards had been issued. In 2017, Metro provided a total of $6.58 million in subsidies through the LIFT program (King County Metro Transit, 2018).

benefits.

We conducted the experiment in two waves, which we refer to as "cohorts." In the first cohort, we enrolled individuals at three CSOs chosen to represent the variety of neighborhoods in the Seattle metropolitan area. These three CSOs include a downtown Seattle office (Capitol Hill), a high-volume office with good transit access in a neighborhood on the edge of Seattle (White Center), and a suburban location between Seattle and Tacoma with more limited transit access (Auburn). In the second cohort, we enrolled individuals at all ten CSOs in King County. Figure 1 shows the locations of the CSOs.

The basic process for enrollment in the study was the same for each cohort. If a client met the income eligibility requirements for LIFT (typically inferred from their pre-established eligibility for other assistance programs), a DSHS customer service specialist asked if that client was interested in a reduced-fare transit card. Those clients who voiced interest in a LIFT card were given the opportunity to participate in a study that could provide them with free public transit for a limited time. If a client agreed to participate, the client signed a consent form and was entered into the study. The client then took a short intake survey that gathered information on baseline transit use and demographics. They were also notified about follow-up surveying that would occur; we discuss these surveys in further detail below.

At that point, a computer random number generator randomly and independently assigned the person to the treatment or control group. In the first cohort, individuals were assigned to treatment with probability one-third and to control with probability two-thirds. In the second cohort, the probability of treatment began at the same one-third rate as the first cohort but subsequently switched to one-half. Because of the change in the probability of treatment, we control for the randomization regime in all results. Overall, we randomly assigned 39% of individuals to the treatment group and 61% to the control group.

The treatment group received a LIFT card pre-loaded with monthly "passport" passes, which allowed the recipient to ride for free on nearly all public Metro buses, commuter buses, light rail, commuter trains, streetcars, and water taxis up through a particular date. After the passport expired, the card reverted to a regular LIFT card that provides reduced (but not zero) fares. The control group received a LIFT card pre-loaded with $10 worth of free transit.[7] After exhausting the $10 pre-loaded value, the control card acts as a regular LIFT card. All treatment and control cards were registered in King County Metro's LIFT registry database, which permits us to track card usage over time.

The enrollment period for the first cohort ran between March 13, 2019 and July 1, 2019. During that time, we assigned 183 individuals to treatment cards and 343 individuals to control cards. Free public transit access for the first cohort expired at one of two dates for the treated group: July 31, 2019 or August 31, 2019. There are fixed end dates because the timeframe for free transit began when Metro printed the cards as opposed to when DSHS customer service specialists issued cards to individuals. In effect, some study participants in the first cohort received free transit for as many as 24 weeks, whereas others received it for as few as four weeks. Panel (a) of Figure 2 shows the distribution of weeks of fare-free public transit for individuals in the treated group in the first cohort. The average treated individual in the first cohort received 16.7 weeks (4.2 months) of fare-free public transit. Given the price of a reduced-fare monthly "PugetPass" of $54 at the time, the implicit value of the card for the average treated individual in the first cohort was $227.

Enrollment in the second cohort began December 13, 2019 and was initially intended to run through April 2020. However, the second cohort was disrupted by sweeping policy measures aimed at stemming the spread of COVID-19, including business and school shutdowns as well as major modifications in public transit service.[8] The pandemic changed the external environment for the experiment considerably. More fundamentally, it forced us to end enrollment prematurely on March 13, 2020. Ultimately, in the second cohort, 509 individuals

[7] A LIFT card pre-loaded with $10 worth of free transit was the standard card provided to public assistance clients who voiced interest in a transit card before and during the enrollment period for the first cohort. It was also what those who declined to participate in the experiment during the enrollment period for the second cohort received for all but a short period during the initial weeks (when LIFT cards with no money pre-loaded were the standard of care).

[8] Brough, Freedman and Phillips (2021) describe the impact of COVID-19 and the associated local policy response on travel behavior in King County.

were assigned to the treated group and 762 individuals were assigned to the control group. This sample is about 25% smaller than originally planned.

The pandemic rendered the treatment inoperable for several months. Metro suspended fare collection from March 23, 2020 to September 30, 2020 due to additional health hazards posed to bus drivers during COVID-19. While we intended the treatment and control groups to face different prices until June 30, 2020, in effect both treatment and control groups had access to free public transit from March 23, 2020 to September 30, 2020. Given this, and in light of pandemic-related state and local policy directives as well as changes in travel behavior as the crisis unfolded in mid-March, we use March 16, 2020 as the effective end date for the second cohort for most of our analysis. Therefore, individuals in the second cohort had at most 14 weeks of the subsidy. The dark bars in panel (b) of Figure 2 show the distribution of weeks of fare-free public transit for individuals in the treated group in the second cohort using March 16, 2020 as the expiration date. At the beginning of the pandemic shutdown, the average treated individual in the second cohort had received 6.1 weeks (1.5 months) of fare-free public transit, which had an implicit value of $81.

Beginning October 1, 2020, Metro began charging fares again. To partially counteract the lower dose received by the second cohort, we extended the treatment group's subsidy from October 1, 2020 to December 31, 2020 and sent notices to study participants in both May and October 2020 informing them of this extension. The more lightly shaded bars in panel (b) of Figure 2 show the distribution of weeks of fare-free public transit for treated individuals in the second cohort including these additional weeks. The number of fare-free weeks for the second cohort including the extension (but excluding the fare non-collection period) ranges from 14 to 27.

3.2 Empirical strategy

Leveraging our experiment, we study the mobility effects of providing free public transit to individuals with low income. Using both administrative and survey data, we examine the impacts of free fares on transit card use as well as payment method substitution, transportation mode substitution, and overall travel volume. In our main analyses, we pool the two cohorts and limit the sample to the time period prior to the COVID-19 pandemic during which the treated group's passports (and thus their access to fare-free public transit) are active and during an equivalent period for the control group.

For each outcome, we follow a basic treatment effects specification:

$$y_i = \alpha + \beta treatment_i + \gamma regime_i + \mathbf{\Omega X}_i + \varepsilon_i \tag{1}$$

where y_i is the outcome of interest for individual i (such as LIFT boardings), $treatment_i$ is a dummy for the treatment assignment, and ε_i is the error term. We include $regime_i$, a dummy for the treatment assignment probability regime (one-third vs. one-half), in all specifications. Because of the randomization, additional controls are not strictly necessary, but in some specifications we include other controls specified in our pre-analysis plan, including age and age squared, days of transit use reported at baseline, dummies for race and ethnicity, DSHS office of enrollment, month of enrollment, and whether a car was used to get to the DSHS office, in the vector of controls for individual i, $\mathbf{X}_i$, to improve precision.[9] In addition to estimating overall treatment effects, we implement tests for heterogeneous effects across various subgroups.

In order to study the time pattern of effects, we also augment (1) as follows:

$$y_{i\tau} = \mu + \sum_{\tau=1}^{T} \theta_\tau week_\tau \times treatment_i + \sum_{\tau=1}^{T} \eta_\tau week_\tau + \phi regime_i + \mathbf{\Psi X}_i + \upsilon_{i\tau} \tag{2}$$

where subscript τ refers to time period (e.g., week) since card issuance. Here, θ_τ captures the effect of treatment on outcomes in each period after card issuance. When we pool cohorts, we estimate these effects for T=14 weeks. Notably, while we estimate these models using data aggregated to the person-week level, we focus primarily on average daily boardings as

[9]We do not include gender, which was in our pre-analysis plan, because we omitted it in the baseline survey, mistakenly believing that it was available in Metro's administrative records.

an outcome for ease of comparison across administrative and survey data.

We also study how transit card use changes when free transit ends and the cards revert to regular LIFT cards that are identical to those received by the control group. We focus on persistence in transit card use for the first cohort, which did not experience the same pandemic-related disruptions as the second cohort. However, in supplemental analyses, we show the same set of results for the second cohort after the treated group's extended free-fare period expired on December 31, 2020. We examine persistence using an event study framework, tracking transit card use in the time leading up to and immediately after the date the subsidy expires. Econometrically, this consists of estimating (2) but with time measured relative to passport expiration rather than card issuance. This specification compares transit card use among the treated to that among the control in the same (calendar) time intervals around passport expiration, thereby controlling for any potential confounding day-of-the-week or weather effects in the days before or following the expiration dates. These results speak to the extent to which the subsidy can generate persistent effects on individuals' transit card use. The variation in the dosage of fare-free transit treated individuals received also allows us to study whether those exposed to free transit for longer are differentially likely to continue using their transit cards.

4 Data and Descriptive Statistics

4.1 Baseline data

For the experiment, participants complete a short intake process that ends with random assignment to the treatment or control group. Prior to random assignment, each participant answers a questionnaire that records basic information about the person's demographics and transit habits at baseline. The questionnaire also records identifiers that allow us to link individuals to other administrative data.

One administrative dataset to which we link our study participants directly is the LIFT registry. The LIFT registry is maintained by Metro and provides an important backbone for data collection in this project. This registry includes name, date of birth, address, LIFT card number, card issuance date, card expiration date, and demographics. It also tracks card renewal and replacement.[10]

The LIFT registry allows us to compare our study participants to other low-income populations. In column (1) of Table 1, we provide descriptive statistics for all 1,797 study participants (pooling both cohorts). In columns (2) and (3), we provide the same statistics for individuals issued a reduced-fare LIFT card at one of the study CSOs while our experiment was running at that CSO and for all individuals issued a LIFT card anywhere during the period in which our experiment was running, respectively.[11] While individuals in the RCT sample are slightly more likely to have only one household member and to speak English as their first language, the racial and age composition of the study sample is similar to that of LIFT card recipients more generally.

Columns (4) and (5) of Table 1 provide the same descriptive statistics on age, race, household size, and language for the total population aged 18-64 and with income at or below 200% of the federal poverty line in King County as well as the U.S. These data are derived from the 2019 American Community Survey. Relative to these populations, study participants, and LIFT cardholders more generally, are disproportionately Black, are more likely to live alone, and are more likely to speak English as a first language.[12]

In Table 2, we report baseline characteristics of the sample by treatment status based on information from the LIFT registry as well as our intake questionnaires. The regression-

[10]We also link study records to all cards on the LIFT registry that (fuzzy) match on name and date of birth. This allows us to measure transit use by study participants that occurs on LIFT cards other than those issued as part of the study.

[11]Individuals in column (2) include those who received a LIFT card at the Capitol Hill, White Center, and Auburn CSOs between March 13 and July 9, 2019 as well as those who received a LIFT card at any of the ten CSOs in King County between December 13, 2019 and March 13, 2020. They include those issued cards as part of the experiment as well as those issued cards but who declined to participate in the experiment. Similarly, individuals in column (2) are a subset of those in column (3).

[12]Some of the difference in reported household size between LIFT cardholders and the broader population of individuals with low income in King County may be the result of "one person household" being the default response for those conducting enrollment for the LIFT program.

adjusted differences in the final column control for the probability of receiving treatment, which changed from one-third to one-half in February 2020. With the exception of the likelihood of speaking English as a first language, there are no statistically significant (at the 5% level) differences in baseline characteristics between treatment and control groups based on the registry data. Intake survey questions that were shared between the cohorts point to a slightly higher number of days using public transit in the past 30 days for the treatment group but no difference in methods of payment for transit conditional on using it in the past month. We asked more detailed intake questions to the second cohort; as shown in the final panel of Table 2, we observe balance between treated and control individuals in the second cohort on mode of transportation to the enrollment site as well as on reasons expressed for not using transit more.

We also included in the more detailed questions for the second cohort a measure of people's willingness to pay for public transit. We asked each respondent if they were willing to pay a randomly selected value (ranging from $0 to $72) for a month of unlimited access to public transit in King County. Appendix Figure A1 shows that, as expected, there is a downward-sloping demand curve for public transit; while 85% of participants reported that they were willing to pay $20 for one month of free transit access, only 25% were willing to pay $60 for one month of free transit access. Appendix Figure A1 also shows that respondents' willingness to pay for transit is balanced across treatment and control groups.

4.2 Outcome data

4.2.1 Administrative data on transit card use

Our primary source of transit card use information comes from ORCA boardings data. Metro records all ORCA card boardings, including those for LIFT, when the person pays the fare. Boarding records include the transit line as well as the date and time of the boarding. These records can be linked to an individual LIFT card with the card's serial number, which we then link to the person using the LIFT registry. For people who match to more than one card, we sum boardings across cards. Our main outcome is the number of LIFT boardings per week since card issuance. A single trip (for example, from home to work) could involve multiple boardings (for example, two buses or a bus and light rail). Therefore, we also approximate "trips" using the boardings data by combining boardings that occur within one hour of each other.

There are several limitations of the ORCA card boardings data. First, outcomes based on ORCA card boardings data will not include boardings when the person paid through another medium (e.g., cash) or did not pay. Another disadvantage is that while a LIFT card is intended for use only by the individual under whose name it is registered, it is possible that a card is used by others as well. LIFT cards might be shared among family members or friends, or even sold to others parties for use. A final drawback of the ORCA card boardings data is that we do not observe alights. Therefore, we cannot determine exact destination or trip length.

4.2.2 Survey data on travel behavior

To help address some of the limitations of the administrative transit records and to better understand the travel behavior of study participants, we supplement our ORCA card boardings data with information collected from follow-up surveys. These surveys include a travel diary that sheds additional light on trip volume as well as substitution across modes of transportation and methods of payment for transit.[13]

For the first cohort, the travel diary was administered using an SMS (text)-based platform. Specifically, the subset of individuals who had a phone that could receive SMS messages received a weekly, text-based survey. Participants in the experiment were asked to initialize the survey during the enrollment process by texting a particular number. Participants could then practice interacting with the SMS travel diary, which asked questions about recent travel behavior. Subsequently, participants received a weekly short survey asking about

[13]The Appendix provides additional detail on the survey instruments, timing, and procedures.

travel in the past day. The survey arrived at randomly chosen times to ensure representative data on transit use.

For the second cohort, we conducted a more in-depth travel diary survey, selecting a random sample of study participants to complete a phone survey and administering a web survey to the non-respondents. These phone and web-based surveys gather similar information as the travel diary collected from the first cohort. However, they also include questions related to trip purposes. The University of Wisconsin Survey Center administered the phone surveys. Individuals who did not respond to telephone surveys were also given a chance to respond to the survey via an emailed and text-messaged web link. We rely on phone and web surveys collected March 3, 2020-March 15, 2020 and November 5, 2020-December 30, 2020. We choose these periods because they align with when Metro charged fares in 2020 (January 1, 2020-March 23, 2020 and again starting on October 1, 2020).[14]

Despite low response rates, there is relatively limited observable selection into responding to the travel surveys. Across the two cohorts, we attempted surveys with 38% of the sample, of whom 33% responded to at least one survey. Pooling cohorts, Appendix Table A3 compares baseline characteristics among survey respondents and non-respondents. Survey respondents are relatively more likely to be White, to speak English as their first language, and to have taken a form of transportation besides transit to get to the enrollment site. Appendix Table A4 shows baseline balance between treatment and control groups remains for most variables when narrowing attention to the survey respondents, though some imbalance by race appears.[15]

[14]Because survey questions differed between the travel diary administered to each cohort, some calculation is needed to construct comparable measures. We describe this procedure in the Appendix. We also discuss in the Appendix how we use follow-up surveys as well as Google Timeline information to validate the administrative data on transit use.

[15]While there are no stark differences between survey respondents and the broader population of study participants, one still might be concerned that our survey respondents are not representative, particularly in terms of their travel habits. To help reduce any bias from selection into responding to the follow-up surveys, we present survey results in the Appendix reweighting survey respondents to match select baseline characteristics of the full sample as well as actual observed transit use in the week prior to the survey response and observed transit use during the treatment period, based on treatment status. Appendix Table A5 shows descriptive statistics for treatment and control groups for this weighted sample; the two groups are more aligned in terms of baseline characteristics, including in particular prior transit use.

5 Results

5.1 Transit card use based on administrative data

5.1.1 Main treatment effects

We first estimate the direct effects of fare-free public transit (relative to paying approximately \$1.50 per ride) on transit card use using the pooled cohort sample. Specifically, we compare measured control group boardings per week to measured treatment group boardings per week during the period before treated individuals' passports reverted to standard LIFT cards.[16]

In Table 3, we show the results of estimating treatment effects on transit card use as in equation (1). We estimate effects over the 14 weeks following enrollment using boardings aggregated to the person-week level, but focus on average daily boardings as the outcome for ease of comparison with subsequent results. We show results including just a dummy for the randomization regime (column (1)) as well as results including additional demographic, time, and residential location controls (columns (2)-(4)). Standard errors are clustered at the person level. We find that, relative to having to pay \$1.50 per ride, providing fare-free public transit increases observed transit use by between 0.92 and 1.04 boardings per day, depending on the specification. If we consolidate boardings that happen within one hour of each other and estimate the same regression for "trips," providing fare-free public transit increases measured transit use by between 0.48 and 0.54 trips per day. The control group mean boardings (trips) per day is 0.27 (0.17), so the results imply that free access increases transit use with LIFT cards by a factor of about 3.5.[17]

In Figure 3, we trace out average daily boardings using LIFT cards for treatment and control groups over the first 14 weeks following enrollment. The left panel shows mean LIFT boardings by week for the treatment and control groups. The right panel shows

[16] Notably, 119 treatment (18 from the first cohort and 101 from the second cohort) and 246 control cards (47 from the first cohort and 199 from the second cohort) were never used. These cards appear in the data as having zero boardings each time period.

[17] Brough et al. (2022) document similar LIFT ridership volumes among indigent defendants who receive free public transit temporarily.

the difference between treatment and control group LIFT boardings each week estimated according to equation (2). Card usage is particularly high the first week after issuance, after which it levels off.[18] In line with the regression results, observed usage levels off at a much higher rate for the treatment than for the control group, and treatment effects are consistently large and significant across weeks.[19]

5.1.2 Heterogeneous effects

We next investigate whether the treatment effects vary across different subgroups. We examine heterogeneous effects by race, ethnicity, age, language, household size, baseline transit use, residential location, day of week, time of day, and bus line load. For the vast majority of subgroups, treatment effects on transit boardings measured using card taps are positive and statistically significant.

In Panel (a) of Figure 4, we show the extent to which the treatment effect varies across different demographic groups. Each row of the panel shows the treatment effect for a different sub-sample. The circle indicates the point estimate of the treatment effect and the shaded bars show the 90%, 95%, and 99% confidence intervals. We see little evidence of differential effects across individuals of different races or ages; while the treatment effect appears to be slightly lower for Hispanic individuals and slightly higher for Black individuals, we cannot statistically rule out that the treatment effect is the same across all groups. Notably, though, we can rule out with at least 99% confidence that the treatment effect is zero for all subgroups.

In Panel (b) of Figure 4, we show results by reported household size. The majority of households in our sample report having one or two members. Overall, we find that smaller households (those with one or two members) have larger treatment effects than larger households. Consistent with our data validation exercises using follow-up travel surveys and

[18]Most individuals in the control group had $10 worth of fare-free public transit due to the pre-loaded money on their cards. This, in addition to perhaps the novelty and salience of the cards right after issuance, could help to explain the control group's relatively higher observed usage in the first week relative to subsequent weeks. The results are very similar if we drop early weeks from the sample.

[19]Results are nearly identical for each of the two cohorts; see Appendix Figures A3 and A4.

geolocation information (see the Appendix), this suggests that intra-household card-sharing is likely not a major contributor to the size of the overall treatment effects. It may also be indicative of the cost of paying fares for an entire family or the difficulty of riding public transportation with children.

In Panel (c) of Figure 4, we show results by baseline transit use as reported in the intake survey. Again, estimated treatment effects are positive for all subgroups. Moreover, we see roughly equally large effects for those with low or even zero reported transit use in the last month as for those with high reported transit use. This suggests that in addition to encouraging additional transit card use among existing riders, the subsidy may be inducing some people who were not familiar with public transit and had little to no experience using it to ride more.

We next consider whether the size of the treatment effect depends on the degree of public transit access near individuals' residences. In Panel (d) of Figure 4, we explore how the treatment effect varies based on the number of public transit stops in a participants' block group of residence. The estimated treatment effects are generally increasing in individuals' public transit access. However, we cannot statistically rule out an equally large treatment effect for those with different degrees of transit access.[20] This suggests that, in terms of inducing more transit card use, the subsidy may be more effective in combination with dense transit access but can still help to compensate for even somewhat limited local transit access.

In Figure 5, we test for differential effects of the treatment on transit card use across days of the week, times of the day, and crowdedness of routes. The impacts along these margins have potential implications for transit system efficiency. We see in Panel (a) that the treatment effects are positive and statistically significant for every day of the week. However, they tend to be larger on weekdays than on weekends. We also see in Panel (b) that, while

[20] The effect for individuals living in block groups with no stops is less precisely measured because of a small sample size. Those listed as not residing in King County may in fact live outside the county, or may be unstably housed and reporting an address of a family member or friend.

the effects on on-peak and off-peak travel using LIFT cards are statistically indistinguishable, the extra trips load more heavily on off-peak hours of the day (on-peak corresponds to 5-9am and 3pm-7pm). This result would be consistent with the low-income population who receive the subsidy using transit to accommodate irregular work/school hours, or using it to conduct other errands during the workweek.[21] In line with these results, as Panel (c) of Figure 5 shows, many of the additional LIFT boardings among the treated group occur on buses with low passenger volume. This result suggests that congestion externalities associated with the additional transit use induced by the subsidy are likely to be small.

5.2 Substitution across payment types and travel modes

The above results using administrative records only reflect public transit using a LIFT card. Treatment effects on LIFT boardings may differ from overall changes in travel for two reasons. First, people pay for transit using other means (e.g., cash). Second, people travel by modes other than public transit. The observed treatment effects could include people switching transit payment methods or substituting from other transportation modes to transit.

Notably, the LIFT card represents a lower-fare alternative to other means of payment for transit, even for the control group. Still, some individuals might use cash if they misplaced or forgot their LIFT card or because depositing money on the LIFT card was too onerous.[22] Additionally, some riders might evade fares. To the extent that individuals in the control group are differentially likely to use alternative payment methods or evade fares, our results using administrative ORCA records will overstate the impact of free fares on actual transit use.

We take advantage of follow-up surveys to examine the role of both payment method and

[21] In their intervention that provided free fares to workers at several firms in Chile for two weeks, Bull, Munoz and Silva (2021) similarly found that most new trip generation occurred in off-peak periods.

[22] One can add value to a LIFT card online, by mail, by phone, or in person at ORCA customer service offices, certain retailers, and ticket vending machines throughout King County. Value added online, by mail, or by phone can take 24-48 hours to show up in one's account (referred to as one's "E-purse"). The minimum value one can add to a LIFT card at a time is $5.

mode substitution. Table 4 summarizes the survey results.[23] We report both control and treatment group means as well as differences; the differences (and standard errors) are from regressions akin to equation (1) in which we control for the same set of baseline characteristics as in column (2) of Table 3.[24]

The first panel of Table 4 uses the administrative ORCA LIFT data to calculate daily treatment effects for the full sample, for the subset of survey respondents, and for the subset of survey respondents for the specific day that they responded to the survey and provided travel diary information. We see very similar magnitude daily transit use effects for these different samples.

The second panel of Table 4 provides the self-reported number of public transit boardings in the prior day for which a LIFT card was used as well as the self-reported number of total transit boardings in the prior day.[25] The second panel also provides self-reported total trips in the prior day using any transportation mode. The survey and administrative data point to a similar-sized treatment effect of approximately one additional LIFT card use per day. However, for both treatment and control groups, self-reported boardings using a LIFT card are higher than those measured in the administrative data. This raises the possibility that survey respondents may not accurately remember or report trips taken in the prior day, or that they indicate different payment methods for transit in the survey than they actually used. Therefore, we consider the implications of alternative assumptions about the accuracy of responses to different survey questions.

First, suppose survey respondents accurately report payment methods but overstate trip-taking in the survey. This might happen if, for example, respondents detail their trips on an earlier day when they did travel rather than the reference day in the survey, when they

[23]Results in which we weight by the propensity to respond to the survey are very similar and appear in Appendix Table A6.

[24]Note that the specification and results here are slightly different than in Table 3, as the data here are at the individual level.

[25]We only ask payment method questions to those who report transit as the mode for a sampled trip. For the first cohort, we only sample the most recent trip. There are 15 survey respondents (11 control and 4 treatment) whom we know have some transit travel but do have information on payment method.

may not have traveled. In this case, the third panel of Table 4 implies a clear shift among the treatment group toward using LIFT cards and away from other payment methods. In particular, LIFT trips account for 80% of the treatment group's transit trips but only 51% of the control group's trips.[26] That is, despite the discounts their LIFT cards provided, substantially more individuals in the control group opted to pay cash or evade fares for some trips. If, based on these results, we assume that the administrative records omit 49% of the control group's boardings and 20% of the treatment group's boardings, providing free fares increases boardings from 0.57 to 1.50 per day. On the survey day itself, instead of over quadrupling (going from 0.23 to 0.94 boardings), transit use nearly triples (going from 0.45 to 1.18 boardings). More generally, if taken at face value, the payment method responses suggest that loading money onto the card may be a barrier to using the card when trips have a positive price.[27]

On the other hand, it is possible that survey respondents report the number of trips taken accurately but misreport payment methods for some transit trips, in particular unpaid or cash transit trips, that are more common among the control group. In that case, combining information on LIFT boardings from the administrative data with transit trips reported in the survey, the treatment group could be using LIFT cards for as few as 42% (0.94/2.24) of their transit trips, while the control group could be using it for as few as 11% (0.23/2.08). Moreover, under the assumption that trips taken are reported accurately, the survey data would suggest a more modest and statistically insignificant increase in overall transit use of 0.36 trips per days, or 17%.

The reality is most likely a mixture of the two cases above; that is, that there is some misreporting of trips taken as well as payment methods in the survey. For example, people

[26]The sample for payment method is restricted to the 147 individuals who used transit on a sampled trip.

[27]Of respondents in the control group with access to a LIFT card at the time of the survey, only 68% indicated it was easy to add value. Respondents identified finding locations at which to load money, knowing how to load money, and tracking the card balance as the main obstacles to adding value to the card. Whether paying with a transit card of with cash, riders are permitted free transfers for up to two hours after the fare is paid. However, whereas the card automatically allows free transfers for two hours, riders receive a paper transfer ticket when paying with cash. Paper transfers may facilitate fare evasion if not checked closely by drivers, and therefore may be preferred by some riders.

with no boardings in administrative records in the week prior to the survey still often report taking trips using ORCA cards (Appendix Tables 7 and 8). Also, while there was some shift in reported payment types when the entire system stopped charging fares due to the COVID-19 pandemic, a nontrivial fraction continued to report paying with a LIFT card even when no payment was required (Appendix Figure 7). These results are consistent with some measurement error of both total trips and payment types. Overall, the results would be consistent with an increase in transit use in response to the treatment, but a much less pronounced increase than the administrative data alone would suggest. If the true effect on daily transit trips lies between the increase of 0.36 trips in the survey data and 0.73 trips implied by the administrative records, then the actual change in transit use is somewhere between half and all of the treatment effect measured by administrative records.

Whether these new transit trips represent new travel or shifts from other modes is less clear. The fourth panel of Table 4 shows how travel mode changes with treatment. On 79% of trips, the treatment group uses transit for at least part of the journey, compared to the control group's 62%. Meanwhile, trips by car and walking are relatively less common among treated individuals.[28] If we start from the administrative records, the shift toward transit appears to be new travel. Transit boardings on the survey day increase from 0.45 to 1.18, and overall trips per day would increase from 0.73 to 1.49 for the treatment group.[29] Thus, transit travel increases by 0.72 trips and overall travel increases by 0.76 trips, suggesting limited substitution across modes. On the other hand, if we estimate total trips more directly from the survey, the point estimate for total trips is negative, -0.24, and not statistically different from zero, implying that free fares lead participants to substitute transit for car travel on existing trips. Thus, whether transit subsidies induce new trips or induce mode switching for existing trips depends on assumptions that are difficult to test. Either way, the results

[28] The sample for mode of transportation is restricted to the 206 individuals who report at least one trip. The proportions of trips by different modes add up to more than 100% because of multi-mode trips.

[29] Our calculations adjust for the proportion of trips that only use non-transit modes. If we instead count each segment of a multi-mode trip as the object of interest, the survey would indicate that 64% of treatment group trip segments use transit and 54% of control group trip segments use transit. This would imply an increase in overall travel from 0.83 to 1.85 trips per day.

on self-reported travel modes in the final panel of Table 4 align with the interpretation that the treatment increased transit use.

Finally, we study changes in trip purposes associated with providing free fares. These results are reported in Figure 6. Notably, we only have data for these outcomes for individuals in the second cohort. As shown in Panel (a), trips taken by those who received free fares tilted more heavily toward work and other essential travel and away from social trips.[30] As shown in the remaining panels, participants largely take added work trips on the bus, and any crowded-out trips were walking or car trips to social activities.

6 Persistence in transit use after expiration

6.1 Main event study results

After the fare-free period ends (i.e., the pre-loaded monthly passes on the treatment cards expire), the treatment cards revert to regular LIFT cards identical to those held by individuals in the control group. Given their exposure to up to six months of fare-free public transit, we might expect those in the treated group to change their routines in ways that would lead to some persistence in their transit card use relative to the control group after the subsidy disappeared. By the time their passports expire, they might have learned more about how to use their transit cards as well as about how to navigate the transit system to reach work, school, or other locations. They might have also just become accustomed to using transit in their daily routines such that, even with a now positive price, they continue using it for at least some of the trips they were regularly taking during the period when it was free.

To examine the persistence of the impacts of providing fare-free public transit, we conduct an event study-style analysis. Specifically, we track transit card use in the time leading up to and immediately after the date when a treated individual's subsidy expires. Since the second cohort was interrupted by COVID-19, which changed the nature of the treatment and

[30] Essential travel includes work, school, health, and social service trips.

external environment for the experiment dramatically, we consider the two cohorts separately in this analysis.

For each cohort, we compare transit card use among the treated to that among the control in the same (calendar) time intervals around the expiration, thereby controlling for any potential confounding day-of-the-week or weather effects in the days before or following the expiration dates. For counterfactual LIFT ridership patterns at each of the passport expiration dates for the first cohort (July 31 or August 31, 2019), we assign control group cards psuedo-expiration dates based on a combination of the card-issuing CSO and issuance date, which together strongly predict treatment card expiration dates.[31] There was only one expiration date that applied to the second cohort (December 31, 2020).

The main results of the event study analysis appear in Figure 7. Panel (a) shows the results for the first cohort, and Panel (b) shows the results for the second cohort. The first figure in each panel shows LIFT boardings per day for treated and control groups in the two weeks immediately before and the two weeks immediately after card expiration. The second figure in each panel shows the difference between treated and control group LIFT boardings and trips per day for the entire study period for the first cohort and for October 1, 2020-January 17, 2021 for the second cohort. The x-axis in each figure shows days in event time, with day zero corresponding to the expiration day of the card. Importantly, because it can take up to two days for the ORCA card readers throughout King County to update to reflect passport expirations, cardholders receive an effective grace period of up to 48 hours. In other words, the last day of free fares for most study participants in the treatment group corresponds to event day two. In the figures in the second column of Figure 7, we have shaded the period between day zero and day two to highlight this effective grace period.

Transit use on treatment cards declines sharply when the period of free fares ends. For each of the two cohorts, the difference in observed boardings and trips between treatment and

[31]We arrived at very similar results if we randomize control group participants to each of the two expiration dates in proportion to the fraction of treated individuals in each of the two groups (which is 49% with July 31, and 51% with August 31).

control vanishes completely within days of when most individuals in the treatment group no longer have access to free fares, and the difference remains zero thereafter. The same pattern holds for the first and second cohorts, although overall ridership using LIFT cards was lower for the second cohort due to the pandemic.

In Table 5, we show results from the regression analogues to our event study design, focusing on LIFT boardings per day for the first cohort. All regressions include event day fixed effects. In columns (2) and (3), we add controls for individual characteristics or individual fixed effects (the latter subsume the former).[32] The positive estimated coefficient on treatment in columns (1) and (2) indicates that transit card use among the treated group is higher than that for the control group prior to passport expiration. The negative estimated coefficient on the interaction of treatment with post-expiration implies that the treatment effect falls sharply after expiration. Indeed, consistent with the results depicted in Figure 7, the coefficient on the interaction is of opposite sign and nearly equal magnitude as the first-order treatment effect, implying a small and statistically insignificant differential in transit card use between treatment and control post-passport expiration. The results are nearly identical with and without controls for individual characteristics. When we add cardholder fixed effects, such that we identify the treatment $\times$ post-expiration effect off within-individual changes in behavior around the time of expiration, our results are again very similar.

6.2 Heterogeneous effects

It is possible that the results in Figure 7 and Table 5 obscure some heterogeneity in the effects of treatment on longer-run transit card use. For example, we might expect to see more persistent effects on transit card use among those exposed to free fares for longer (and who therefore might have grown more accustom to using their cards or more familiar with the transit system). We might also expect the effect of treatment on longer-run transit card use to vary by baseline transit use and usual payment method.

[32] A control for the randomization regime is not necessary since the probability of treatment was a constant one third for the first cohort.

In Table 6, we show results from several regressions that build on our event study design to test for heterogeneous effects on LIFT boardings per day. In column (1) of Table 6, we run the same specification as in column (3) of Table 5, but also include interactions of days of exposure to free fares with post-expiration and treatment $\times$ post-expiration.[33] We define days of exposure as the number of days between card issuance and passport expiration (predicted expiration) for treatment cards (control cards). For ease of interpretation, we use the z-score of days of exposure to free fares in the regressions. A greater treatment "dosage" neither amplifies nor attenuates the decline in transit card use among the treated group after passport expiration. The triple interaction coefficient is small and statistically insignificant; that is, there is very little indication that longer exposure to free fares has a meaningful effect on the persistence of the treatment's effects on behavior. Column (2) shows similar homogeneity in the expiration effects for people with heavy, light, and no transit use prior to enrollment.[34] As shown in column (3), we find a similar result for people who report paying for transit with cash as opposed to other payment methods at baseline.

Overall, based on the ORCA card boardings data, there is little indication that providing fare-free public transit for a limited time has long-run implications for transit card use. There are several potential explanations for the seeming lack of persistent effects. First, individuals' price elasticity of demand for public transit relative to other modes could be very high at prices near zero. Second, adding money to the LIFT card might represent a large barrier for many individuals. In that case, even though rides are cheaper if paid for with a LIFT card, individuals might switch to other forms of payment (e.g., cash) once rides are no longer free. Such a pattern would be consistent with the high baseline use of cash to pay for transit, as well as the relatively frequent reported use of cash among the control group in the follow-up surveys. If many are switching to cash at passport expiration, individuals in the treatment

[33] The event day and individual fixed effects subsume the first- and second-order terms of post-expiration, treatment, days of exposure, and treatment $\times$ days of exposure.

[34] We divide the sample into three groups: people who reported no transit use in the 30 days prior to RCT enrollment ("new users"), people who reported 1-15 days of use in the 30 days prior to RCT enrollment ("light users"), and people who reported 16 or more days of use in the 30 days prior to RCT enrollment ("heavy users").

group might be riding public transit at similar levels as before their passports expired, but we do not observe their trips in the data. Third, some in the treated group might begin evading fares as soon as they face a positive price for public transit. Again, those who ride public transportation without paying cannot be tracked in our data.

7 Conclusion

In this paper, we evaluate the effects of subsidized transit fares for low-income riders using a field experiment in which a randomly selected group of public assistance clients in King County, Washington received up to six months of free public transit. We find that providing fare-free public transit to low-income individuals increases boardings with a transit card by about 1 per day, relative to a baseline policy requiring $1.50 per bus or train ride. The effects are similar across demographic groups, with positive treatment effects for nearly every subgroup. Importantly from a transit system efficiency perspective, we also find that free fares increase card boardings primarily during off-peak hours during the workweek and along transit routes that are not already crowded. We additionally find that while the subsidy may be more effective in transit-rich environments, it can still help to compensate for even somewhat limited local transit access.

Using a combination of SMS (text), phone, and web-based surveys, we document the extent to which providing free public transit to low-income individuals affects overall mobility as well as payment method and transportation mode substitution. While free transit does induce some substitution of payment method (away from cash and fare evasion, and toward use of the transit card), most of the treatment effect we observe appears to be due to increases in transit use. The data are ambiguous about whether increased transit use results from mode substitution (away from driving, and toward public transit) or new trips.

Finally, we use an event-study approach to estimate the extent to which providing free public transit has any lingering impact on transit card use after the subsidy period ends.

We find that transit card use among treated and control groups converge quickly once the subsidy expires. This implies that the subsidy had little persistent effect on travel mode choices, or at least payment methods for transit, in the long run.

This study makes important contributions to the urban, transportation, and behavioral economics literatures. First, our results speak to well-known theories of urban location and spatial mismatch in which transportation costs play a key role in determining economic outcomes, particularly for low-income populations. Second, we contribute to a literature in transportation economics that estimates the elasticity of demand for different modes of transportation by using experimental variation in transit prices. Third, we shed light on the importance of habit formation in the context of transportation decisions and demonstrate how certain types of transaction costs might affect take-up of subsidies among low-income individuals.

Our findings have immediate policy relevance for local governments that are introducing means-tested transit subsidies for residents. At the same time, there is substantial scope for additional work on how transit fares shape individuals' travel behavior. Future research could consider not only the direct impacts on participants, but also any general equilibrium effects of implementing permanent free or reduced-fare programs at scale, as many local governments in the U.S. and around the world are currently considering. Future research could also explore the importance of non-price barriers to using transit, including those related to loading money onto transit cards, in influencing individuals' use of public transportation and travel behavior more generally.

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Figures and Tables

Figure 1. King County Metro Routes and CSOs

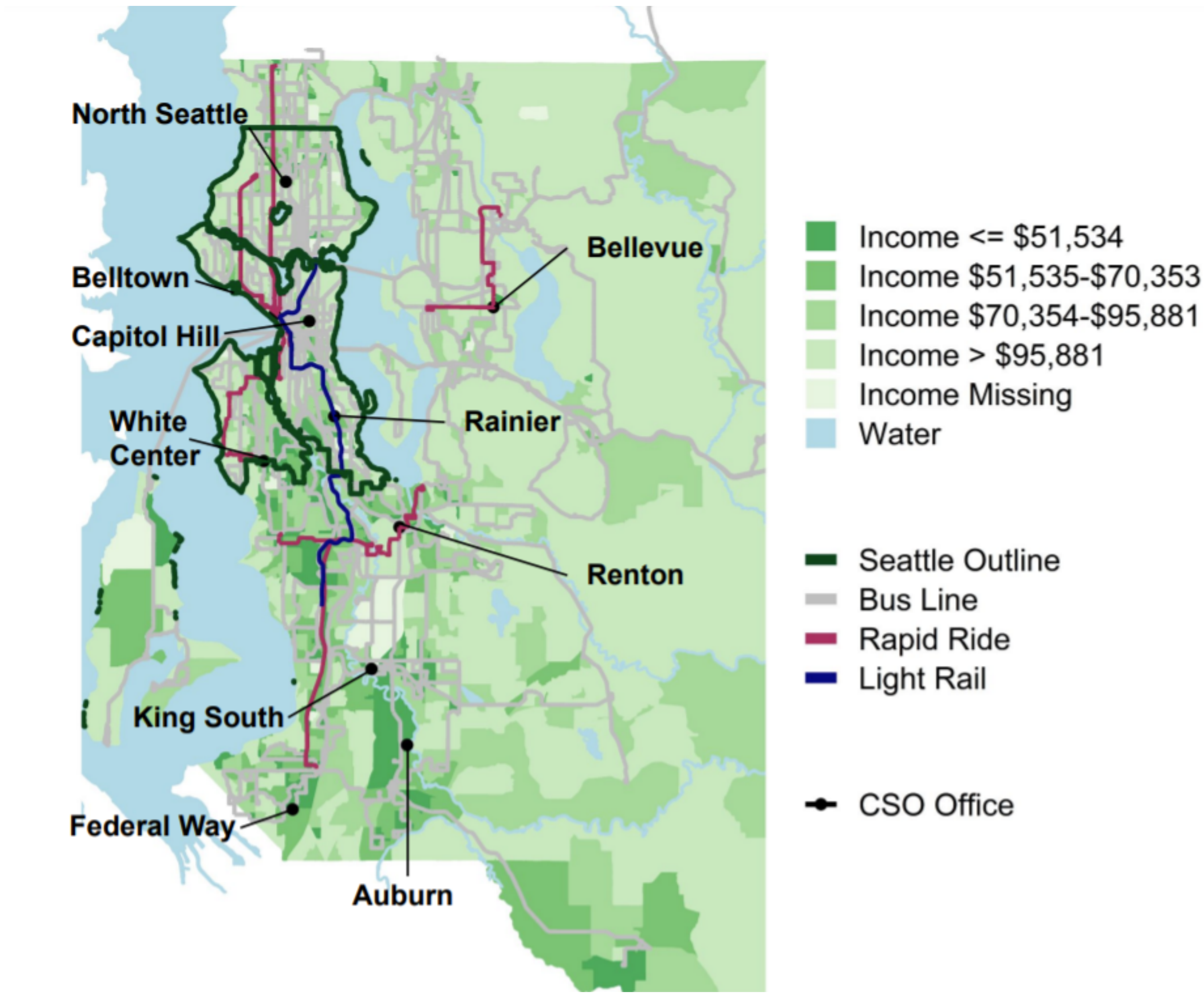
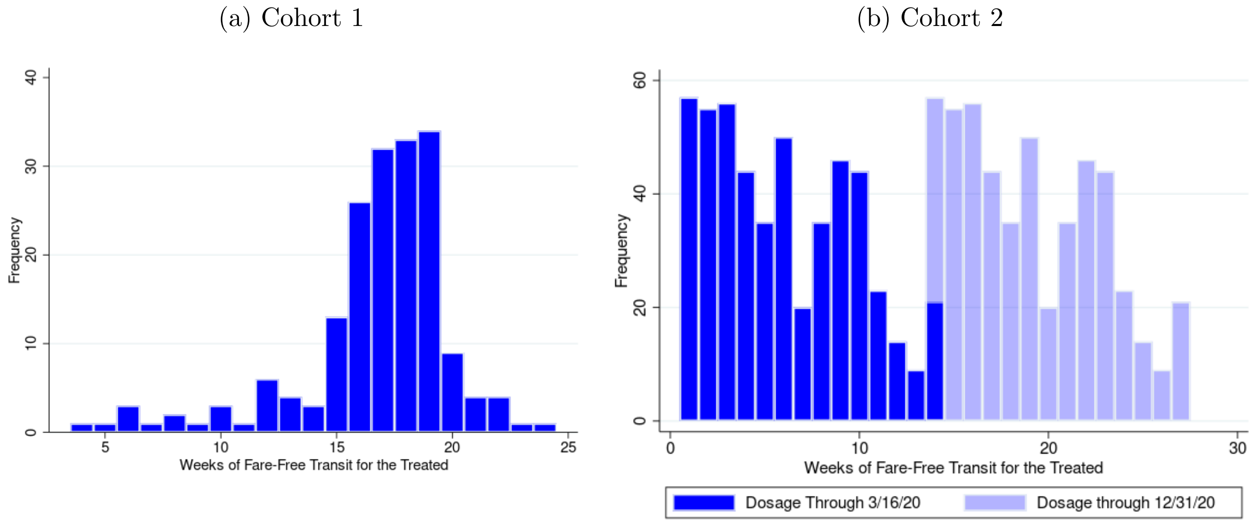


Figure 2. Distribution of Fare-Free Weeks for the Treatment Group

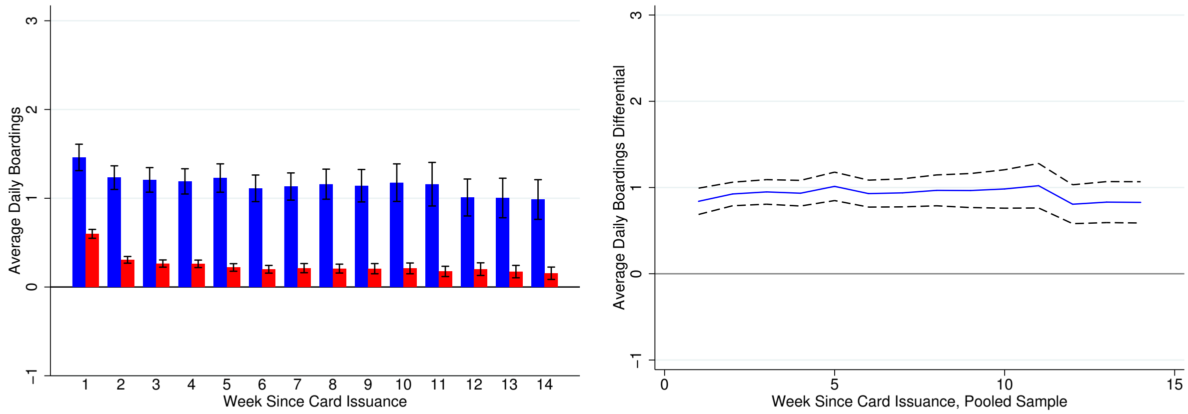


Notes: These figures display the treatment dosage among participants in the first cohort (Panel (a)) and the second cohort (Panel (b)). In Panel (b), the darker bars count only treatment weeks prior to March 16, 2020, whereas the lighter bars also include the subsidy extension between October 1, 2020 and December 31, 2020. The treatment dosage varies for individuals in each of the cohorts because, while enrollment dates varied, passport expiration dates were fixed and depended on when the card was printed as opposed to issued.

Figure 3. Boardings by Week since Card Issuance

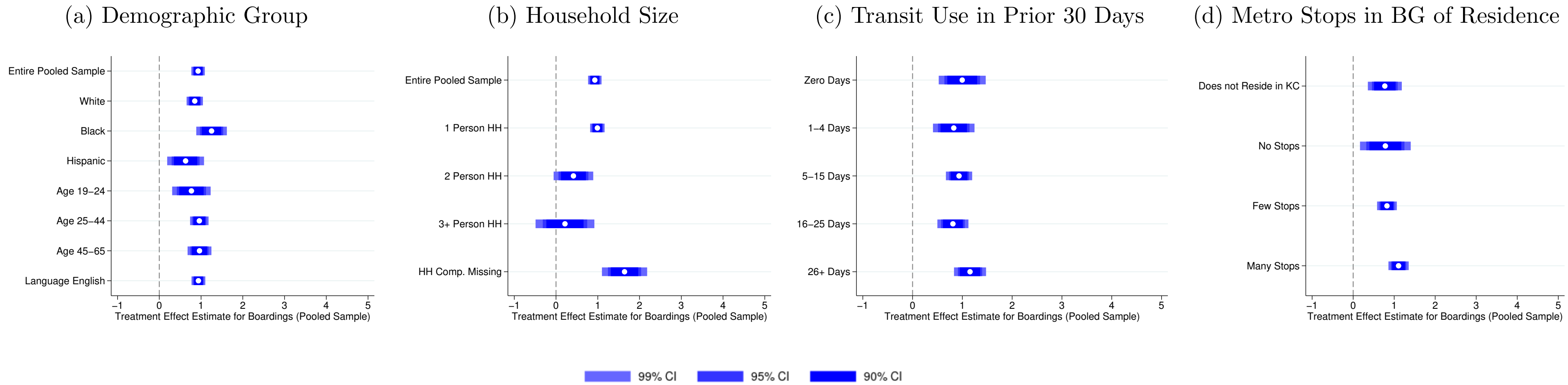
(a) Treatment and Control Boardings

(b) Regression-Adjusted Difference in Boardings



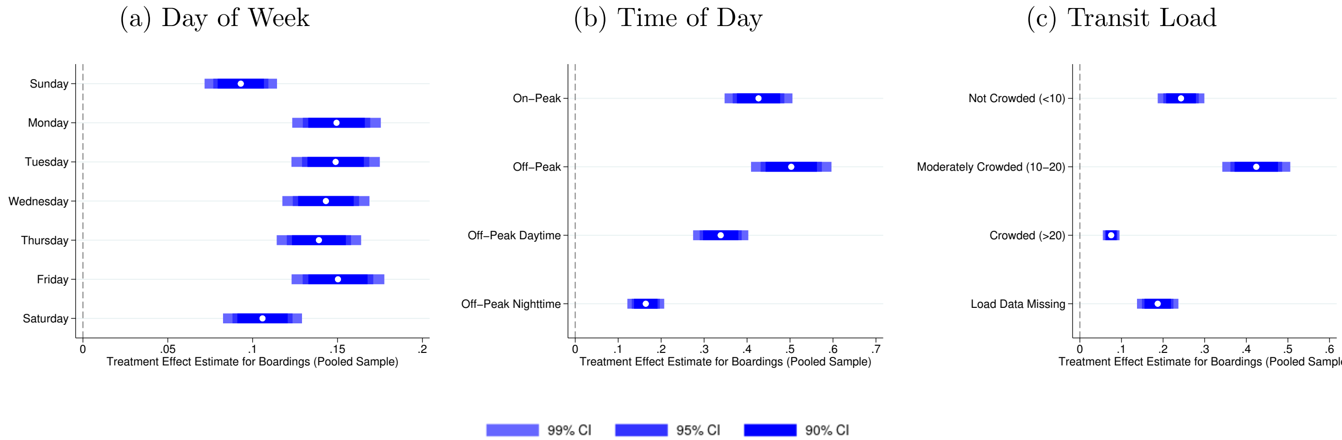
Notes: These figures display the average number of boardings paid for by LIFT for the pooled sample. Boardings are counted by week but re-scaled to daily boardings. Panel (a) shows treatment (blue) versus control (red), and Panel (b) reports a regression-adjusted difference. The reported differential in average daily boarding in Panel (b) is the treatment regression coefficient controlling for randomization regime, age, age squared, race, site of enrollment, month of enrollment, use of transit in the 30 days prior to study enrollment, and whether a car was used to get to the DSHS office. We report the treatment effect only up to 14 weeks following receipt of the study LIFT card as this treatment dosage is observed in both cohorts. Standard errors are heteroskedasticity robust and clustered at the person level.

Figure 4. Treatment Effects by Individual Characteristics



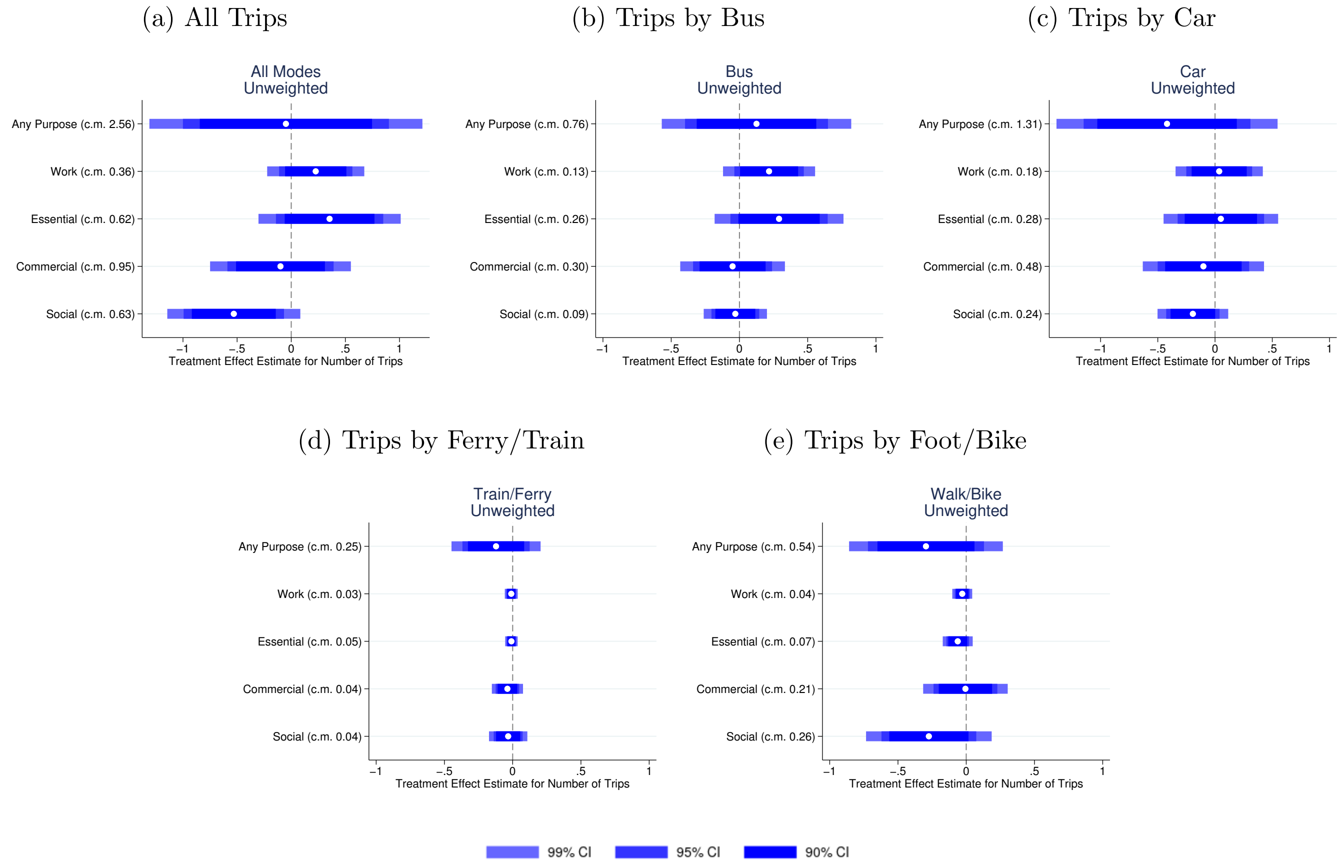
Notes: These figures show heterogeneity in treatment effects by different baseline characteristics. Panel (a) displays treatment effects by race/ethnicity and age. Panel (b) displays treatment effects by household size. Panel (c) displays treatment effects by usage of public transit in the 30 days prior to study enrollment. Panel (d) shows treatment effects by number of bus stops in the individual's census block group (BG) of residence. Each circle represents the treatment coefficient, controlling for randomization regime, age, age squared, race, site of enrollment, month of enrollment, use of transit in the 30 days prior to study enrollment, and whether a car was used to get to the DSHS office. Standard errors are heteroskedasticity robust and clustered at the person level. The bars show 90, 95, and 99 percent confidence intervals as different shades of blue.

Figure 5. Treatment Effects on Transit Use Patterns



Notes: These figures show treatment effects for transit card use patterns. Panel (a) displays treatment effects by boarding day of week. Panel (b) displays treatment effects by time of day; here, on-peak is 5-9am and 3pm-7pm, off-peak is 9am-3pm and 7pm-5am, off-peak daytime is 9am-3pm, and off-peak nighttime is 7pm-5am. Panel (c) displays treatment effects classifying boardings by the average number of passengers riding the same route during the same time of day. Each circle represents the treatment coefficient, controlling for randomization regime, age, age squared, race, site of enrollment, month of enrollment, use of transit in the 30 days prior to study enrollment, and whether a car was used to get to the DSHS office. Standard errors are heteroskedasticity robust and clustered at the person level. The bars show 90, 95, and 99 percent confidence intervals as different shades of blue.

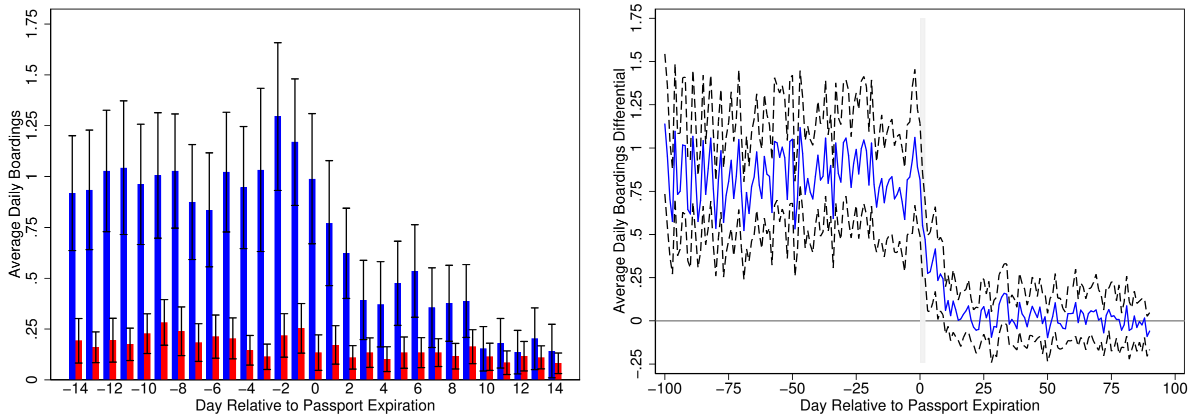
Figure 6. Changes in Self-Reported Travel by Mode and Activity Type, Cohort 2



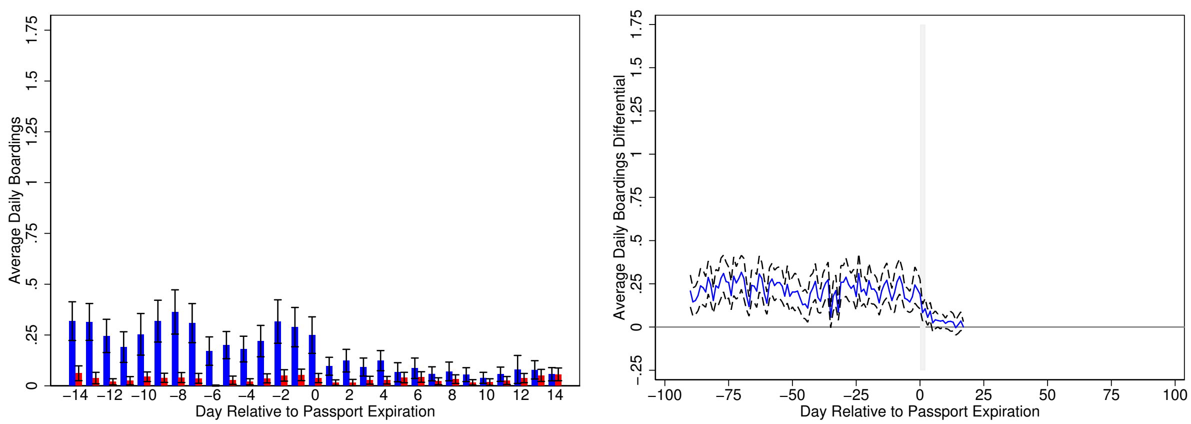
Notes: These figures use responses to the second cohort's travel diaries to compare trip composition between treatment and control groups. Panel (a) displays the treatment effect on all self-reported trips, by trip purpose. Panels (b), (c), (d), and (e) show the same for different modes. Work trips include only work trips. Essential trips include work, school, health, and social service trips. Commercial trips include shopping and errands. Social trips include visits with family, religious/community activities, and recreational activities. Each circle represents the treatment coefficient, controlling for randomization regime, age, age squared, race, site of enrollment, month of enrollment, use of transit in the 30 days prior to study enrollment, and whether a car was used to get to the DSHS office. Standard errors are heteroskedasticity robust. The bars show 90, 95, and 99 percent confidence intervals as different shades of blue.

Figure 7. Transit Use around the Date of Passport Expiration

(a) Boardings per Day, Cohort 1
(April 22, 2019 - November 29, 2019)



(b) Boardings per Day, Cohort 2
(October 1, 2020 - January 17, 2021)



Notes: These figures use Metro's administrative records to show daily boardings as the treatment card subsidy nears expiration and reverts to the standard LIFT discount price. Panel (a) shows results for the first cohort (where time zero corresponds to either July 31 or August 31, 2019), and Panel (b) shows results for the second cohort (where time zero corresponds to December 31, 2020). The first figure in each panel shows the average number of daily boardings for treatment (blue) and control (red) groups in the 14 days before and 14 days after expiration. The second figure in each panel reports the differential in average daily boarding controlling for randomization regime, age, age squared, race, site of enrollment, month of enrollment, use of transit in the 30 days prior to study enrollment, and whether a car was used to get to the DSHS office. Standard errors are heteroskedasticity robust and clustered at the person level.

Table 1. Baseline Characteristics of Study Participants and Other Populations

	(1) Study Participants	(2) Issued LIFT Card at Study CSOs	(3) Issued LIFT Card Anywhere	(4) King Cty Pop 18-64 200% Poverty Line	(5) U.S. Pop 18-64 200% Poverty Line
Age	40	40	39	37	38
White	0.41	0.38	0.36	0.51	0.63
Black	0.29	0.30	0.21	0.14	0.19
Hispanic	0.09	0.08	0.10	0.15	0.25
Asian or Pacific Islander	0.06	0.06	0.09	0.18	0.05
American Indian or Alaska Native	0.01	0.01	0.02	0.02	0.01
Multi-Racial	0.05	0.04	0.03	0.09	0.03
Other Race	0.06	0.07	0.06	0.06	0.07
Missing Race	0.03	0.05	0.12		
1 Household member	0.89	0.85	0.76	0.46	0.35
2 Household Members	0.04	0.05	0.09	0.20	0.19
3+ Household Members	0.06	0.08	0.14	0.33	0.45
Missing No. of Household Members	0.01	0.02	0.01		
Resident in Seattle	0.50	0.55	0.45	0.42	
English Speaking	0.90	0.87	0.82	0.64	0.71
Commutes by Transit				0.20	0.06
Observations	1,797	2,675	14,832		
Population				239,873	57,029,961

Notes: The first three columns of this table use King County Metro administrative records to compare the demographic characteristics of study participants to those of broader populations of individuals issued a LIFT card. Column (1) includes all individuals who enrolled in the study (pooling cohorts). Column (2) includes all individuals, including study participants, who received a LIFT card at one of the participating DSHS offices in King County during the relevant enrollment period (March 2019-July 2019 for the first cohort and December 2019-March 2020 for the second cohort). Column (3) includes all individuals who were issued a LIFT card during the enrollment periods regardless of where the card was issued. Columns (4) and (5) use 2019 American Community Survey data to provide demographic characteristics for King County and the entire United States of the population aged 18-64 that reports income less than or equal to 200% of the federal poverty line; we use the American Community Survey person weights to calculate population characteristics and counts in columns (4) and (5).

Table 2. Baseline Balance for Pooled Sample

	Control N	Control Mean	Treatment N	Treatment Mean	Reg-Adj Diff. (SE)
Registry Data					
Age	1105	40	692	41	1.05*
					(0.63)
White	1105	0.41	692	0.39	-0.03
					(0.02)
Black	1105	0.29	692	0.29	0.00
					(0.02)
Hispanic	1105	0.09	692	0.08	-0.01
					(0.01)
Asian	1105	0.03	692	0.05	0.02
					(0.01)
American Indian	1105	0.01	692	0.01	0.00
					(0.01)
Pacific Islander	1105	0.02	692	0.03	0.01
					(0.01)
Multi-racial	1105	0.05	692	0.05	0.01
					(0.01)
Other Race	1105	0.06	692	0.06	0.01
					(0.01)
Missing Race	1105	0.04	692	0.03	-0.01
					(0.01)
1 Household Member	1105	0.89	692	0.89	-0.00
					(0.02)
2 Household Members	1105	0.04	692	0.05	0.00
					(0.01)
3+ Household Members	1105	0.06	692	0.05	-0.00
					(0.01)
Missing No. of Household Members	1105	0.01	692	0.01	0.00
					(0.01)
Resident in Seattle	1105	0.49	692	0.53	0.04
					(0.02)
English Speaking	1105	0.89	692	0.92	0.03**
					(0.01)
Intake Survey Questions					
No. Days Used Transit in 30 days Prior to Enrollment	1105	15	692	16	1.00*
					(0.53)
Usually Uses Cash for Public Transit at Baseline	970	0.80	612	0.81	0.01
					(0.02)
Intake Survey Questions Asked of Cohort 2 Only					
Used Car to Get to Enrollment Site	762	0.20	509	0.17	-0.03
					(0.02)
Used Bus to Get to Enrollment Site	762	0.53	509	0.52	0.00
					(0.03)
Cost Never Prevents Using Public Transit	762	0.18	509	0.16	-0.03
					(0.02)
Cost Sometimes Prevents Using Public Transit	762	0.30	509	0.34	0.01
					(0.03)
Cost Usually Prevents Using Public Transit	762	0.22	509	0.23	0.02
					(0.02)
Cost Always Prevents Using Public Transit	762	0.31	509	0.27	-0.00
					(0.03)

Notes: This table uses both King County Metro administrative records and survey data collected at enrollment to compare demographic characteristics as well as travel behavior among study participants assigned to the treatment and control groups. The top panel reports information derived from the LIFT registry for all participants in the first and second cohorts. The second panel reports information collected at baseline in intake surveys for all participants in the first and second cohorts. Individuals were only asked if they usually use cash to pay for public transit if they reported using public transit at all in the prior 30 days. Additional questions about transportation habits were asked of the 1,271 participants in the second cohort; these data are reported in the final panel. The final column in the table reports the difference between treatment and control for each characteristic, conditioning on the probability of receiving treatment (which changed from one-third to one-half in February 2020). Standard errors reported in parentheses are heteroskedasticity robust. Statistically significant at *10%, **5%, and ***1%.

Table 3. Main Treatment Effects for Pooled Sample

	(1)	(2)	(3)	(4)
	Boardings per day			
Treatment	0.923***	0.929***	0.930***	1.037***
	(0.064)	(0.063)	(0.063)	(0.070)
Control Group Mean	0.27			
	Trips per day			
Treatment	0.481***	0.485***	0.485***	0.542***
	(0.032)	(0.031)	(0.031)	(0.035)
Control Group Mean	0.17			
Randomization Regime FEs	✓	✓	✓	✓
Individual Controls		✓	✓	✓
Weeks Since Card Receipt FEs			✓	✓
Block Group FEs				✓
Observations	15274			

Notes: This table reports treatment effects on daily public transit over the treatment period for the pooled cohorts. The treatment period for the first cohort lasts until the card's expiration and for the second cohort is restricted to prior to March 16, 2020. All regressions control for randomization regime. Individual controls include age and age squared, race and ethnicity dummies, DSHS office of enrollment, month of enrollment, days of transit use reported at baseline, and whether a car was used to get to the DSHS office. Observations are at the person-week level, and standard errors reported in parentheses are heteroskedasticity robust and clustered at the person level. Statistically significant at *10%, **5%, and ***1%.

Table 4. Follow-up Survey Responses by Treatment Status

	Control		Treatment		Reg-Adj Diff.
	N	Mean	N	Mean	(SE)
Admin Data Boardings					
Daily ORCA LIFT Boardings - Full Sample	1105	0.29	692	1.20	0.89***
					(0.06)
Daily ORCA LIFT Boardings - Survey Responders	122	0.32	106	1.04	0.80***
					(0.14)
Daily ORCA LIFT Boardings on Survey Date	122	0.23	106	0.94	0.90***
					(0.18)
Self-Reported Travel					
ORCA LIFT Boardings	111	1.03	102	1.87	1.02***
					(0.24)
All Transit Boardings	122	2.08	106	2.24	0.36
					(0.27)
Total Trips, Any Mode	122	3.42	106	2.92	-0.24
					(0.30)
Payment Method for Public Transit Trips					
% of Public Transit Trips Paid for by ORCA LIFT	78	0.51	69	0.80	0.26***
					(0.07)
% of Public Transit Trips Paid for by Cash	78	0.38	69	0.15	-0.19**
					(0.07)
% of Public Transit Trips Not Paid For	78	0.04	69	0.01	-0.03
					(0.03)
% of Public Transit Trips Paid for by Other Means	78	0.04	69	0.04	0.00
					(0.02)
Mode					
% of Trips by Public Transportation	116	0.62	90	0.79	0.16**
					(0.08)
% of Trips by Car	116	0.36	90	0.27	-0.09
					(0.07)
% of Trips by Foot	116	0.15	90	0.18	-0.04
					(0.06)
% of Trips by Bike	116	0.01	90	0.00	-0.02
					(0.02)

Notes: This table reports combined responses to travel diary surveys conducted in March, November, and December 2020 for participants in second cohort, and conducted weekly after enrollment and throughout the treatment period for participants in the first cohort. In total, we have survey responses for 228 participants. We only have payment method information for the 213 participants for whom a sampled trip was taken by transit. The bottom two panels condition on respondents reporting at least one relevant trip in the travel day. As such, we observe 147 individuals responding to payment questions and 206 individuals responding on mode type. The final column displays the regression coefficient of treatment on each variable, controlling for randomization regime, race, age, age squared, site of enrollment, month of enrollment, use of public transit in the 30 days prior to enrollment, and whether a car was used to get to the DSHS office. Standard errors reported in parentheses are heteroskedasticity robust. Statistically significant at *10%, **5%, and ***1%.

Table 5. Event Study Regressions for First Cohort

	(1)	(2)	(3)
		Boardings per Day	
Treatment	0.825***	0.836***	
	(0.096)	(0.097)	
Treatment × Post-Expiration	-0.807***	-0.799***	-0.801***
	(0.091)	(0.091)	(0.091)
Control Group Mean		0.19	
Event Day FEs	✓	✓	✓
Individual Controls		✓	
Individual FEs			✓
Observations		118,882	

Notes: This table reports treatment effects on daily public transit boardings over the treatment period and up to 90 days after it for participants in the first cohort. Individual controls include age and age squared, race and ethnicity dummies, DSHS office of enrollment, month of enrollment, days of transit use reported at baseline, and whether a car was used to get to the DSHS office. Each observation is at the person-day level, and standard errors in parentheses are heteroskedasticity robust and clustered at the person level. Significant at *10%, **5%, and ***1%

Table 6. Event Study Regressions for First Cohort, Heterogeneity Tests

	(1)	(2)	(3)
	Boardings per Day		
Treatment × Post-Expiration	-0.805***	-0.727***	-0.831***
	(0.091)	(0.226)	(0.167)
Treatment × Post-Expiration × Days of Free Fares	-0.012		
	(0.085)		
Treatment × Post-Expiration × Light User		0.204	
		(0.254)	
Treatment × Post-Expiration × Heavy User		-0.283	
		(0.267)	
Treatment × Post-Expiration × Usually Pay Cash			0.035
			(0.198)
Control Group Mean		0.19	
Event Day FEs	✓	✓	✓
Individual FEs	✓	✓	✓
Observations		118,882	

Notes: This table reports treatment effects on daily public transit over the treatment and up to 90 days post treatment period for participants in the first cohort. Light users report using transit 1-15 days over the past 30 days at baseline, and high users report 16 trips or more. The omitted category is 0 days of use in the past 30 days. All regressions include person fixed effects and day fixed effects. Each observation is at the person-day level, and standard errors in parentheses are heteroskedasticity robust and clustered at the person level. Significant at *10%, **5%, and ***1%

Experimental Evidence on the Effects of Means-Tested Public Transportation Subsidies on Travel Behavior

Appendix

Rebecca Brough, Matthew Freedman, and David C. Phillips

A Travel Diaries

A.1 Travel Diary Questions - Cohort 1

Num.	Question	Response Format
1	Hi [Name], ORCA/DSHS ChatBot here with weekly travel survey. Responding will enter you in this week's lottery for a $5 Safeway giftcard! ([Winner name]+ 5 others won last week). I am going to ask about the place where you are right now. Public transportation includes buses and trains. Did you take public transportation to get here? (y/n)	Free Response
2	*If responds "yes" to question 1* Ok. How did you pay for the ride? (Examples: cash on board, ORCA card, paper ticket, transfer, did not pay)	Free Response
3	How did you get here? (Examples: walk, bike, train, drove, taxi, Uber, Lyft, got a ride)	Free Response
4	How many times did you get on a bus or train in the past 24 hours? (Respond with a number and count transfers as more than one bus)	Free Response
End	Got it, thanks! You've been entered into today's $5 Safeway gift card lottery. Have a great rest of the day.	NA

A.2 Cohort 1 - Surveying Procedure

For the first cohort, the travel diary was administered using an SMS (text)-based platform. During the baseline intake survey, 331 people indicated they had devices with SMS capabilities and that they were interested in participating in SMS surveys. Those individuals were asked to initialize the survey during the enrollment process by texting a particular number. Participants could then try out interacting with the SMS travel diary, which asked questions about recent travel behavior (these practice responses were not considered as survey responses).

Subsequently, those who initialized the travel diary (and a set of people who failed to initialize themselves, but to whom the travel diary reached out directly using the phone numbers they provided) received a weekly short survey asking about travel in the past day. The survey arrived at randomly chosen days and times to ensure representative data on transit use. Survey participants continued to receive the opportunity to respond to the SMS survey for a chance of winning a $5 Safeway gift cards weekly until September 2019.

In our study, we only consider survey responses that occurred before the end the subsidy period (for some, this was July 31, 2019, and others August 31, 2019). 118 of 331 individuals responded to at least one SMS survey during the subsidy period.

A.3 Travel Diary Questions - Cohort 2

After listing up to 10 places the respondent went the prior day, the survey randomly selects 3 trips (up to 6 places) to ask about in more detail. This section of the survey is listed below.

Introduction: Now we are going to ask about three trips you made yesterday. For trips made using public transportation, tell us where you were going (e.g., to workplace, grocery store, etc.). You don't need to include the bus stops, train stations, or transfer points on your way there.

	Question	Response Format
1	Where is [randomly selected place N]?	Free Response
2	Where is [randomly selected place N+1]?	Free Response
3	How did you get from [randomly selected place N] to [randomly selected place N+1]?	Select all that apply: - Bus - Train/Light Rail/Sound Transit - Ferry - Car - Bike - Walk - Other
4	*If respondent indicated using a public transit card. How did you pay the fare?*	Select one: - ORCA Card/LIFT card - Cash/Paper Transfer - Other - Did not pay
5	*If respondent indicated using a public transit card.* Where did you receive this card?	Select one: - DSHS - Somewhere else
6	What was your main activity at [randomly selected place N+1]?	Select one: - Work - School - Shopping - Other Errands - Recreation/Entertainment - See Friends/Family - Healthcare - Religious/Other community activities - Benefits/Social Service Agencies - Other

A.4 Cohort 2 - Surveying Procedure

For the second cohort, we conducted a more in-depth travel diary survey. Overall, these phone and web-based surveys gather similar information as the travel diary collected from the first cohort, but they also collected some additional information, provided greater incentives to respond, were completed by phone and web rather than text message, and were split across two points in time due pandemic-related disruptions.

On February 12, 2020, 176 participants providing a valid telephone number (89 control, 87 treatment) were randomly selected to be surveyed by phone. Only individuals with enrollment dates before February 12, 2020 were selected to participate in this first round of surveying. Telephone surveys would subsequently occur from March 4, 2020 to March 16, 2020. Individuals not responding to this survey were also given the opportunity to respond to the travel diary via the web. In this first round, 43 participants responded by phone and 29 by web.

In May 2020, all remaining individuals providing their telephone or email were randomly assigned to one of 11 2-week survey periods. During each 2-week survey period, individuals would receive two text messages and two email reminders to complete the survey by web.

After the completion of 5 of 11 of these 2-week survey batches, the research team decided to select a portion of the unsurveyed group (batches 6-11) to be included in a second phone survey (as opposed to the web). At this point, 175 participants (88 control, 87 treatment) were to be included in the second round of phone surveying. Individuals selected in this round were required to have a valid phone number and an enrollment date after February 11, 2020.

In October 2020, the final survey group was selected to be surveyed by phone in November 2020. 250 individuals were selected for this round. The 250 individuals included all 175 individuals originally selected to be surveyed in this second round; the 43 individuals responding to the first round of phone surveying; the 29 individuals who responded to the first round of web surveying; and 3 individuals who we randomly selected from the non-respondents to the first round (to both to web and phone surveys). Individuals in this group were given the chance to respond to the travel survey both by phone and by web. Of these 250 individuals surveyed, we obtained 88 responses.

A.5 Construction of Survey Variables

Because survey questions differed between the travel diary administered to each cohort, some calculation is needed to construct comparable measures. For both cohorts, when a participant responds to the survey more than once, we average values across their responses.

To obtain the number of self-reported boardings, we use responses to questions that explicitly ask cohort 1 participants how many times they used public transit in the past 24 hours; in cohort 2, we instead ask participants to list all their trips on the previous day (up to 10) with follow-up questions on mode, payment type, and trip purpose for three randomly selected trips. The percentage of the three randomly selected trips taken by public transit is scaled up by the total number of reported trips to obtain the number of self-reported public transit trips.

To obtain the number of self-reported LIFT boardings, we combine the total boardings estimate with information on payment method. For cohort 1, we only observe payment method for the most recent trip and assume that the method used for the most recent trip applies to all transit trips. If the most recent trip was not by transit, then we have no information on payment method and cannot compute ORCA boardings. For cohort 2, the percentage of the three randomly selected trips taken by public transit using an ORCA card is scaled up by the total number of reported trips.

We can also impute measures for the total number of trips. For cohort 1, to get total trips by any mode, we calculate average transit boardings and then inflate it by the inverse of the percentage of people taking transit on their most recent trip. For cohort 2, we can measure total trips directly and do so in separate analyses of only cohort 2 responses. However, when we pool across cohorts, we impute total trips in a similar manner as cohort 1, taking our estimate of total transit trips and inflating by the inverse of the percentage of the three sampled trips that were by public transit. In practice, we estimate these ratios by seemingly unrelated regressions to allow for inference. While this imputation introduces some noise, we show in Appendix Figure A2 that measures of the number of ORCA boardings for an individual are positively correlated across the survey and administrative records.

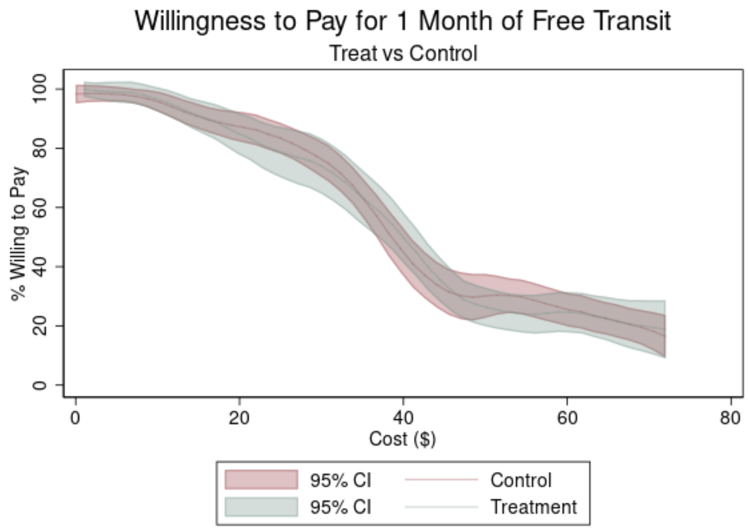
A.6 Validation of Administrative Records on Transit Use

Our follow-up surveys help validate the administrative data on transit use. In Panels (a) and (b) of Appendix Figure A2, we plot transit boardings on the survey day paid for by ORCA card as recorded by self-reports versus the administrative data. In each case, we find a strong positive relationship. This indicates that we are capturing similar notions of transit use with each of the two datasets. It also suggests that the amount of card-sharing is limited; if card sharing or selling were pervasive, we would expect a disconnect between survey-reported transit use and observed boardings using the card.

We also collected Google Timeline data from eight participants in the second cohort. Google Timeline tracks individual movements continuously using an individual's smartphone GPS and automatically imputes mode of transportation between points. In Panel (c) of Appendix Figure A2, we compare bus boardings as measured in the Google Timeline data to boardings measured using administrative records. While we have limited power with the Timeline data, again transit use as measured in these different sources lines up closely.

Appendix Figures and Tables

Figure A1. Willingness to Pay



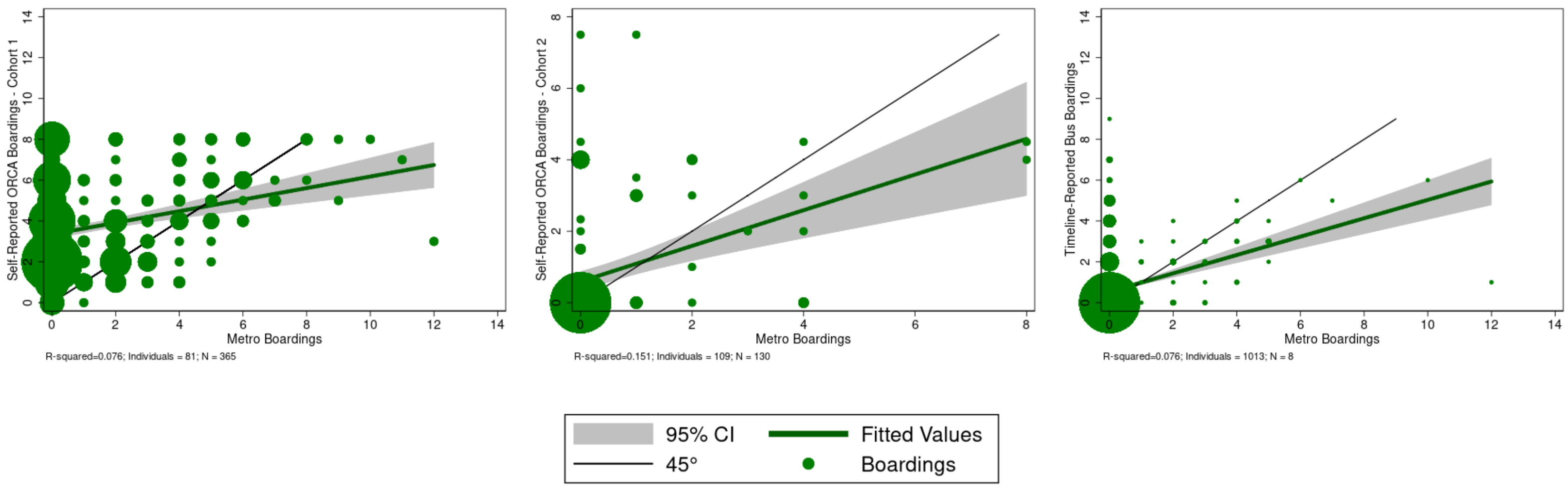
Notes: This figure displays responses to questions about Cohort 2 participants' willingness to pay for 1 month of free transportation. Each baseline survey was programmed with a randomly selected number between \$0 and \$72. Individuals were asked whether they would be willing to pay this randomly selected value for a month of free transportation. This figure displays results of a kernel-weighted local polynomial regression of price on the percentage of respondents willing to pay the randomly selected price assigned to them. Responses are split by treatment status and show balance in responses among treatment and control groups.

Figure A2. Data Validation of Administrative Records

(a) Travel Diary (Cohort 1) vs. Admin Data

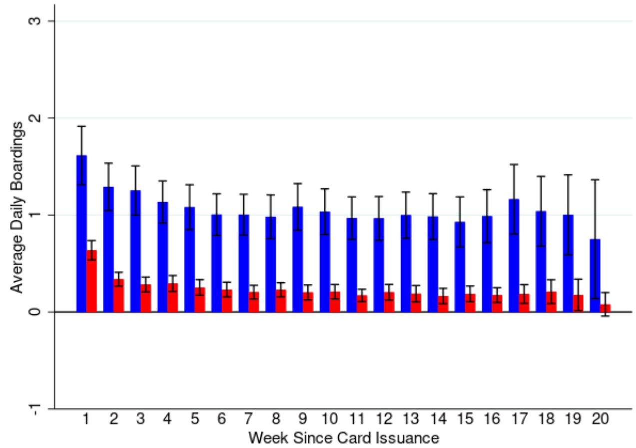
(b) Travel Diary (Cohort 2) vs. Admin Data

(c) Google Timeline (Cohort 2) vs. Admin Data



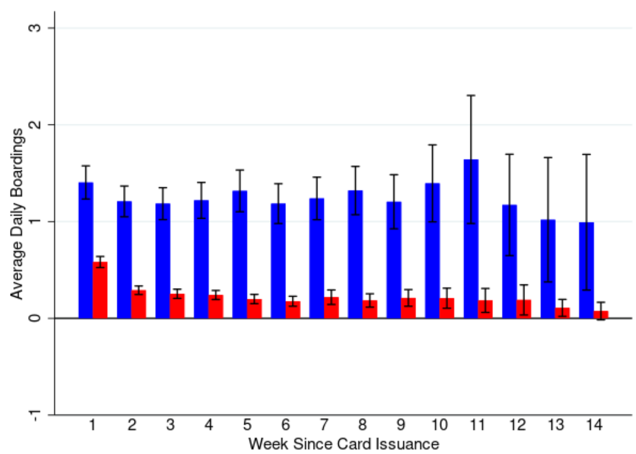
Notes: Panels (a) and (b) compare the number of self-reported trips by LIFT on the date surveyed to the number of observed boardings on the same date according to Metro's administrative records. Each observation in Panels (a) and (b) is a person-survey date unit. Panel (c) uses data Google Timeline data to compare Metro's administrative records to the number of bus trips reported by Google Timeline. Panel (c) uses 1013 day-person observations across eight individuals.

Figure A3. Boardings by Week since Card Issuance, Cohort 1



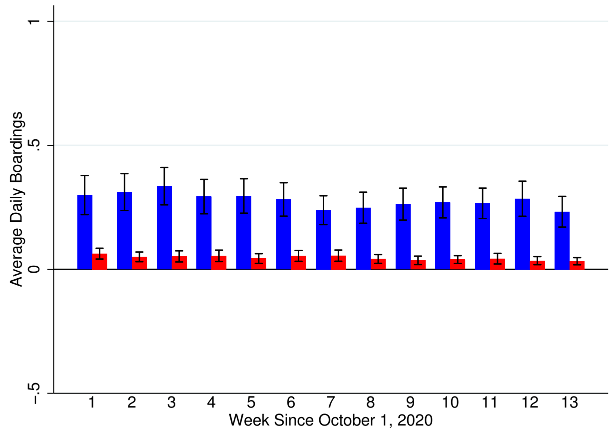
Notes: This figure displays the average number of daily boardings paid for by LIFT for treatment (blue) and control (red) groups. The sample includes all Cohort 1 participants. Standard errors are heteroskedasticity robust and clustered at the person level.

Figure A4. Boardings by Week since Card Issuance, Cohort 2



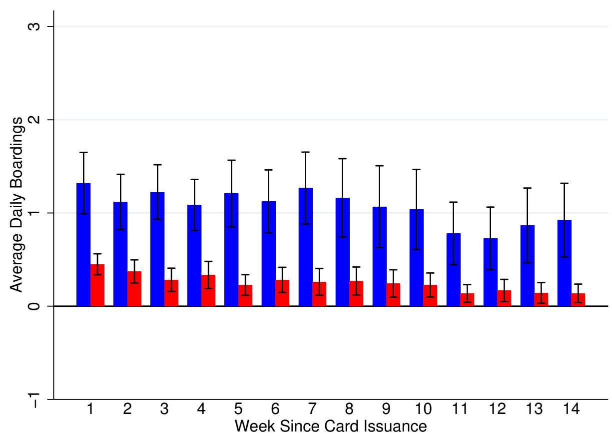
Notes: This figure displays the average number of daily boardings paid for by LIFT for treatment (blue) and control (red) groups. The sample includes all Cohort 2 participants. We only report ridership during the main treatment period, prior to when public transit was affected by the COVID-19 pandemic (March 16, 2020). Standard errors are heteroskedasticity robust and clustered at the person level.

Figure A5. Boardings by Week since October 1, 2020, Cohort 2



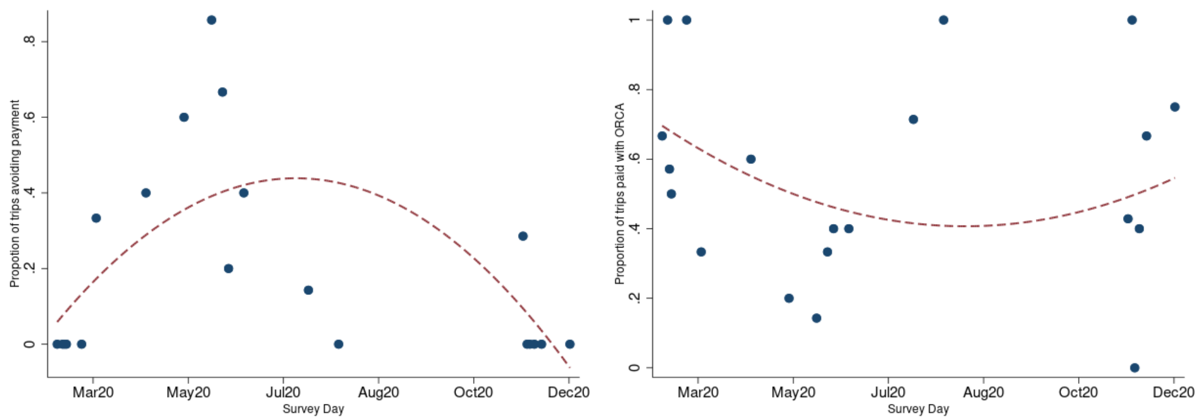
Notes: This figure displays the average number of daily boardings paid for by LIFT for treatment (blue) and control (red) groups. The sample includes all Cohort 2 participants. We focus on card usage during the additional treatment dosage period between October 1, 2020 and December 31, 2020.

Figure A6. Boardings by Week since Card Issuance, Survey Sample



Notes: This figure displays the average number of daily boardings paid for by LIFT for treatment (blue) and control (red) groups. The reported sample is pooled among survey respondents in the first and second cohorts. We report the treatment effect only up to 14 weeks following receipt of the study LIFT card as this treatment dosage is observed in both cohorts. For the second cohort, we only report ridership prior to when public transit was affected by the COVID-19 pandemic (March 16, 2020).

Figure A7. Proportion Paying by Different Methods over Time, Survey Responses



Notes: These figures use survey responses to measure payment method. We expand the sample from the main text to also include observations that responded to the survey during the time that Metro was not charging fares, from March 24, 2020 to September 30, 2020. Each plotted point shows average proportion of trips paid for by the given method for ventiles of the survey date. The curve shows a quadratic fit for the underlying data.

Table A1. Baseline Characteristics, Cohort 1

	Control N	Control Mean	Treatment N	Treatment Mean	Reg-Adj Diff. (SE)
Registry Data					
Age	343	39	183	40	1.06
					(1.16)
White	343	0.47	183	0.44	-0.03
					(0.05)
Black	343	0.33	183	0.32	-0.01
					(0.04)
Hispanic	343	0.07	183	0.06	-0.01
					(0.02)
Asian	343	0.03	183	0.04	0.02
					(0.02)
American Indian	343	0.01	183	0.01	-0.01
					(0.01)
Pacific Islander	343	0.01	183	0.05	0.04***
					(0.01)
Multi-racial	343	0.01	183	0.02	0.01
					(0.01)
Other Race	343	0.02	183	0.03	0.02
					(0.01)
Missing Race	343	0.06	183	0.03	-0.03
					(0.02)
1 Household member	343	0.90	183	0.92	0.02
					(0.03)
2 Household members	343	0.03	183	0.05	0.01
					(0.02)
3+ Household members	343	0.05	183	0.03	-0.02
					(0.02)
Missing num of household members	343	0.02	183	0.01	-0.01
					(0.01)
Resident in Seattle	343	0.40	183	0.43	0.03
					(0.05)
English Speaking	343	0.92	183	0.96	0.03
					(0.02)
Intake Survey Questions					
Use of Public Transit in 30 days Prior to Enrollment	343	15	183	15	0.96
					(1.02)
Usually uses cash for public transit at baseline	300	0.81	156	0.89	0.08**
					(0.04)

Notes: This table uses both Metro administrative records and survey data collected at enrollment to compare demographic and transit usage characteristics among study participants assigned to the treatment and control groups in the first cohort (those enrolling March-July 2019). The first panel reports Metro administrative data for all participants in the first cohort. The second panel reports collected baseline data for all participants in the second cohort. Individuals are only asked if they usually use cash to pay for public transit if they reported using public transit at all in the prior 30 days. The final column reports the difference in means. Standard errors reported in parentheses are heteroskedasticity robust. Statistically significant at *10%, **5%, and ***1%.

Table A2. Baseline Characteristics, Cohort 2

	Control N	Control Mean	Treatment N	Treatment Mean	Reg-Adj Diff. (SE)
Registry Data					
Age	762	40	509	41	1.05
					(0.76)
White	762	0.39	509	0.38	-0.03
					(0.03)
Black	762	0.28	509	0.29	0.01
					(0.03)
Hispanic	762	0.10	509	0.09	-0.01
					(0.02)
Asian	762	0.03	509	0.05	0.01
					(0.01)
American Indian	762	0.01	509	0.02	0.01
					(0.01)
Pacific Islander	762	0.02	509	0.02	-0.00
					(0.01)
Multi-racial	762	0.06	509	0.06	0.01
					(0.01)
Other Race	762	0.08	509	0.07	0.00
					(0.02)
Missing Race	762	0.03	509	0.03	0.00
					(0.01)
1 Household member	762	0.88	509	0.88	-0.01
					(0.02)
2 Household members	762	0.05	509	0.05	0.00
					(0.01)
3+ Household members	762	0.06	509	0.06	0.00
					(0.01)
Missing num of household members	762	0.01	509	0.01	0.00
					(0.01)
Resident in Seattle	762	0.52	509	0.57	0.04
					(0.03)
English Speaking	762	0.88	509	0.91	0.03
					(0.02)
Intake Survey Questions					
Use of Public Transit in 30 days Prior to Enrollment	762	15	509	16	1.02
					(0.62)
Usually uses cash for public transit at baseline	670	0.79	456	0.78	-0.01
					(0.03)
Intake Survey Questions Asked of Cohort 2 Only					
Used car to get to enrollment site	762	0.20	509	0.17	-0.03
					(0.02)
Used bus to get to enrollment site	762	0.53	509	0.52	0.00
					(0.03)
Cost never prevents using public transit	762	0.18	509	0.16	-0.03
					(0.02)
Cost sometimes prevents using public transit	762	0.30	509	0.34	0.01
					(0.03)
Cost usually prevents using public transit	762	0.22	509	0.23	0.02
					(0.02)
Cost always prevents using public transit	762	0.31	509	0.27	-0.00
					(0.03)

Notes: This table uses both Metro administrative records and survey data collected at enrollment to compare demographic and transit usage characteristics among study participants assigned to the treatment and control groups in the second cohort (those enrolling December 2019-March 2019). The first panel reports Metro administrative data for all participants in the second cohort. The second panel reports collected baseline data questions asked to participants in both the first and second cohorts. Individuals are only asked if they usually use cash to pay for public transit if they reported using public transit at all in the prior 30 days. Additional questions about transportation use were asked of participants in the second cohort. The final column reports the regression-adjusted difference in means, controlling for the randomization regime at study intake. Standard errors reported in parentheses are heteroskedasticity robust. Statistically significant at *10%, **5%, and ***1%.

Table A3. Survey Respondents vs. Non-Respondents

	Non-Responders N	Mean	Responders N	Mean	Reg-Adj Diff. (SE)
Registry Data					
Age	1570	40	227	39	-0.77 (0.92)
White	1570	0.40	227	0.46	0.07* (0.03)
Black	1570	0.30	227	0.26	-0.04 (0.03)
Hispanic	1570	0.09	227	0.06	-0.04* (0.02)
Asian	1570	0.04	227	0.04	0.00 (0.01)
American Indian	1570	0.01	227	0.02	0.01* (0.01)
Pacific Islander	1570	0.02	227	0.01	-0.01 (0.01)
Multi-racial	1570	0.05	227	0.03	-0.02 (0.02)
Other Race	1570	0.06	227	0.06	0.00 (0.02)
Missing Race	1570	0.03	227	0.06	0.03** (0.01)
1 Household member	1570	0.89	227	0.86	-0.03 (0.02)
2 Household members	1570	0.04	227	0.05	0.01 (0.01)
3+ Household members	1570	0.05	227	0.07	0.02 (0.02)
Missing num of household members	1570	0.01	227	0.01	0.00 (0.01)
Resident in Seattle	1570	0.50	227	0.52	0.01 (0.04)
English Speaking	1570	0.90	227	0.96	0.06*** (0.02)
Intake Survey Questions					
Use of Public Transit in 30 days Prior to Enrollment	1570	15	227	16	0.58 (0.78)
Usually uses cash for public transit at baseline	1364	0.80	218	0.83	0.04 (0.03)
Intake Survey Questions Asked of Cohort 2 Only					
Used car to get to enrollment site	1162	0.18	109	0.24	0.06 (0.04)
Used bus to get to enrollment site	1162	0.54	109	0.42	-0.11** (0.05)
Cost never prevents using public transit	1162	0.17	109	0.19	0.03 (0.04)
Cost sometimes prevents using public transit	1162	0.31	109	0.37	0.06 (0.05)
Cost usually prevents using public transit	1162	0.23	109	0.20	-0.02 (0.04)
Cost always prevents using public transit	1162	0.30	109	0.24	-0.06 (0.05)

Notes: This table reports summary statistics for survey non-respondents and respondents. The final column reports the regression-adjusted difference in means, controlling for the randomization regime at study intake. Results are unweighted. Standard errors reported in parentheses are heteroskedasticity robust. Statistically significant at *10%, **5%, and ***1%.

Table A4. Balance among Survey Respondents, Unweighted

	Control N	Control Mean	Treatment N	Treatment Mean	Reg-Adj Diff. (SE)
Registry Data					
Age	122	39	105	40	0.95
					(1.71)
White	122	0.52	105	0.40	-0.12*
					(0.07)
Black	122	0.26	105	0.25	-0.01
					(0.06)
Hispanic	122	0.06	105	0.06	0.00
					(0.03)
Asian	122	0.02	105	0.07	0.05*
					(0.03)
American Indian	122	0.00	105	0.05	0.04**
					(0.02)
Pacific Islander	122	0.00	105	0.02	0.02
					(0.01)
Multi-racial	122	0.03	105	0.03	-0.00
					(0.02)
Other Race	122	0.04	105	0.09	0.05
					(0.03)
Missing Race	122	0.07	105	0.05	-0.02
					(0.03)
1 Household member	122	0.88	105	0.85	-0.03
					(0.05)
2 Household members	122	0.05	105	0.06	0.01
					(0.03)
3+ Household members	122	0.07	105	0.08	0.00
					(0.03)
Missing num of household members	122	0.01	105	0.02	0.01
					(0.02)
Resident in Seattle	122	0.51	105	0.52	0.01
					(0.07)
English Speaking	122	0.97	105	0.94	-0.03
					(0.03)
Intake Survey Questions					
Use of Public Transit in 30 days Prior to Enrollment	122	15	105	16	1.31
					(1.46)
Usually uses cash for public transit at baseline	117	0.84	101	0.83	0.00
					(0.05)
Intake Survey Questions Asked of Cohort 2 Only					
Used car to get to enrollment site	51	0.27	58	0.21	-0.07
					(0.08)
Used bus to get to enrollment site	51	0.41	58	0.43	0.03
					(0.10)
Cost never prevents using public transit	51	0.20	58	0.19	-0.01
					(0.08)
Cost sometimes prevents using public transit	51	0.37	58	0.36	-0.02
					(0.09)
Cost usually prevents using public transit	51	0.18	58	0.22	0.05
					(0.08)
Cost always prevents using public transit	51	0.25	58	0.22	-0.02
					(0.08)

Notes: This table compares summary statistics for survey respondents by treatment status. The final column reports the regression-adjusted difference in means, controlling for the randomization regime at study intake. Results are unweighted. Standard errors reported in parentheses are heteroskedasticity robust. Statistically significant at *10%, **5%, and ***1%.

Table A5. Balance among Survey Respondents, Weighted

	Control N	Control Mean	Treatment N	Treatment Mean	Reg-Adj Diff. (SE)
Registry Data					
Age	122	41	105	40	-0.59
					(1.96)
White	122	0.51	105	0.41	-0.11
					(0.08)
Black	122	0.25	105	0.25	0.01
					(0.07)
Hispanic	122	0.07	105	0.04	-0.03
					(0.04)
Asian	122	0.02	105	0.08	0.06
					(0.04)
American Indian	122	0.00	105	0.06	0.06**
					(0.03)
Pacific Islander	122	0.00	105	0.02	0.02
					(0.02)
Multi-racial	122	0.06	105	0.02	-0.03
					(0.04)
Other Race	122	0.05	105	0.08	0.03
					(0.04)
Missing Race	122	0.04	105	0.04	0.00
					(0.02)
1 Household member	122	0.87	105	0.83	-0.04
					(0.06)
2 Household members	122	0.06	105	0.06	0.00
					(0.04)
3+ Household members	122	0.07	105	0.09	0.02
					(0.04)
Missing num of household members	122	0.00	105	0.02	0.02
					(0.02)
Resident in Seattle	122	0.51	105	0.51	-0.00
					(0.08)
English Speaking	122	0.96	105	0.96	-0.00
					(0.03)
Intake Survey Questions					
Use of Public Transit in 30 days Prior to Enrollment	122	17	105	16	0.01
					(1.76)
Usually uses cash for public transit at baseline	117	0.83	101	0.83	-0.00
					(0.06)
Intake Survey Questions Asked of Cohort 2 Only					
Used car to get to enrollment site	51	0.22	58	0.17	-0.05
					(0.08)
Used bus to get to enrollment site	51	0.43	58	0.46	0.03
					(0.10)
Cost never prevents using public transit	51	0.17	58	0.18	0.01
					(0.08)
Cost sometimes prevents using public transit	51	0.36	58	0.33	-0.02
					(0.10)
Cost usually prevents using public transit	51	0.20	58	0.24	0.04
					(0.09)
Cost always prevents using public transit	51	0.27	58	0.24	-0.03
					(0.10)

Notes: This table compares summary statistics for survey respondents by treatment status, weighted to account for selection in responding to the survey. Weights are created separately for participants in the first and second cohorts, and include a different set of baseline characteristics based on what was collected in intake data. Weights for the first cohort are constructed using indicators for study enrollment site, average ORCA boardings during treatment period, and ORCA boardings in the first week one is eligible to be surveyed. Weights for the second cohort are constructed using indicators for study enrollment site, whether a participant used a car to arrive at the enrollment site, average ORCA boardings during the treatment period, and ORCA boardings in the week prior to the administered survey. The final column reports the regression-adjusted difference in means, controlling for the randomization regime at study intake. Standard errors reported in parentheses are heteroskedasticity robust. Statistically significant at *10%, **5%, and ***1%.

Table A6. Follow-Up Survey Responses, Weighted

	Control N	Mean	Treatment N	Mean	Reg-Adj Diff. (SE)
Admin Data Boardings					
Daily ORCA LIFT Boardings - Full Sample	1105	0.28	692	1.11	0.83***
					(0.07)
Daily ORCA LIFT Boardings - Survey Responders	122	0.27	106	1.02	0.77***
					(0.13)
Daily ORCA LIFT Boardings on Survey Date	122	0.14	106	0.76	0.66***
					(0.15)
Self-Reported Travel					
ORCA LIFT Boardings	111	0.71	102	1.62	0.88***
					(0.22)
All Transit Boardings	122	1.65	106	2.00	0.27
					(0.34)
Total Trips, Any Mode	122	3.48	106	2.94	-0.49
					(0.33)
Payment Method for Public Transit Trips					
% of Public Transit Trips Paid for by ORCA LIFT	78	0.50	69	0.79	0.24***
					(0.07)
% of Public Transit Trips Paid for by Cash	78	0.37	69	0.12	-0.19**
					(0.08)
% of Public Transit Trips Not Paid For	78	0.06	69	0.01	-0.05
					(0.05)
% of Public Transit Trips Paid for by Other Means	78	0.05	69	0.07	0.03
					(0.04)
Mode					
% of Trips by Public Transportation	116	0.57	90	0.80	0.19
					(0.12)
% of Trips by Car	116	0.49	90	0.31	-0.11
					(0.11)
% of Trips by Foot	116	0.20	90	0.20	-0.04
					(0.08)
% of Trips by Bike	116	0.01	90	-0.00	-0.02
					(0.01)

Notes: This table reports combined responses to travel diary surveys conducted weekly after enrollment and throughout the treatment period for participants in the first cohort, and conducted in March, November, and December 2020 for participants in the second cohort. In total, we have survey responses for 228 participants. We only have payment method information for the 147 participants for whom a sampled trip was taken by transit. The bottom two panels condition on respondents reporting at least one relevant trip in the travel day. As such, we observe 147 individuals responding to payment questions and 206 individuals responding on mode type. The final column displays the regression coefficient of treatment on each variable, controlling for randomization regime, race, age, age squared, site of enrollment, month of enrollment, use of public transit in the 30 days prior to enrollment, and whether a car was used to get to the DSHS office. Standard errors in parentheses are heteroskedasticity robust. Statistically significant at *10%,**5%, ***1%. Here, results are weighted by inverse propensity scores. Inverse propensity scores are created for the treatment and control groups by predicting the probability of responding to the survey based on transit use in the week of the survey, transit use in the treatment period, and baseline characteristics. Baseline characteristics for participants in Cohort 1 include enrollment CSO. Baseline characteristics for participants in Cohort 2 include enrollment CSO and whether a car was used to travel to the enrollment site.

Table A7. Follow-up Survey Responses by Treatment Status, Sub-Sample with Any Boardings in Week Prior

	Control		Treatment		Reg-Adj Diff.
	N	Mean	N	Mean	(SE)
Admin Data Boardings					
Daily ORCA LIFT Boardings - Full Sample	241	0.54	286	1.86	1.15***
					(0.10)
Daily ORCA LIFT Boardings - Survey Responders	41	0.64	53	1.54	1.05***
					(0.26)
Daily ORCA LIFT Boardings on Survey Date	41	0.49	53	1.81	1.53***
					(0.35)
Self-Reported Travel					
ORCA LIFT Boardings	38	1.46	53	2.50	1.49***
					(0.53)
All Transit Boardings	41	2.66	53	3.03	0.86*
					(0.47)
Total Trips, Any Mode	41	3.67	53	3.29	0.29
					(0.55)
Payment Method for Public Transit Trips					
% of Public Transit Trips Paid for by ORCA LIFT	34	0.56	46	0.84	0.20
					(0.14)
% of Public Transit Trips Paid for by Cash	34	0.32	46	0.14	-0.11
					(0.13)
% of Public Transit Trips Not Paid For	34	0.05	46	0.00	-0.05
					(0.04)
% of Public Transit Trips Paid for by Other Means	34	0.06	46	0.02	0.01
					(0.02)
Mode					
% of Trips by Public Transportation	40	0.80	48	0.93	0.17
					(0.11)
% of Trips by Car	40	0.20	48	0.16	-0.06
					(0.08)
% of Trips by Foot	40	0.15	48	0.07	-0.10
					(0.07)
% of Trips by Bike	40	0.03	48	-0.00	-0.02
					(0.01)

Notes: This table is identical to Table 4 except it limits the sample to respondents with positive ORCA boardings in administrative records in the week prior to the survey date.

Table A8. Follow-up Survey Responses by Treatment Status, Sub-Sample with No Boardings in Week Prior

	Control N	Control Mean	Treatment N	Treatment Mean	Reg-Adj Diff. (SE)
Admin Data Boardings					
Daily ORCA LIFT Boardings - Full Sample	864	0.22	406	0.74	0.50***
					(0.06)
Daily ORCA LIFT Boardings - Survey Responders	81	0.16	53	0.54	0.29**
					(0.12)
Daily ORCA LIFT Boardings on Survey Date	81	0.10	53	0.07	0.03
					(0.10)
Self-Reported Travel					
ORCA LIFT Boardings	73	0.81	49	1.19	0.76**
					(0.31)
All Transit Boardings	81	1.79	53	1.45	-0.05
					(0.44)
Total Trips, Any Mode	81	3.35	53	2.36	-0.60
					(0.44)
Payment Method for Public Transit Trips					
% of Public Transit Trips Paid for by ORCA LIFT	44	0.48	23	0.72	0.31**
					(0.12)
% of Public Transit Trips Paid for by Cash	44	0.43	23	0.17	-0.26*
					(0.13)
% of Public Transit Trips Not Paid For	44	0.04	23	0.04	-0.05
					(0.06)
% of Public Transit Trips Paid for by Other Means	44	0.02	23	0.07	0.03
					(0.05)
Mode					
% of Trips by Public Transportation	76	0.53	42	0.62	0.10
					(0.16)
% of Trips by Car	76	0.44	42	0.39	-0.14
					(0.14)
% of Trips by Foot	76	0.16	42	0.30	0.09
					(0.11)
% of Trips by Bike	76	0.00	42	0.00	-0.00
					(0.00)

Notes: This table is identical to Table 4 except it limits the sample to respondents with no ORCA boardings in administrative records in the week prior to the survey date.