Pre-Analysis Plan

The impact of subsidized transit passes on health and well-being for people with low incomes

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I. Introduction

Place matters for economic success. Growing evidence indicates that the neighborhood environment affects future economic outcomes (Chetty and Hendren, 2016a; Chetty and Hendren, 2016b). An important channel is access to jobs; long, tiring, and unpredictable commutes can hinder job search (Phillips, 2014; Phillips, forthcoming) and lower productivity (Van Ommeren and Gutierrez, 2011). However, housing vouchers that provide incentives to "move to opportunity" do little to encourage adult employment (Ludwig et al., 2013). Targeted transit subsidies represent an alternative policy lever, potentially allowing low-income households to commute to opportunity instead. In an effort to increase access to jobs and other amenities, local governments in Seattle, San Francisco, and Portland have recently made reduced transit fares available to all low-income riders (Cabanatuan, 2018; Redden, 2018). New York City, Los Angeles, and Washington DC are considering similar programs (Goodman and Mays, 2019).This evaluation will focus on the impact of King County's recently introduced fully-subsidized annual pass program to provide, to our knowledge, the first rigorous evidence of how at-scale fare-free public transit (FFPT) can impact transit use, employment, use of public benefits, healthcare, mobility, and criminal justice outcomes.

King County is home to 2.2 million people, making it the largest county in the state of Washington and 13th largest in the U.S. by population. It includes the city of Seattle as well as 38 other cities and towns. In Washington, 30% of the population, 40% of jobs, and 50% of payroll reside in King County. The government of King County operates with an annual budget of $6 billion.

In October 2020, King County Metro Transit (Metro) launched a fare-free public transit (FFPT) program to provide fare-free annual transit passes to people with incomes ≤80% FPL who also receive cash public benefits. We will recruit 6,000 people who receive public benefits and have incomes ≤80% FPL. Of these, one-third will be eligible for the existing free transit program because they receive cash public benefits and we will be invited to enroll them in FFPT. Another two-thirds will meet the income requirement but be ineligible for the existing program because they receive only non-cash public benefits. We will randomly extend FFPT to half of the latter group. In a randomized controlled trial (RCT), we compare outcomes for otherwise ineligible people who are offered versus not offered FFPT. To test external validity, we will conduct a difference-in-differences analysis to measure treatment effects among the eligible group by comparing their outcomes to those of the RCT control group. We will study the effect of fully-subsidized public transportation on transit use, health, financial well-being, and a series of secondary outcomes for low-income residents in King County.

II. Sample Construction and Random Assignment

First, study participants will be identified through the already-existing ORCA LIFT registry. Possible participants will have enrolled or previously in Metro's reduced fare program that verifies income less than 200% of the federal poverty level. Among this group, we will focus on those who qualified via enrollment in state benefits programs and who have not already enrolled in FFPT.

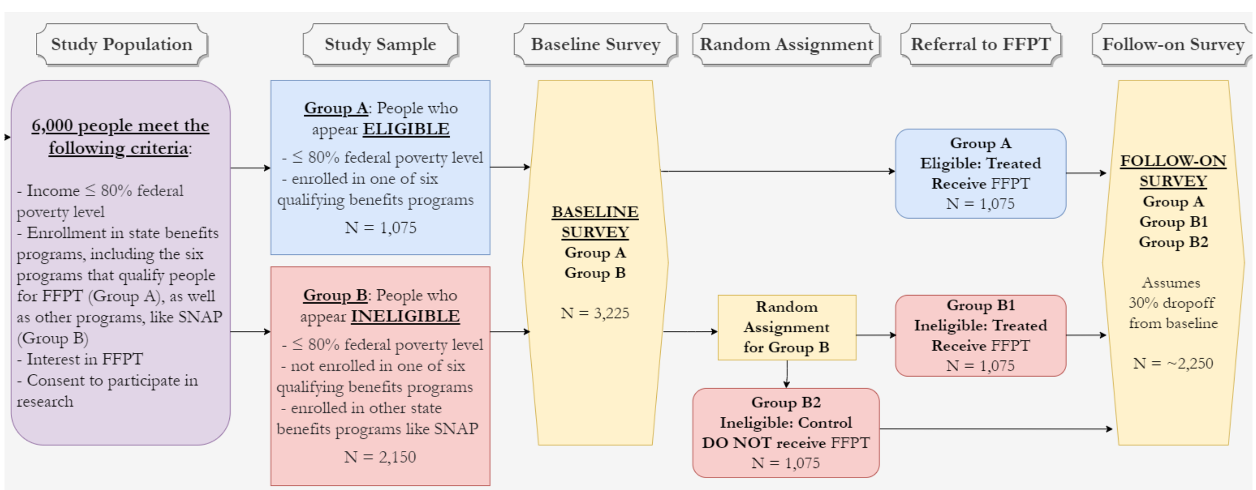
We will contact these individuals for a screening survey that will identify people willing to participate in the study. We will include only those who also have income below 80% FPL, have enrolled in state benefits programs (like SNAP), who reside in the area (King/Snohomish/Pierce counties), and who have used transit in the past. A survey firm will contact participants with this screening survey.

Our study sample will include three groups of people:

Group A: Eligible – Treated
Group B1: Ineligible – Treated
Group B2: Ineligible – Control

In our study sample, Group A consists of people in the LIFT registry who are eligible for FFPT and who, after the baseline survey, are immediately connected for enrollment in FFPT. Group B1 is comprised of people in the LIFT registry who are ineligible for FFPT because they are not enrolled in one of the six State cash benefit programs, who are screened for comparability with Group A, and, after the baseline survey, are randomly assigned to immediate referral for enrollment in FFPT. Group B2 is the same as Group B1, except that they are randomly assigned to not receive FFPT and remain enrolled in the ORCA LIFT discounted fare program.

An RCT (B1 vs. B2) allows us to make an internally valid comparison of the impacts of FFPT on people with incomes ≤80% FPL but who are not receiving one of the six State cash benefit programs that make one eligible for FFPT. This directly informs decisions policymakers face about potential expansion of the FFPT eligibility criteria. A difference-in-differences analysis comparing people who are currently eligible for FFPT (Group A) with the control group from the RCT (B2) provides policymakers with relevant information regarding the external validity of the RCT results to people currently receiving FFPT, thereby informing decisions regarding both continuation and expansion of FFPT as well as decisions by other transit agencies in the region about joining FFPT.



III. Key Data Sources

At the time of filing of this pre-analysis plan, the researchers have established access to internal King County Metro transit records. The research team has executed a data-sharing agreement with King County Metro which provides access to transit records of ORCA products. Researchers also have access to consumer reference data from Infutor Data Solutions, which provides information on residential addresses. Finally, the research team is pursuing a data application to the Research and Data Analysis team housed in the Washington Department of Social and Human Services in order to access additional outcomes. Analysis of these outcomes are contingent upon successfully receiving approval for this application.

A) King County Metro Registry, Boarding, Sales, and Access Databases

We will measure transit outcomes, including number of boardings; number of trips; timing of boardings and trips; routes used; and usage of the ORCA LIFT program using King County Metro transit records. King County Metro maintains de-identified transit data on the cards distributed to the treatment and control groups. This dataset also contains residential information for all ORCA LIFT clients; this will be aggregated to the block-group level in order for researchers to analyze transit use based on differing block-group characteristics. King County Metro has also constructed and granted researchers access to measures of transit access for all block groups within King County. This dataset will allow researchers to determine the number of low-income jobs, total jobs, schools and community service centers that are within a one-hour public transit commute from participants' residence.

B) Survey

We will contact the screened population for a baseline survey. The time in between the screening survey and the baseline survey should be approximately three to four weeks. Once it has been determined who of the participants will receive the fare-free transit pass, they will be put in contact with King County Public Health or King County Metro to receive the pass. This process will occur immediately after the baseline survey is conducted. We will then conduct the check-in surveys that will occur twice at four month intervals after the baseline survey. They will also conduct the final follow-on survey that occurs one year after the baseline survey. We expect some attrition so that while 6,000 participants comprise the study sample and consent to participate, approximately 2,250 will complete the final follow-on survey. At baseline, we predict that 3,225 people will complete the initial survey. 1,075 will be assigned to the Eligible: Treated group (Group A); 1,075 will be assigned to the Ineligible: Treated group (Group B1); and another 1,075 will be assigned to the Ineligible: Untreated Group (Group B2). In all, 2,150 participants will receive the fully-subsidized annual pass.

The survey is composed of three major modules: demographic information, travel history and transit use, and health. The demographic information collected includes: county of residence, disability status, homelessness status, and self-rated neighborhood quality. The survey also asks participants to recount their travel destinations, purposes, and modes of transportation over the previous 24-hour period. It also asks participants their general usage of public transit (and other modes of transportation), as well as the changes they'd like to make to the transit system. The survey also asks participants a series of questions about their psychological well-being using Kessler-6, a validated health measure. Participants are also asked to rate their own health, and questions about their loneliness & connection to others in their family or community.

C) DSHS Research and Data Analysis

The Washington DSHS Research and Data Analysis team maintains linked administrative records on statewide arrests, public assistance, earnings, healthcare visits, etc. If the information request is approved, we will use this data for statewide outcomes on employment, use of public benefits, and health. Because study recruitment occurs among DSHS clients, we expect there will be a high match rate between our study population and the RDA administrative database.

D) Experian

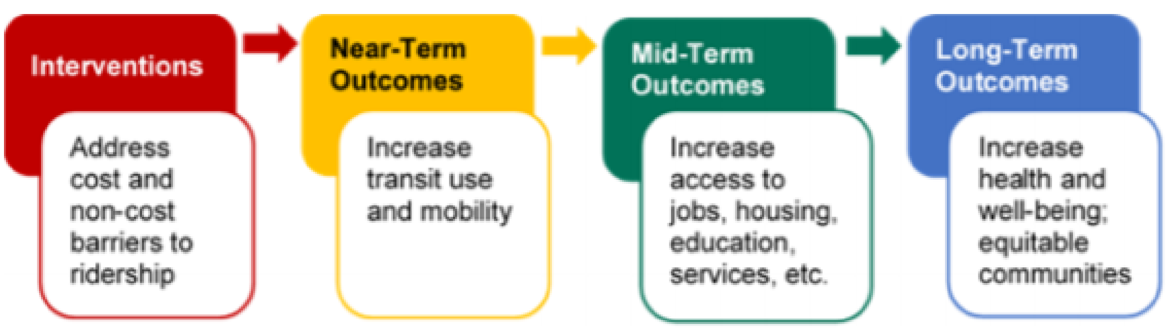
We will use Experian credit records to measure access to credit recorded by credit reporting agencies.

E) Infutor

We will also measure housing stability using comprehensive consumer reference data on household addresses in the U.S. These data allow us to determine how frequently study participants move or have an official address—information that is difficult to obtain through surveys or administrative data records. Infutor is a consumer reference data company that aggregates records from various sources (e.g. utility bills) to construct address histories for most people in the United States. The existence of a formal address in such data is a comprehensive measure of homelessness as it can provide information on unsheltered homelessness and those depending on others for housing

IV. Hypotheses – Analysis by Outcome Domains

We will analyze outcomes by domain. Primary domains are the main focus of the evaluation. Secondary domains cover other aspects of the causal chain connecting the intervention to final outcomes. Within each domain, we indicate a primary measure, which will be the focus of our analysis. We also list alternative measures of interest, which we may investigate to further understand the main effects on the primary outcome measure.



Primary domain: Transit use and transportation outcomes

- Primary measure: Number of boardings on public transit at agencies participating in the ORCA LIFT program
    - Measures the number of boardings on all ORCA cards
        - Continuous measure of the number of boardings
        - Constructed using King County Metro boardings data
    - Hypothesis: expect treatment group to board transit more frequently as compared to the control group
- Alternative measures:
    - Survey data: Total trips by any mode; trips disaggregated by travel mode; payment method; trip purpose; travel time
    - Metro data: Timing of transit; Mode of transit

Primary domain: Financial well-being

- Primary measure: Hours worked per quarter
    - Measures hours employed
        - Continuous measure for hours worked per quarter
        - Constructed using data from Employment Security Department (RDA data)
    - Hypothesis: Expect treatment group to be more likely to be employed as compared to the control group
- Alternative measures:
    - Survey data: Trips for employment
    - RDA data: Earnings, wage rate, being employed, job exits, job starts, job-to-job moves
    - Experian data: Presence of a credit score, credit score, credit delinquencies

Primary domain: Health status

- Primary measure: Psychological distress
    - Measures between-group differences in self-reported psychological distress
        - Constructed using baseline and follow-up surveys using the summed score from the Kessler 6 (K6) scale
    - Hypothesis: Expect the mobility gains for those who receive FFPT will result in better access to social services, social connection, job opportunities, and income during COVID-19 recovery and, in turn, these will translate to improved, lower K6 scores
- Alternative measures
    - Survey data: Self-reported physical health

Secondary domain: Healthcare access

- Primary measure: Annual preventive care visit
  - Measures between-group differences in annual preventive care visit
    - Constructed using data from the Washington State Health Care Authority based on the "Adult Access to Preventive/Ambulatory Health Services" measure used in the Healthcare Effectiveness Data and Information Set by the National Committee for Quality Assurance.
  - Hypothesis: Mobility gains for those who receive FFPT will result in greater utilization of annual preventive health care services among low-income populations who often experience limited access to preventive healthcare due to barriers such as transportation; and, preventive care visits have known mortality benefits
- Alternative measures:
  - Survey data: Trips for healthcare purposes
  - RDA data: Substance use disorder treatment; Mental health treatment; Prescription fills; Vaccinations; Hospitalizations; Emergency Department; Outpatient visits; Dual eligibility (Medicare AND Medicaid); Costs of care

Secondary domain: public benefit access

- Primary measure: Enrolled in SNAP
  - Measures enrollment in SNAP
    - Indicator variable for enrollment in SNAP
    - Constructed using data from Washington State's Research and Data Analysis division
  - Hypothesis: Access to transit allows people to access public benefits.
- Alternative measures:
  - Survey data: Trips for social services
  - RDA data: enrolled in different public benefit programs operated by ESA(TANF, etc.)

Secondary domain: housing

- Primary measure: Housing moves
  - Measures if the person changes addresses over the study period
    - Indicator for having an existing address end or a new address begin
    - Constructed using data from Infutor
  - Hypothesis: expect treatment group to be more likely to move
- Alternative measures:
  - Infutor data: having a formal address
  - Survey data: travel time from home to downtown, neighborhood characteristics, number of recent days spent unhoused
  - King County data: eviction filings, homelessness program use

Secondary domain: social connections

- Primary measure: Loneliness scale
  - Measures perceptions of loneliness

        - Summed score of 5-item fixed length form
        - Constructed using the Loneliness scale from the National Institute of Health Toolbox. Responses given at baseline and follow-up surveys
    - Hypothesis: expect treatment group to be less lonely than the control group
- Alternative measures:
    - Survey data: Trips to see family and friends

V. Sub-Group Analysis

We are interested in determining whether the intervention is more effective for certain populations relative to others.

A) Gender---Identifies as female vs. does not identify as female at baseline.

B) Kids vs. no kids---Identifies if a recipient of FFPT has children or not.

C) Accessibility to public transit services
Identifies whether the client lives in a residential area that is considered highly accessible to transportation; moderately accessible to transportation; or not at all accessible to transportation. Transit access measures will be constructed using the number of bus stops accessible within one's residential block group

D) Predicted Transit Use
We will predict transit use at follow up in the control group using a regression that includes all available baseline characteristics. We will then predict transit use for all observations using observed characteristics and the coefficients from that regression. Finally, we will split the sample into halves (e.g., greater vs lesser transit use) based on this predicted outcome and test for heterogeneous effects in these two groups. To avoid endogenous stratification, we compute these statistics with a repeated split sample procedure as in Abadie, Chingos, and West (2018, RESTAT).

E) Predicted Outcomes
For each outcome, we will predict the outcome in the control group using a regression that includes all available baseline characteristics. We will then predict the outcome for all observations using observed characteristics and the coefficients from that regression. Finally, we will split the sample into halves (e.g., higher likelihood of employment vs. lower) based on this predicted outcome and test for heterogeneous effects in these two groups. To avoid endogenous stratification, we compute these statistics with a repeated split sample procedure as in Abadie, Chingos, and West (2018, RESTAT).

VI. Data Analysis

A) Estimates

For all outcomes, we will estimate treatment effects by OLS using the following regression:

$$Y_i = \alpha_0 + T_i\beta_0 + X_i\gamma_0 + \epsilon_i$$

Y is an outcome – for example, our K6 primary outcome measures psychological distress. Treat is an indicator variable representing whether an individual was randomly selected to be offered FFPT. X is a set of demographic control variables to improve precision. ε is the individual error.

The sample for this RCT is restricted to people who respond to survey screening questions that indicate they would not be eligible for FFPT outside the study. In this OLS regression, β0 is the estimate of the change in psychological distress resulting from being offered FFPT as compared to being enrolled in the ORCA LIFT discounted fare program. As specified, the above equation is the intent-to-treat (ITT) model as it will compare outcomes for all individuals offered FFPT to those not offered FFPT. The ITT effect can be re-scaled by take-up rates to estimate the treatment-on-the-treated effect (TOT). The TOT parameter measures how much receiving FFPT affects the outcome. If all clients offered FFPT take it, then ITT and TOT are identical. If not, then researchers can use the treatment assignment indicator variable as an instrumental variable in a 2SLS regression model to determine the effect of actually receiving FFPT.

Randomizing otherwise ineligible people into FFPT cleanly answers policy-relevant questions. Random assignment creates an internally valid comparison between a group receiving FFPT and an, on average, identical control group. The measured treatment effects will directly inform decisions by King County Metro and its partners regarding expanding eligibility for FFPT to include all people with incomes ≤80% FPL, not just those enrolled in one of the six State benefit programs.

We will also compute difference-in-differences effects on health and well-being outcomes by comparing those in the sample who are eligible for FFPT (Group A: Eligible – Treated) to the same control group from the RCT (B2: Ineligible – Control). The treatment group consists of people who have income ≤80% FPL and are enrolled in one of the six State cash benefit programs that qualify them to receive FFPT. The comparison group consists of people who have income ≤80% FPL, do not receive one of the six qualifying State cash benefit programs, and who are not randomized into receiving FFPT at the end of the baseline survey.

Formally, we will estimate the following regression:

$$Yit = \alpha 1 + \beta 1 Eligiblei * Postt + \beta 2 Eligiblei + \beta 3 Postt + Xit\, \delta 1 + \epsilon 1i$$

This equation will use panel data, including both baseline and follow-on survey measures for each person. The two new variables, Post and Eligible, are indicators of whether the data comes from the follow-on survey and whether the person meets the program's eligibility criteria. Other variables are defined as above. The coefficient on the interaction, $\beta 1$, measures the change in the outcome over time for both eligible (A) and ineligible (B2) groups and then takes the difference in those differences. As before, we focus on ITT effects and could measure TOT effects using 2SLS.

The main motivation for the difference-in-differences analysis is to assess the external validity of the RCT findings. If both methods provide similar results, then policymakers could reasonably conclude that the benefits of FFPT observed among otherwise ineligible people randomized into FFPT (B1) also apply to the program's existing participants (A).

If the results of the RCT and difference-in-differences analysis disagree, we will evaluate whether that is due to a difference in program effects between groups or a violation of the difference-in-differences assumptions. To measure variation in the treatment effect, we will extrapolate treatment effects from the RCT to the eligible population using observables29 and marginal treatment effects methods30. We will test the difference-in-differences assumption by comparing pre-treatment trends of eligible and ineligible people in administrative records and matching on observable characteristics.

B) Covariates

We will report all analyses without covariate adjustment and with covariate adjustment. We plan to include the following list of covariates in our regression:

1. Value of dependent variable at baseline, if applicable
2. Age and age-squared
3. Gender (1 = female, 0 otherwise)
4. Set of mutually exclusive variables for race/ethnicity
5. Days of transit use at baseline

C) Standard Errors

Standard errors will be clustered at the individual-level, as treatment assignment is randomized on the individual-level.

D) Multiple Hypothesis Testing

We have limited our primary outcomes to a causal chain with one primary outcome per domain, making multiple hypothesis testing less of a concern. Nonetheless, we will report classic p-values. This provides the reader with full information that they can use to make multiple hypothesis testing corrections if they desire.

VII. References

Cabanatuan, M. (2018). Pedestrian Safety: SF's Plan to Increase Crossing Times between Signals. *SFChronicle.Com*. https://www.sfchronicle.com/bayarea/article/Pedestrian-safety-SF-s-plan-to-increase12902258.php.

Chetty, R., Hendren, N., & Katz, L. F. (2016). The effects of exposure to better neighborhoods on children: New evidence from the Moving to Opportunity experiment. *American Economic Review*, *106*(4), 855-902.

Chetty, R., Hendren, N., Lin, F., Majerovitz, J., & Scuderi, B. (2016). Childhood environment and gender gaps in adulthood. *American Economic Review*, *106*(5), 282-88.

Goodman, J. D., & Mays, J. C. (2019, January 4). Of 800,000 poor New yorkers, only 30,000 can get the New Half-priced metrocards. *The New York Times*. https://www.nytimes.com/2019/01/04/nyregion/fair-fares-metrocard-discount-nyc.html.

Ludwig, J., Duncan, G. J., Gennetian, L. A., Katz, L. F., Kessler, R. C., Kling, J. R., & Sanbonmatsu, L. (2013). Long-term neighborhood effects on low-income families: Evidence from Moving to Opportunity. *American economic review*, *103*(3), 226-31.

Phillips, D. C. (2014). Getting to work: Experimental evidence on job search and transportation costs. *Labour Economics*, *29*, 72-82.

Phillips, D. C. (2020). Do low-wage employers discriminate against applicants with long commutes? Evidence from a correspondence experiment. *Journal of HumanResources*, *55*(3), 864-901.

Van Ommeren, J. N., & Gutiérrez-i-Puigarnau, E. (2011). Are workers with a long commute less productive? An empirical analysis of absenteeism. *Regional Science and Urban Economics*, *41*(1), 1-8.