The welfare effects of subsidies: A case study of public transport

Jorge Luis Ochoa Rincón*

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Abstract

This paper estimates welfare gains using detailed data from a public transport subsidy experiment in Bogota, Colombia. The effective experimental variation in subsidy allocation allows the identification of key parameters in a discrete choice model, resulting in credible estimates of welfare gains for the beneficiaries of the intervention. The program increased participants' average monthly welfare, measured as consumer surplus, by 12.84 USD or 3.1% of average monthly household income. Monthly increases in welfare are almost 5 times smaller for commuting for work than for other reasons. Much of the heterogeneity is explained by travel times and less flexibility in commuting times.

Key words: Transportation modes, Discrete decision modeling, Welfare, Subsidies
JEL Classification: D12, H42, I38, R41, R48

*Department of Impact Evaluation (DIME), The World Bank. Contacto: jochoarincon@worldbank.org.

1 Introduction

Significant changes in the costs of access to public transportation can have major impacts on labor market, housing market, and migration dynamics (Abebe et al. 2021; Bryan et al. 2020; Tsivanidis 2018). However, provision of public transportation subsidies does not affect everyone equally. Variables such as perception of transport quality, household income level, affordability and availability of access to public transport systems vary demand for mobility and may have an indirect impact on other economic variables (Guzman et al. 2021b; Bryan et al. 2020; Desmet and Rossi-Hansberg 2013). Understanding how subsidies affect different population groups is key to understanding mobility demand and its welfare impacts to guide transportation policy decisions. This is important in a developing context, where high urban growth[1] has not been connected with infrastructure investments in public transport.

The study of welfare gains in public transport subsidy programs remains a challenge. Previous attempts are limited by endogeneity considerations in demand estimates and the lack of micro-level data on transport decisions. To address these issues, I use data from a demand-side experiment in the "*Sistema Integrado de Transporte Público*" (SITP) in the city of Bogotá, Colombia. The experiment randomly provided monthly subsidies in the SITP within a four-month period. Participants were randomly assigned into three groups: i) those offered monthly subsidies of $COP28,000 ($7.5 USD); ii) those offered monthly subsidies of $COP21,000 ($5.6 USD), and iii) a control group. The experiment did not attempt to change the conditions faced by users, but to reduce access cost to the system. Thus, the study participants face normal SITP access fees[2]. Furthermore, we use weekly participant-level information on mode decisions to determine changes in demand *vis-à-vis* the provision of subsidies.

This paper makes use of a detailed combination of weekly diaries under an experimental framework to make three contributions to our knowledge of welfare impacts of subsidies. First, it estimates welfare gains from public transport programs using a discrete choice random utility model. Welfare variation is estimated using two statistics: i) subjective value of time (VOT), estimating the marginal rate at which individuals are indifferent between exchanging travel time units with monetary units; and ii) changes in Consumer Surplus (CS) to estimate the distribution of welfare variation in the intervention population. Second, it shows how to estimate the value of time saved (VTTS) from weekly mobility diaries, using the exogenous variation induced by the provision of subsidies in the SITP. Third, it estimates the welfare gains from subsidies under the random util-

[1] Along with prolonged population growth in urban areas, Latin America and the Caribbean could reach 660 million people living in urban areas by 2050, suggesting that 87.8% of the population of Latin America and the Caribbean will be living in urban areas. These predictions assume an annual urban population growth rate of between 1.0% and 0.4% annually.

[2] For the period analyzed, these fees were set at $COP2,500 ($0.67 USD) for the BRT component and $COP2,300 ($0.56 USD) for the bus component of the SITP.

ity model and compares them with the VTTS to highlight the importance of structural models for evaluating the gains from subsidy programs.

Results of the study show three principal findings. First, subsidies increase demand for both of the SITP components. BRT demand increases on average by 107%, while Bus demand increases by 27.8% in the higher subsidy treatment group. However, demand for both SITP components remains constant in the lower treatment group. This results are consistent with previously presented results in Guzman et al. (2023). Furthermore, I present suggestive information supporting that the SITP works both as a complement and substitute for other transport modes in the city of Bogota. Second, subsidies reduce travel time in treated participants. Individuals assigned to the treatment group decrease, on average, travel times by 10.6 % versus the control group. This effect is driven by travel time reductions in the treatment group with monthly subsidies of $COP28,000 (19.7 % less travel times compared to the control group). Third, our estimates of welfare gains show that treated participants by the intervention increase their CS compared to the control group. Monthly estimations show that on average, treated participants increase their CS by 3.1% of their monthly average household income. This effect corresponds to an increase in their monthly average household income of 3.8% and 2.5% for the higher and lower treatment group participants respectively.

We find additional results of transport subsidies on welfare gains when controlling for motive of the trip. Estimates indicate that monthly variation in CS is significantly higher for trips for other reasons ($COP100,096 or 6.5% of average household income) than for work trips ($COP20,951 or 1.3% of average household income). Furthermore, participants respond negatively to travel cost and travel time, however, these effects are greater for work trips. Trips for other reasons report, on average, consistently lower travel times than work trips for all modes of transportation used. Moreover, disaggregating by income level, the poorest quintile of the sample has comparable travel times for work trips, but visibly higher travel times for other trips. These results are consistent with the literature. Households with lower incomes make greater work trips, higher percentage of their income on transportation and have longer travel times (Guzman and Oviedo 2018; Bocarejo et al. 2016). In addition to this, the distribution of work trips is concentrated in the time slots between 4 a.m. and 9 a.m., coinciding with the city's common rush hour. On the other hand, trips for other reasons show a lower concentration of trips in the peak hour. We use estimates of CS, trip characteristics and individuals to determine the mechanisms behind these differences. It is found that trips with other motives have a positive effect relative to work trips on the CS. Also, compared to the peak hour time slot, the trip start time increases CS significantly, showing suggestive evidence of the effect of congestion on CS. Similarly, a positive income elasticity of CS of less than one is estimated, validating the previous postulates. This last calculation corresponds to the first estimation of the income elasticity of CS in public transport subsidy programs in the literature.

Results presented in this study should be taken into account under the following caveats. First, due to its experimental approach, one consideration is that results might not extrapolate to other contexts and under non-experimental conditions. Second, empirical strategy used does not consider general equilibrium effects in large-scale transportation subsidy programs. Thus, impacts of subsidy programs may involve effects on a wide variety of variables that are beyond the scope of this study.

This work contributes to different branches of the literature. The first strand is the literature of modal decision of individuals. This strand builds on the seminal work of (McFadden 1974), recognizing the problem of estimating demand for mobility using standard regression analysis. Thus, studies along this strand of the literature make use of discrete choice models to approximate demand estimation. Using behavioral and structural models, these studies estimate and predict the modal share in cities (Ben-Akiva and Lerman 1975; McFadden et al. 1977; Train and McFadden 1978). For the case of Latin America, modal market share has been extensively studied (Guzman et al. 2021a; Lizana et al. 2021; Guzman et al. 2022; Peña et al. 2022; Iglesias et al. 2022). While recent empirical literature has made advances, this research paper contributes to the literature by using experimental data to estimate and validate a discrete mode choice model.

A second strand of the literature explores the effect of experimental transport subsidies programs. This growing empirical strand of the literature investigates the relationship between monetary reductions in transport costs and labor market outcomes (Phillips 2014; Franklin 2018; Abebe et al. 2021), increases in demand for mobility (Christensen and Osman 2021; Bull et al. 2021; Brough et al. 2022; Guzman et al. 2023), and migration decisions in rural areas (Bryan et al. 2014). This paper overcomes some of the shortcomings of the literature by proposing alternative measures of the impact of a program. In particular, the distribution of welfare gains is estimated, allowing us to determine individual variations in the population studied. Comparing the results of this work with the previous impact evaluation of the program presented in (Guzman et al. 2023), we estimate welfare gains up to 2.7 times higher. This difference in estimates is due to two possible reasons. First, empirical strategies of the two papers are not comparable. Second, the impact evaluation presented in (Guzman et al. 2023) uses only the demand for the SITP, while this paper incorporates mobility decisions in other modes of transport, allowing to recover substitution effects induced by the subsidy.

Finally, this research paper contributes to the literature analyzing VTTS. Building on the seminal work of (McFadden 1974; McFadden et al. 1977; Train and McFadden 1978), this branch of the literature measures the benefits of time savings by analyzing revealed preference surveys based on mode choice. (Small and Verhoef 2007) performs extensive analysis of the literature to present theory and stylized facts. More recent literature studies willingness to pay for time reductions (Buchholz et al. 2020) and VOT estimates (Goldszmidt et al. 2020) on ride-hailing platforms.

(Tsivanidis 2018; Allen and Arkolakis 2022) evaluate the welfare impact of public transport infrastructure improvements in cities. This study complements this literature by estimating VOT and VTTS using experimental data on the provision of public transport subsidies. For this case study, it is observed that the conventional measure of time savings benefits underestimates the indirect welfare gains from transportation subsidy programs. Therefore, highlighting the importance of using structural models to measure the impact on welfare gains.

The research paper is organized as follows. Section 2 describes the study setting and section 3 describes the data. Section 4 presents the random utility and the difference-in-differences model to evaluate the gains in welfare. Section 5 presents the results and section 7 concludes.

2 Study Setting & Experimental Design

Bogota has an urban area of 417 km^2 and a population of 7.38 million inhabitants (DANE 2018). The city is home to nearly 25% and 15% of Colombia's GDP and population, respectively. Within its territory, Bogota has a heterogeneous population distribution in income levels and opportunities (Guzman et al. 2017b). Nearly 73% of the population of the urban area resides in strata 2 (38.4%, with 2.836 million people) and 3 (35%, with 2.588 million people) zones. These zones are associated with the highest rates of unemployment, population density, lower access to opportunities and low income levels in the city (Cantillo-García et al. 2019). Spatially these low-income areas are located in the southern and western peripheries of the city (See Figure B.3), having low rates of affordability to public transportation (Guzman and Oviedo 2018) and greater distance to the city's employment centers (Guzman et al. 2017a). Middle-income households are predominantly located downtown, while higher-income households tend to be located in the northeastern part of the city.

In recent decades, Bogotá has undertaken a reorganization of its public transportation structure. At the turn of the century, Bogota's local administration advanced the process of modernizing public transport, leaving behind an obsolete model based on the outsourcing of transportation to bus operators, and moving towards centralization through the structure of a BRT (Bus Rapid Transit) system through TransMilenio. Currently, Bogota's public transport is known as the "*Sistema Integrado de Transporte Público*" (SITP for its initials in spanish), which comprises two essential components in its operation: BRT and Bus. The BRT component is characterized by its BRT structure[3], with a total of 157 stations and an average of one million daily users. The newly introduced TransMiCable infrastructure was added to this component in 2018, in order to provide a solution to the accessibility of neighborhoods in the southern part of the city. The nominal value of the BRT component fare during the time of our intervention was $COP2,500 (or $0.67 USD).

[3]This type of infrastructure makes use of buses that travel on exclusive lanes on the city's road infrastructure. BRT systems also use stations which have access through a transport card and fee is payed upfront before accessing the boarding or disembarking platforms.

Second, the bus component is characterized by having smaller capacity buses and using the city's road infrastructure without exclusive lanes for transit. This component uses buses that connect the city's zones with the BRT component. By 2021, the bus component had more than 450 routes and mobilized an average of about 830 thousand daily passengers. This component has some connector routes (feeders) free of fare. However, the nominal value of the fare of the Bus component during the time of our intervention was $ COP2,300 (or $x0.56 USD).

Bogota has an average of 16 million daily trips as of 2019. The vast majority were taken by walking (24.5%), followed by private modes (20%), BRT (15.6%), bus (15.3%), and remaining modes of transport (24.6%). However, modal choices are highly dependent on the income level of individuals. Low-income households tend to make multimodal trips, with greater distances traveled and longer travel times. Thus, travel times and costs are key determinants in the modal choice of commuting for low-stratum households (Guzman and Oviedo 2018).

In this context, Bogotá offers two main characteristics as an attractive context for an empirical analysis. First, the existence of a public transport subsidy experiment in one of the largest BRT systems in the world. Second, the city's public transport system handles one of the highest volumes of daily commuters in the world, making it an interesting case study for understanding the incentives and welfare gains of transport subsidy programs.

2.1 Experimental design

I study the demand response induced by an experimental reduction in access costs provided by a subsidy to the public transport system of Bogota, Colombia. The program was designed to estimate the impact on demand for public transport using experimental variation of a provided public transport subsidy. Results of the impact evaluation are reported in (Guzman et al. 2023). The experimental design provided monthly subsidies over a period of 4 months for treated participants in the program. Treated individuals were randomly assigned into two groups: **treatment A**, with monthly subsidies of $COP28,000 ($7.5 USD); **treatment B**, with monthly subsidies of $COP21,000 ($5.6 USD). Participants in the control group were not eligible for the monthly transfers. The experimental design did not attempt to change the conditions faced by users, but simply to reduce the access costs to the system. Thus, both control and treated groups continue to face standard fares for both BRT and Bus components of the SITP. Participants in the experiment were selected from the sample universe of frequent SITP users[4] without any active subsidy in the system. For further details on the recruitment process of the participants, please refer to the recruitment section in (Guzman et al. 2023).

[4] The definition used in the sample design of the SITP frequent user experiment consisted of two characteristics: 1) having a personalized card (a personalized card allows generating an identification profile of the cardholder such as name, age, gender and contact information) and 2) having at least nine validations in the SITP in February 2020

2.2 Randomization and Enrollment

The research strategy used a two-stage randomization of the program. Following a first approach and confirmation of participation in the study, individuals were randomly assigned to the control or treatment group. In a second stage, treated assigned participants were once again randomly assigned into one of two treatment groups: treatment A, eligible for monthly cash transfers of $COP28,000 ($7.5 USD); and treatment B, eligible for monthly cash transfers of $COP21,000 ($5.6 USD). The value of the subsidy (at the nominal fares in effect on the date of the study) covered up to a total of 12 and 9 trips on the SITP for treatment A and treatment B, respectively. The total number of participants in the experiment was 1,607 individuals, with the control group comprised of 806 participants, treatment A group of 402, and treatment group B with 399 individuals. The double randomization design allows us to estimate effects on subsidy allocation and heterogeneous effects by subsidy intensity.

3 Data

Two sources of data collected during the intervention are used: baseline survey and follow-up surveys. Figure B.1 shows the temporality of data collection. The experimental design contemplated a baseline survey and a total of 15 follow-up surveys under a weekly basis for each participant. Baseline information is collected prior the start of the intervention, while follow-up surveys could either be collected prior and/or after the start of the intervention. Survey data were collected between March and November 2021. The baseline survey information was collected through home visits, while the follow-up surveys had the versatility of being conducted by telephone or through a web application provided in the intervention. The main information used in this paper comes from the weekly mobility diaries collected in the baseline survey and the follow-up surveys. This information includes an indicator of whether the person made a trip the day before the survey, motive of the trip, modes of transportation used, time of departure, time of arrival, value of the trip(s) made, etc. A possible threat to the research strategy is the conformation of the choice set available to participants across time. During the intervention period, two possible concerns arise relating modes of transport availability. First, COVID-19 restrictions could potentially interfere with transport mode decisions made by participants. (Mejía Paz et al. 2022) study the effect of *stay-at-home* and *mobility restrictions* alike policies in the top biggest cities in Colombia. Authors report that COVID-19 policies were in place up until the second week of February of 2021. However, after this period no restrictive policies were in operation. Second, choice set composition could vary with the evolution of Bogota's 2021 strikes. Figure B.2 shows the number of surveys collected and the number of demonstrations/happenings reported by the Secretary of Security and Justice of Bogota. The Figure shows that baseline surveys did not overlap with protest. However, early follow-up surveys collected coincide with the beginning (highest number of reported protests) of the 2021 National Strike. This suggests that some modes of transportation were not available on the dates of data collection for all participants.

One advantage of the data collected is the panel structure. Evidencing different transport mode decisions for the same participant over time, when different modes of transport were available, strengthens the empirical strategy. Considering individual variation in the choice set and aggregate random variation provided by the intervention lead us to capture information on first and second transport mode decisions under different conditions. Additionally, given our sample characteristics, I am able to estimate heterogeneous treatment effects by level of household income (see Figure B.3).

In addition to the information from the mobility diaries, the baseline survey includes socio-demographic characteristics of the participants in the experiment. This information includes gender, age, marital status, type of residence, stratum, monthly household income, number of people in the household, current work status (hours and days worked), highest educational level attained, modes of transportation available to the household, etc. Furthermore, participants were asked their perception on all different transport modes, using a scale of 1 to 10, where 1 means "very low quality" and 10 means "very high quality". This information allows to control for characteristic attributes of the transport modes. In an effort to present credible estimates on welfare gains, perception variables are included in the main specifications of the empirical analysis in order to address concerns about omitted variable bias in the estimates of the CS (León and Miguel 2017).

Table A.3 presents descriptive statistics and balance tests using baseline period information. The sample is composed of 71.8% women (28.2% men) with an average age of 43.5 years and an average SISBEN 3 score of 56.6. 22.7% of the participants are married and 61.7% live in their own home with 3.7 people living in it. 86.7% of participants report moving for work purposes. The average workday of the sample is 9 hours per day, 5.2 days per week. However, 5.9% of the workers report doing so from home. On the other hand, 3.1% of the participants report commuting for study purposes. In terms of education level, 83.4% report having high school studies, 41.4% undergraduate studies and 3.3% graduate studies. The average monthly household income in the sample is \$COP1,537,632 (\$411 USD) and using the measure of average persons in the household, the per capita income of the sample is \$COP413,765 (\$110 USD). Figure B.3 shows the spatial distribution of participants by treatment group and the average monthly household income by city neighborhood. Participants in our experiment are concentrated in the wourthen an western peripheries of the city. Areas typically associated with low average monthly household incomes. Additionally, data from the 2021 multipurpose survey of the city of Bogota shows an average monthly salary of \$COP2,132,160 (\$570 USD), placing our sample in the poorest quintile of the city's income distribution($\leq$ \$COP905,000 or \$242 USD).

Table 1 shows modal shares for the experiment participants during the entire program period (baseline and follow-up surveys) by treatment group. Column 1 shows the modal shares of the complete sample, while columns 3 and 5 show the modal share by control and treatment group, respectively. Overall (column 1), the most used mode of transport in the sample is the bus component of the SITP with 52.1% of times chosen. The second most used mode of transport is the BRT component of the SITP with 32.7% of the times chosen. Thus, the public transport system accounts for 83.82% of the total trips made by the participants. This modal share was expected based on the sample design of the experiment: frequent SITP users. However, it is important to note the difference between the SITP components, with participants preferring the bus component of the public transport. The remaining 16.18% of trips are distributed as follows: car and motorcycle, with 5.8%; walking, with 3.3%; some type of taxi, with 3.2%; other modes of transportation, with 3.8%.

Table 1: Modal choices

	Treatment Groups					
	Complete sample (N = 1,607)		Control (N = 806)		Treatment (N = 801)	
Transport Mode	Mean	Stand. Dev.	Mean	Stand. Dev.	Mean	Stand. Dev.
Bus	0,5111	0,4999	0,5179	0,4997	0,5051	0,5000
BRT	0,3271	0,4692	0,3034	0,4598	0,3485	0,4765
Automobile and Motorcycle	0,0583	0,1610	0,0622	0,1644	0,0547	0,1578
Walk	0,0332	0,1792	0,0407	0,1976	0,0264	0,1606
Taxi	0,0322	0,1766	0,0346	0,1828	0,0301	0,1709
Other	0,0381	0,1914	0,0413	0,1991	0,0352	0,1842

Note: This table presents the average and standard deviation of the probability of choosing each mode category in the sample. Columns 1 and 2 present the mean and standard deviation for the full sample respectively. Columns 3 and 4 present the mean and standard deviation for the sample of experiment participants who were assigned to the control group. Within this subsample are 806 people. Columns 5 and 6 present the mean and standard deviation for the participants assigned to the treatment group. This treatment group is comprised of individuals in both treatment group A $COP28,000 and treatment B $COP21,000. Within this subsample are 801 individuals. Each row represents an indicator variable for each survey answered by participants against the modal decision in their commute. Thus, the rows represent the proportion of use of each category by mode of transport used by sample type.

4 Using theory to measure impacts of transportation subsidies

This section describes the random utility model, decomposing the demand responses induced by experimental variation in the allocation of subsidies. Using both baseline and follow-up surveys, I have information on the mode of transportation used, start time, arrival time, monetary cost, and perceptions of the mode used for each of the trips reported by the participants. This information is used to model demand by mode under a discrete choice framework. In this way it is possible to estimate the demand by mode, the trade-offs between cost and travel time, modal split and the variations in welfare as consumer surplus.

4.1 Discrete Choice Mixed Logit Model

In this section, I lay out a discrete choice travel model. Considering recent contributions to the literature for the study case of Bogotá (Guzman et al. 2021a, 2022; Peña et al. 2022), the main differences in my research strategy are: 1) use of experimental data to estimate and validate a discrete choice model by modes of transport and 2) inclusion of the allocation of the intervention in the utility of individuals. Thus, the model approach must take into account how random assignment to treatment induces changes in mode choices. The model presented below is based on (León and Miguel 2017). However, relevant modifications to study the mode decision are taken into account.

I model person's i to use transport mode j ($j \in J$, for a discrete and finite set of transport modes J) in period t ($t \in T$, for a discrete and finite set of number of mobility surveys responded) to move around the city using a random utility model of discrete choice:

$$y_{ijt} = \begin{cases} 1 & \text{,if individual } i \text{ uses transport mode } j \text{ in period } t \\ 0 & \text{, otherwise} \end{cases} \tag{1}$$

Where, person i must use a transport mode j in period t ($\sum_j y_{ijt} = 1$) and all alternatives $j \in J$ have a positive probability of being chosen ($Pr(y_{ijt}) > 0; \forall j$). The choice set is composed of 6 alternatives of transportation modes to move around the city: walking, private transportation (cars and motorcycles), Taxi, BRT component of SITP, Bus component of SITP and other modes of transportation. Where $j_t = 1, \ldots, J_t$ correspond to the "indoor goods" available to participant i in period t, while $j = 0$ denotes the "outside good" for all periods. In this case study, walking is denoted as the outside good. Participant's i utility from choosing alternative j in period t is:

$$U_{ijt} = \underbrace{\overbrace{\underbrace{\theta_i \text{Price}_{jt}}_{\text{Monetary cost: } c^m_{jt}} + \underbrace{\beta_i \text{Travel\_Time}_{ijt}}_{\text{Opportunity costs: } c^o_{ijt}}}^{\text{Total cost: } c_{ijt} = c^m_{jt} + c^o_{ijt}} + \tau \text{Treatment}_i + \Omega' \mathbf{X}_{ijt}}_{\text{Observed utility: } V_{ijt}} + \overbrace{\varepsilon_{ijt}}^{\text{Unobserved utility}} \tag{2}$$

Where θ_i and β_i are individual random coefficients per person, while τ and Ω are fixed coefficients for each mode of transportation j. c^m_{jt} is the monetary cost of choosing alternative j in period t. c^o_{ijt} is the opportunity cost measured as the time spent by participant i in completing the trip (Travel_Time$_{it}$) while choosing alternative j in period t. We define the total costs faced by participant i in choosing alternative j in period t by $c_{ijt} = c^m_{jt} + c^o_{ijt}$. Treatment$_i$ is an indicator variable equal to 1 if participant i was assigned to one of the two treatment groups, zero otherwise. X_{ijt} is a vector of observable attributes. V_{ijt} is the observed part of utility and ε_{ijt} is an unobserved error term i.i.d. type I extreme value. This assumption on the unobserved part of the utility implies: first, $\varepsilon_{ijkt} = \varepsilon_{ijt} - \varepsilon_{ikt}, \forall j,k \in J$ and $\forall j \neq k$ follows a logistic distribution; second, participant's i probability of choosing alternative j in period t and the CS exhibit closed forms.

Empirically, I estimate the VOT and CS using a Logit framework (McFadden 1974; Train 2009). Thus, participant's i conditional probability of choosing alternative $j \in J$ in period t is defined as:

$$P_{ijt} = \Pr(y_{ijt} = 1) = \frac{\mathrm{Exp}(V_{ijt})}{\sum_{k \in J} \mathrm{Exp}(V_{ikt})} \tag{3}$$

Up to this point, the model proposed corresponds to the estimation of a conditional logit model (Train 2009). However, the simplicity of these models plays an important role in the limitations it incorporates in the estimation of demand: i) it imposes the Independence of Irrelevant Alternatives (IIA) assumption; ii) it does not include random variation of participants' preferences; iii) it does not allow for correlation in utility over alternatives and autocorrelation of unobserved factors over time; and, iv) it assumes that all participants in the sample have the same preferences (Train 2009; León and Miguel 2017). The IIA assumption is potentially restrictive in this study case. Given the panel structure of the data, having multiple trips made by the same participant over time and under the different decision sets of alternatives (see Section 3 and Figure B.2 for more information) this condition is hardly meet. To address these limitations, a mixed logit model is used by introducing heterogeneity in the preferences of individuals (Berry and Haile 2021), allowing to estimate coefficients at the individual level and to recover the full distribution of consumer surplus in the population (León and Miguel 2017).

The unconditional probabilities of a mixed logit model correspond to the integrals of the probabilities of a conditional logit model over the distribution of the parameters. This probability takes the form of:

$$P_i(\gamma) = \int S_i(\gamma)\mathbf{f}(\gamma|\varsigma)d\gamma \tag{4}$$

However, due to the panel structure present in the data, the integral must include the product of all logit formulas, one for each time period. This product defines the observed sequence of decisions by person i as:

$$S_i(\gamma) = \prod_{t=1}^{T} P_{ijt}(\gamma) \tag{5}$$

Where the product includes the probability in equation 3 for each period. Here, $\mathbf{f}(.)$ is a density function and $S_i(\gamma)$ corresponds to the observed sequence of decisions of the observed part of the utility (V_{ijt} and where $\gamma = (\theta_i, \beta_i, \tau, \Omega)$). Thus, the probabilities of a *mixed logit* model are the weighted average of equation 3 evaluated at different values of γ. Weights are assigned by the distribution $\mathbf{f}(\gamma|\varsigma)$ (known widely in the literature as *mixing distribution*). The use of a triangular distribution is assumed. This distribution has desirable characteristics, such as continuity and symmetry. Additionally, a triangular distribution implies estimation of a single ς parameter for each random variable, making the estimation computationally amenable. The distribution is also characterized by the lack of broad tails, a main feature of other distributions (normal and lognormal[5]).

4.2 Quantification of the impact of transportation subsidies on welfare

Consumer surplus: To answer the research question, welfare gains are approximated by estimating the consumer surplus for each participant. Using the framework described in (Train 2009), CS is defined as the utility, in monetary terms, that participant *i* perceives given their decision of alternative *j*. By definition, the CS is $CS_{it} = (1/\theta_i)\max_j(U_{ijt})$, where θ_i is participant's *i* marginal utility of income. (Train 2009) proposes travel cost as an alternative to the marginal utility of income due to their equivalence. "A one-dollar reduction in costs is equivalent to a one-dollar increase in income, since the person gets to spend the dollar that he saves in travel costs just the same as if he got the extra dollar in income" (Train 2009). Since U_{ijt} is not observed, the observable part of the utility, V_{ijt} and the distribution of the unobserved part of the utility (ε_{ijt}) are used. Thus, it is possible to compute the expected CS using all possible values of ε_{ijt}. (Small and Rosen 1981) demonstrated that if each ε_{ijt} is i.i.d. extreme value type 1 and the utility is linear in income, then the consumer surplus is defined as:

$$\mathbb{E}(CS_{it}) = \frac{1}{\alpha_i} \ln\left(\sum_{j=1}^{J} e^{V_{ijt}}\right) + C \tag{6}$$

Where C is an unknown constant representing the fact that the total level of utility cannot be measured. Equation 6 describes the average CS for the population having the same utility

[5]As in (León and Miguel 2017), estimates using the normal and lognormal distributions present less precise estimators of the coefficients in the empirical application of the intervention and tend not to converge. For these reasons, results using a normal distribution are presented.

as participant i. Consumer surplus in the population is then estimated as the weighted sum of equation 6, with the weights reflecting the number of people in the population facing the same representative utilities as the experiment participants. The change in consumer surplus resulting from the intervention is computed from equation 6. In particular, the consumer surplus is calculated twice: 1) under conditions before the intervention, 2) under conditions during the intervention. The difference of the two results in the change in consumer surplus:

$$\Delta \mathbb{E}(CS_i) = \frac{1}{\alpha_i} \left[\ln \left(\sum_{j=1}^{J^{\text{During}}} e^{V_{ijt}^{\text{During}}} \right) - \ln \left(\sum_{j=1}^{J^{\text{Before}}} e^{V_{ijt}^{\text{Before}}} \right) \right] \tag{7}$$

It is important to note that the constant C cancels out because it enters the consumer surplus before and during the intervention and therefore can be ignored in the analysis. However, the staggered adoption of the treatment raises concerns of self-selection into treatment, likely biasing the estimates of the change in the consumer surplus. To address this issue, I estimate the change in welfare using the estimator proposed in (Gardner 2022). This estimator implements a two-stage regression analysis, solving the common problems exposed in the literature (Goodman-Bacon 2021; Sun and Abraham 2021; Athey and Imbens 2022). The process follows in two steps. In the first stage, cohort and time effects are identified for the control group. In the second stage, cohort and times effects are residualized from the outcome variable, allowing to identify the average effect on the treated (ATT) by comparing treated and control participants.

5 Results

Discrete choice model estimates: Table 2 presents estimates of the preferred mixed logit model. Results presented correspond to the estimates of the regressions of the indicator variable for mode choice on total costs, treatment group assignment indicator, and a vector of control variables (age, gender, number of people, indicator variable for any vehicle in the household, and perceptions of safety). Table 2 presents the estimates for the random coefficients included in the model: cost and total travel time. Estimates for the treatment group assignment indicator and controls are presented in Figures B.5a and B.5b respectively. Each observation represents an individual commuting decision in the city. Within the estimates, random coefficients of the random utility are assumed to follow a triangular distribution. The table presents model estimates for the full sample (column 1), trips for work (column 2), trips for other reasons (column 3), before (column 4) and during the intervention (column 5).

Results show that participants prefer modes of transportation with lower monetary costs and shorter travel time (rows 1 and 2). Estimates for the monetary costs are significantly negative for all specifications except for trips with other motives. Columns 4 and 5 report significantly lower estimates of the marginal utility of trip price for the sample before the intervention (-0.461) and the sample during the intervention (-0.237). This implies a decrease in the price sensitivity of travel monetary costs before and during the intervention. Coefficients for the cost of opportunity are statistically negative in all columns. Additionally, random allocation of subsidies increases demand for the SITP. For treatment group A, demand for the BRT component increases[6] by 107 relative to the use of the walk and the control group, while for the Bus component it increases by 27.8% relative to the walk and control group (Figure B.5a). On the other hand, estimates show that random assignment of treatment group B does not increase demand for any mode of transport compared to the use of walking and the control group.

Modal share: Does assignment to the treatment group lead to changes in the modal share within the sample? Figure 1 shows the estimates of equation 5 using specifications for the complete sample (column 1), before intervention (column 4) and during (column 5) of the preferred mixed logit model specification presented in Table 2. Figure 1 shows that the intervention had an impact on the modal share of the experiment participants. During the intervention, the modal share of the BRT component increased by 7.6 percentage points (p.p.) compared to the pre-intervention period. At the same time, the modal share of the Bus component decreased by 7.6 percentage points (p.p.) compared to the pre-intervention period. For the taxi, walk, private and other alternatives, there were no significant differences in the urban transport market share before and during the treatment. These results suggest that subsidies generate a reconfiguration of people's travel preferences compared to walking.

Consumer surplus estimates: Following equation 6, the monetary cost coefficient (θ_i) is used to estimate the average CS. Table 2 presents the average CS for each model and estimated subsample. The average CS for the full sample by trip is estimated to be \$COP12.311 (3.3 USD in column 1), which is significantly different from zero. Splitting the sample by trip purpose, the analogous result is statistically lower for work trips (\$COP6.893 or 1.84 USD) than for all other trips (\$COP32.015 or 8.55 USD). Similarly, the CS is lower for the sample before treatment (\$COP9.383 or 2.5 USD) than during the intervention (\$COP13.005 or 3.47 USD).

The main concern, as in most discrete choice literature, is the possible omitted variable bias. As an example, private transport (private car) has low levels of passenger densities, is safer, exposed to higher levels of congestion, and can be considered as a high "status" alternative. On the other hand, the BRT component of the SITP has higher passenger densities, is less safe, is exposed to lower levels of congestion and can be considered by people as a low "status" alternative. Thus, alternatives with desirable characteristics usually have higher prices because their characteristics

[6]The reported coefficient is 0.7249 (standard error of 0.3113). Because Stata reports relative-risk ratios, the transformation to obtain the percent change in the odds ratios is $100\% \times [\exp(\beta) - 1]$. Thus, $106.45\% = 100 \times [\exp(0.7249) - 1]$.

Table 2: Transportation decisions - Mixed Logit model estimates with controls

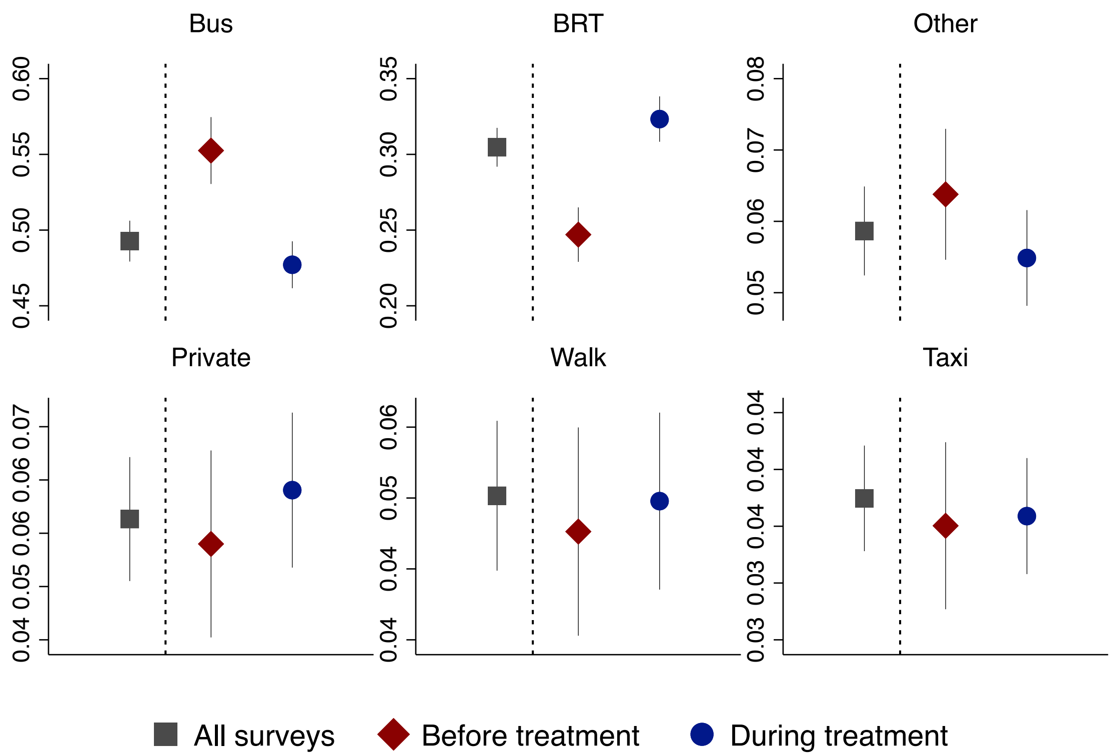
	Dependent variable: *Alternative choosen*				
	Complete	Trip motive		Timing	
	Sample	Work trips	Other trips	Before	During
	(1)	(2)	(3)	(4)	(5)
Random coefficients					
Monetary costs (θ_i)	-0,259	-0,997	-0,0544	-0,461	-0,237
	(0,0326)	(0,0885)	(0,0390)	(0,0786)	(0,0374)
Opportunity costs (β_i)	-0,0272	-0,0369	-0,0300	-0,0250	-0,0330
	(0,0018)	(0,0037)	(0,0024)	(0,0034)	(0,0019)
Observations	88.518	58.908	29.610	23.958	64.560
Controls	Yes	Yes	Yes	Yes	Yes
Standard Errors	Participant	Participant	Participant	Participant	Participant
Log-likelihood	-13,861	-6,737	-5,588	-3,663	-9,958
Number of participants	1,564	1,396	1,282	1,455	1,345
Number of trips	14,753	9,818	4,935	3,993	10,760
Average CS (***COP***)	12.311	6.893	32.015	9.383	13.005
Percentile 5	7.411	4.250	11.502	6.176	7.024
Percentile 95	17.439	9.685	55.067	12.641	19.398

Note: This table presents the estimates of the mixed logit model. The data come from the follow-up survey and the follow-up surveys. The estimates correspond to the estimates of the regressions of the indicator variable for mode choice on total costs, treatment group assignment and control variables. The control variables correspond to age, gender, number of people in the household, presence of a vehicle in the household, and perceptions of safety in the sector where they live (with a scale where 5 is strongly agree and 1 is strongly disagree). The table presents only the estimates of the random coefficients of trip price and trip time. The random coefficients are estimated using a triangular distribution, while the other coefficients are presented in Figure B.5 and are assumed fixed for each alternative. The CE presented corresponds to the estimate of the equation 6. Clustered standard errors at the person level are shown in parentheses.

are costly to provide or because they increase demand. Thus, not taking into account the correlation between price and mode-specific characteristics can bias coefficient estimates and hence the calculation of consumer surplus. To address this concern, individual and mode-specific variables are included as control variables. The Table A.2 presents the model estimates with and without this described variables across different subsamples. Once we control for specific participant characteristics and mode of transportation, coefficients of interest (price and travel time) decrease in magnitude (except for the pre-intervention sample) compared to the specifications without these variables. However, the estimates are not statistically different.

The stability of the coefficients of interest is explained by the strengths of the case study. First, random assignment of participants into the treatment groups generates exogenous variation in people's monthly income. Following the postulates in (Train 2009), a one-dollar reduction in costs is equivalent to a one-dollar increase in income. Making use of this equivalence, the random provision of the transportation subsidy generates sufficient exogenous variation to unbiasedly identify the price coefficient (θ_i). Second, panel data structure strengthens the research strategy. Having

Figure 1: Market share - Mixed Logit estimates



travel history for participants allows to make use of variation in decisions at times when different choice sets were available. Thus, I am able to evidence first and second decisions in some cases. Third, estimation using a *mixed logit* model allows recovering heterogeneity in individuals' preferences. Thus, approximating "naturally" substitution patterns of participants in the experiment (Berry and Haile 2021).

Table 3 shows the estimates for the monthly welfare gains in the experiment[7] comparing the consumer surplus before and after using the transport subsidy. To address the potential bias in the estimates due to self-selection of treatment participants, we use the method proposed by (Gardner 2022). This methodology implements a two stages difference-in-differences estimator that allows to obtain unbiased results of treatment adoption on the variation of CS. The estimates presented correspond to the ATT of the subsidies in welfare gains. Standard errors of the estimates correspond to a bootstrap procedure with 1,000 random samples because the dependent variable in the

[7]First, individuals make during the intervention the average number of trips reported per week in the baseline survey. This number is presented in Table A.3 and corresponds to 4.7483 trips per week. The second assumption corresponds to the number of weeks that make up a month. It is assumed that a month is composed of a total of 4 weeks. Thus, the final measure of the monthly CS corresponds to the multiplication of the CS in the equation equation 6 by the average number of weekly trips in the sample and the number of weeks in a month

specification corresponds to an estimate. The table presents in panel A estimates for the monthly welfare gains using estimates from the model without controls, and in panel B the monthly welfare gains using the model estimated with controls. For each model the effect is disaggregated by treatment group assignment (row 1) and by subsidy intensity: treatment A (row 2) and treatment B (row 3). Additionally, the welfare gains are presented for 4 different subsamples (trip purpose and participant's gender). Panel B shows large welfare gains impacts of the transport subsidy program. Treatment assignment increase monthly welfare by $48,085 (12.84 USD - 3.1% of average household income) compared to the control group. By disaggregating estimations of welfare gains by subsidy intensity, it is possible to evidence heterogeneous effects by treatment intensity. Participants assigned to treatment group A ($7.5 USD), have a $COP 58,336 increase in the average monthly welfare or an increase of 3.8% of the average household income in the sample. However, participants assigned to treatment group B ($ 5.6 USD), increased their monthly welfare by $COP38,121 ($10.18 USD) or an increase of 2.5% of the average household income. Differences in economic gains between treatment groups can be largely attributed to heterogeneous treatment effects across treatment intensity: increased demand for the BRT component, see Figure B.5a; and changes in travel times, see Figure 2.

Table 3: Heterogeneous effects in welfare change by treatment group

	Monthly welfare change ($ COP)				
	Complete sample	Trip motive		Gender	
		Work trips	Other trips	Feminine	Masculine
Panel A. Mixed Logit model without controls					
Treatment	54.135	26.958	94.434	53.148	58.876
	[50.288, 57.983]	[22.018, 31.897]	[85.627, 103.241]	[48.832, 57.465]	[51.755, 65.997]
Treatment A: $COP28.000	65.263	37.786	105.053	64.483	67.944
	[61.219, 69.306]	[32.648, 42.925]	[95.823, 114.284]	[59.887, 69.080]	[60.223, 75.666]
Treatment B: $COP21.000	43.376	16.570	83.320	40.870	50.852
	[39.292, 47.460]	[11.344, 21.796]	[74.421, 92.220]	[36.366, 45.373]	[43.307, 58.398]
Panel B. Mixed Logit Model with controls					
Treatment	48.085	20.951	100.096	79.481	62.124
	[42.777, 53.392]	[14.695, 27.207]	[90.629, 109.563]	[74.227, 84.735]	[53.368, 70.880]
Treatment A: $COP28.000	58.336	29.637	115.295	92.451	69.401
	[52.183, 64.490]	[22.418, 36.856]	[104.762, 125.829]	[86.282, 98.621]	[59.262, 79.540]
Treatment B: $COP21.000	38.121	12.594	84.149	65.431	55.587
	[31.710, 44.533]	[5.129, 20.059]	[74.240, 94.059]	[59.332, 71.530]	[45.576, 65.598]

Note: This table presents the estimates of the monthly change in CE before and after having received the treatment. For all columns, the dependent variable corresponds to the monthly CE. This is obtained by multiplying the EC per trip in the]equation 6 by the average number of weekly lapses in the sample (see Table A.3) and a four-week average for each month. Because of the possible self-selection bias to treatment, the estimates presented make use of the estimator presented in Gardner (2022). Thus, the table reports the ATT in the monthly change in the EC given by the transportation subsidy program. Panel A presents the estimates using the estimates from the mixed logit model without controls, and with random coefficients on trip price and travel time and fixed coefficients on treatment assignment. Panel B presents the estimates using the estimates from the mixed logit model with controls from column 1 of Table 2. The "Treatment" row presents the monthly variation using the unified treatment group. The columns "Treatment A: $COP 28.00" and "Treatment B: "Treatment A: $COP 21.00" present the ATT estimates of monthly variation in EC by treatment intensity respectively. The 95th percentile confidence interval using standard errors from a bootstrap procedure with 1,000 random samples is presented in square brackets.

6 Policy implications

Governments around the world are responding to the growth of population and the growth in demand for mobility in a number of different ways. (Christensen and Osman 2021) estimate the policy implications of subsidies on ride-hailing services. (Abebe et al. 2021; Brough et al. 2022; Bull et al. 2021) estimate the effect of public transport costs reduction and their policy implications. However, the result in this paper can shed light into a wide range of question facing public administrations. Moreover, this paper help to better understand the effect of transport subsides in a development context under one of the largest BRT systems in the world. I limit my discussion to the specific impact of transport subsidies on travel times and participants characteristics that determine the welfare gains within the sample.

6.1 Travel time

Giving the potential for specific treatment effects of transport subsidies besides SITP demand, this section presents empirical strategy and result of transport subsidies on travel times. In order to estimate this effect it is necessary to use a different empirical strategy other than a discrete choice model. As treatment groups assignment generates exogenous variation in assignment to treatment, a simple comparison of means would allow estimate the average effect of treatment across treated participants. However, the staggered use of treatment (see Figure B.4) does not allow to approximately estimate the counterfactual busing a naïve comparison of means. To address this concern, a *Two Way Fixed Effects* (TWFE) model is used. The model to be estimated is:

$$\text{Travel\_time}_{ie} = \delta_i + \phi_e + \text{Treatment}_{ie} + \mathbf{X}'_{ie}\Omega + \vartheta_{ie} \tag{8}$$

Where Travel_time_{ie} corresponds to the reported travel time. Travel times are calculated for each participant using the difference between the reported start and end time of the trip. As participants were not asked to distinguish between 1) travel time to the mode of transportation, 2) waiting time, and 3) travel time on the chosen mode of transportation, the measure used comprises a complete aggregation of the total time for each trip. Treatment_{ie} is an indicator variable equal to one from the survey e in which treatment use occurred, zero otherwise. δ_i and ϕ_e are participant and survey number fixed effects respectively. However, the model in the equation **??** presents an important concern: self-selection into treatment use. In detail, given the characteristics of the intervention, participants assigned to the treatment group can make use of the cash transfers at any time during their availability (see Figure B.4). The decision to make use of the treatment may present a problem in the estimates. To assess the importance of self-selection, changes in travel time relative to treatment exposure are studied. Thus, an event study specification is used. The estimation is described as follows:

$$\text{Travel\_time}_{ie} = \delta_i + \phi_e + \sum_{s\neq -1}^{S} \tau_s \times \text{Treatment}_{ies} + \mathbf{X}'_{ie}\Omega + \vartheta_{ie} \tag{9}$$

Where Travel_time$_{ie}$ δ_i y ϕ_e are defined above. Treatment$_{ies}$ is an indicator variable equal to one if in the follow-up survey e person i used the treatment in event s, zero otherwise. Thus, τ_s allows to recover the effect relative to the occurrence of the event (up to 16 weekly mobility diaries; 1 baseline and 15 follow-up surveys. See section 3 for more information). Negative values of s denote the number of follow-up surveys preceding treatment use and positive values of s refer to the number of surveys following treatment use. Thus, $s = 0$ indicates the instantaneous effect of the treatment on travel times. $\mathbf{X}_{ie}$ is a vector of controls with variance per participant i and follow-up survey e. This vector contains total travel cost, day of week indicator, and mode of transportation used indicator. Models presented in equation **??** and equation **??** yield unbiased effects of the causal effect of transportation subsidies on participants' travel time if the parallel trends assumption is met. A conventional practice used to support the assumption of parallel trends is to test whether participants in the treatment and control groups have different effects on the outcome before treatment. The idea is to demonstrate visually that, if treatment had not been assigned, ATT in the post-treatment periods would not allow rejection of the null hypothesis of no difference in travel times between the two groups, as in the pre-treatment periods. Figure 2 provides suggestive information on the fulfillment of this assumption.

Parameter estimates: Table 4 shows estimates for the model in equation 8. Each column represents a regression, with columns 1 and 2 using the first stage of treatment randomization (assignment to treatment group), while columns 3 and 4 present the estimates using the second stage of treatment randomization (treatment intensity). The dependent variable is the difference in minutes between the reported time of arrival and the start time of travel. Given the construction of the treatment variables for the TWFE model, results presented refer to the ATT. The table shows reductions in travel time in individuals assigned to the treatment group. This effect corresponds to a 10-minute reduction in travel time (column 2) or 10.6% with respect to the control group. When disaggregated by subsidy intensity, treatment group A decreases reported travel time by up to 19 minutes per trip versus the control group. This effect represents a 19.7% decrease compared to the average reported travel time of the control group. On the other hand, there is no significant effect for participants in treatment group B.

Now, we explore how do travel times change by length of exposure to the treatment. Figure 2 presents the effects of the program on travel times according to the number of follow-up surveys a

Table 4: Effect of transport subsidies on travel times

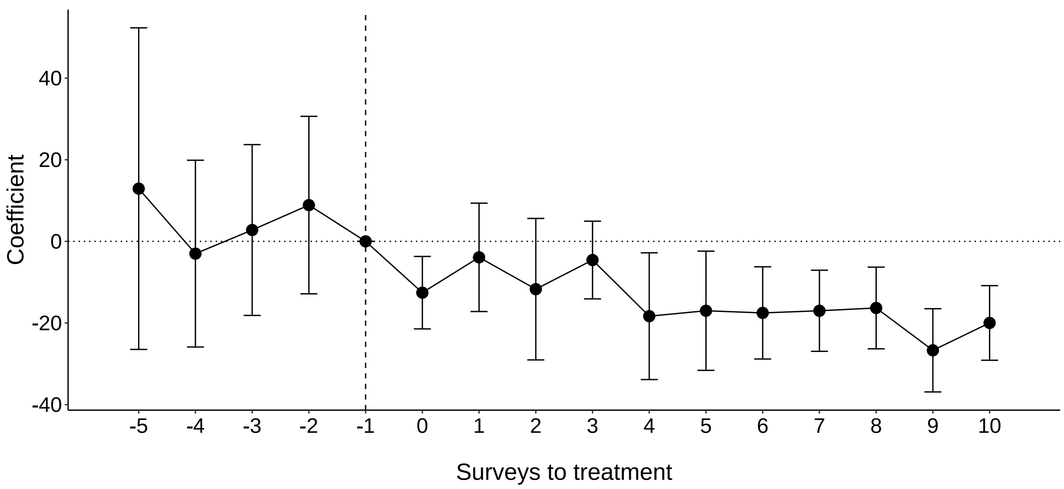
	Dependent variable: *Travel times*			
	Sample			
	Assignment to treatment		Treatment intensity	
	(1)	(2)	(3)	(4)
Treatment group	-10,19	-10,06		
	(3,680)	(3,686)		
Treatment A: $COP28.000			-19,56	-18,66
			(7,512)	(7,425)
Treatment B: $COP21.000			-1,000	-1,605
			(4,021)	(4,283)
Observations	14.610	14.610	14.610	14.610
R^2	0,2077	0,2179	0,2081	0,2183
Controls	No	Yes	No	Yes
Fixed Effects: Survey	Yes	Yes	Yes	Yes
Fixed Effects: Participant	Yes	Yes	Yes	Yes

Note: This table presents results of equation 8. All regressions were estimated using function `feols` using the `R` package `fixest` (Bergé (2018)). The treatment variable estimates represent the average effect on those treated. The dependent variable in all columns is the travel time reported for each trip in the follow-up surveys. Travel time represents the aggregation of 1) travel time to the mode of transportation, 2) waiting time, and 3) commuting time. In columns 1 and 2, the treatment variable is equal to one in the follow-up survey that used the conditional treatment to be previously assigned to the treatment group, zero otherwise. On the other hand, in columns 3 and 4 the treatment variables are equal to one in the follow-up survey conditional on the amount of the subsidy to which they were chosen, zero otherwise. Columns 2 and 4 present estimates using the vector of controls $\mathbf{X}_{ie}$. The control variables included are total commuting cost, day of the week indicator, and mode of transportation used indicator. Clustered standard errors by person and follow-up survey number are presented in parentheses.

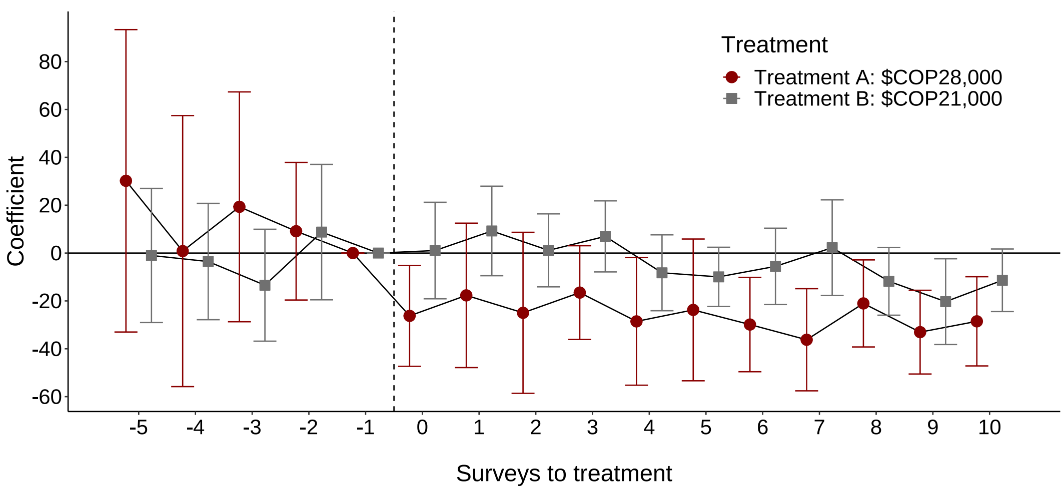
person has been exposed to. Each point in the figure represents the ATT of the subsidies relative to the occurrence of treatment use. Negative values on the x-axis represent the preceding effect of subsidies on reported travel time. Positive values represent the subsequent effects of subsidies on travel time. Vertical lines represent the 95th percentile confidence intervals of the ATT estimator. In the pre-treatment periods it is not possible to reject the null hypothesis of no significant program effect, providing evidence of compliance with the assumption of parallel trends. Panel 2a presents the estimates using the first stage of treatment randomization treatment allocation, while Panel 2b presents estimates using the intensity of the subsidies. Estimates show a persistent effect on travel time reductions for people assigned to the treatment group. For the first follow-up survey after treatment use, subsidies reduce travel times by 10 minutes (significant at 1 percent), representing a 10% decrease compared to the control group average. However, this effect disappears between surveys 1 to 3. Nevertheless, the treatment reduces travel times after the 4th survey and the effect remains statistically significant. Subsidies reduce, on average, travel times up to 22 minutes in the ninth survey (significant at 1%), representing a decrease of 24% compared to the control group. Panel 2b shows the effect of treatment exposure disaggregated by treatment intensity. Participants assigned to treatment group A ($7.5 USD) decrease their travel times as treatment exposure increases., with time reductions of up to 32 minutes or a 34.2% decrease from the control group by the seventh survey. On the other hand, participants assigned to treatment group B ($5.6 USD) do not appear to reduce their travel times as shown in Table 4.

Figure 2: Effect of transport subsidies on travel times by length of exposure

(a) Complete sample



(b) Treatment groups



Note: This figure presents results of equation 8. All regressions were estimated using function `feols` using the `R` package `fixest` (Bergé (2018)). The figure presents the effect of transport subsidies on travel times by length of exposure. Travel time represents the aggregation of 1) travel time to the mode of transport, 2) waiting time and 3) travel time. The x-axis presents the effect relative to the occurrence of the event, in this case treatment use. Negative values denote the number of follow-up surveys preceding the use of the treatment and positive values correspond to the number of surveys after the use of the treatment. Thus, 0 corresponds to the instantaneous effect of the treatment on travel times. Panel 2a presents estimates using the unified treatment group, while panel 2b presents estimates using treatment intensity. Both panels use a vector of controls comprising commuting cost, days-of-the-week and alternative fixed effects. Standard errors are clustered at the person $\times$ follow-up survey level.

6.2 Determinants of welfare gains

Using a mixed logit model allows to estimate the complete distribution the CS. Panel B.6a of Figure B.6 shows the monthly CS distribution for the complete sample, while Panel B.6c divides monthly welfare by trip motive. An overlap between the two samples is observed in the tails of the distributions. However, it is evident that the distribution of the monthly consumer surplus of the remaining trips is concentrated towards higher values compared to work trips. Table 3 shows in columns 2 and 3 the monthly welfare gains by trip motive. The table shows that monthly welfare gains for work trips ($COP20,951 or 1.4% of average household income) are statistically different and lower than the welfare gains for other reasons ($COP100,096 or 6.5% of average household income). This difference represents about 5 times the welfare gains by work trips. To exploit the differences in the distributions and better understand CS determinants, I use two different hypotheses that help understand welfare gains diferences across groups within the sample.

Two hypotheses could potentially explain differences in the CS estimates. First, households with low monthly incomes make longer commutes to work, have longer travel times and spend a higher percentage of their income on transportation expenses (Bocarejo et al. 2016; Guzman and Oviedo 2018). Thus, participants in the lowest quintile of the income distribution have lower levels of welfare compared to participants in the richest quintile of the income distribution. Second, starting time of a commutes affects participants indirect utility. Recent literature has shown that commute start time affects commuters' utility levels (Thorhauge et al. 2020; Lizana et al. 2021), specifically through a correlation with congestion levels in cities. Thus, restrictions on the flexibility of working hours may explain the difference in CS by trip motive.

Figure B.7 shows observable differences between work trips and other motives trips. Panel B.7a shows a clear difference between the mode of transport used for their commute and trip motive. It is evident that the majority of work trips are taken using both components of the SITP, while the Bus component accounts for the vast majority of trips for other reasons. The above result characterizes an important part of the trips: travel time. Panel B.7c of Figure B.7 shows the breakdown of travel times by mode of transport used. It is possible to observe differences in travel times in all alternatives by trip motive, with trips for other reasons taking less travel time. Additionally, disaggregating travel times by income, there are no differences in travel times for commuting to work (Panel B.7d of Figure B.7). However, for trips for other motives, participants in the richest quintile of the income distribution visibly have different travel times comprared to the poorest quintile. These results suggest that travel times are a key factor in explaining differences in CS estimates by travel motive. Finally, and consistent with the literature, work trips are highly concentrated in the morning hours, while trips for other reasons are more evenly distributed throughout the day (Panel B.7b).

Table A.1 examines the validity of the previously stated assumptions and other individual and commuting characteristics to determine the variation in the estimates of the CS. Consumer surplus is used as the dependent variable as shown in equation 6. Standard errors correspond to a bootstrap procedure with 1,000 random samples because the dependent variable is an estimate. The table presents estimates of the treatment effect, progressively adding gender, trip purpose, logarithm of monthly household income, perception of SITP, transportation expenditures, age, minimum distance from residence to the nearest BRT station, and an indicator of trip start time as control variables. Finally, column 6 presents the preferred specification using all the variables described. The random assignment to treatment groups A and B presents a significant difference in the EC compared to the control group, corroborating the results of Table 2 and Table 3.

Now, there is a negative and significant relationship between CS and female participants (columns 2 and 6). On the other hand, estimates show that trips for other reasons, compared to work trips, significantly increase CS (columns 2 and 6). This is consistent with the estimates on Table 3 and the facts in Figure B.7. Additionally, in columns 3 and 6, we estimate the income elasticity of EC, finding a positive relationship of less than one. This estimate represents the first estimate of the income elasticity of CS in transportation subsidy programs in the literature. The positive effect of the elasticity is consistent with the visible differences between low-income and high-income people in travel times Figure B.7, panel B.7b). Finally, estimates regarding the start time of the trip use as a base alternative the 4 a.m. to 8 a.m. time slot, a time commonly used for work commuting (Figure B.7, Panel B.7a). Thus, compared to the baseline category, commuting between 9 a.m. and 24 p.m. significantly increases CS: effects can be attributed to high levels of congestion, travel times and stress.

Column 6 shows the determinants of CS including all variables. When all variables are included in the analysis, the coefficients on treatment assignment remain stable, increasing CS in the sample. However, when all variables are included, the coefficients on trip motive and gender change in magnitude. Thus, differences in perceptions, age, distance, income and the other variables in column 6 seem to explain to some extent the differences in CS by trip purpose. However, it is not possible to fully determine the determinants of CS by trip purpose, opening the research agenda for the future.

7 Conclusion

This paper makes a distinct contributions to the knowledge of the welfare impacts of public transport subsidy programs. The study estimates a discrete choice random utility model to assess the welfare gains impacts of program participants under a developing context in one of the largest BRT systems in the world. Using exogenous variation induced in the allocation of transportation subsidies, welfare gains are estimated for different subsamples, highlighting heterogeneous effects by treatment intensity, gender, and trio motive.

The paper finds that the transportation subsidy program increases the monthly welfare of treatment group participants by \$12.84 USD (3.1% of average household income), with this increase being larger for treatment group A ($15.57 USD or 3.8% of average household income) than for treatment group B ($10.18 USD or 2.5 percent of average household income). In addition, the paper shows that the benefits of subsidies are significantly lower for commuting for work than for other reasons. Suggestive evidence is presented explaining that these differences are partly explained by disparities in travel times by income level and trip start time between the two groups. Additional results show an increase in demand for SITP given assignment to the treatment group. On average, participants in treatment group A increase demand for the BRT component by 107%, while demand for the Bus component increases by 27.8%. However, for treatment group B, there is no evidence of increased demand for the SITP.

These results imply two public policy considerations. First, the amount of the subsidy has heterogeneous effects on welfare and demand increases. This has important implications for policy makers, since it implies the development of subsidy targeting strategies in order to generate welfare increases in the most needy populations. Second, individuals are more likely to use the SITP in the presence of subsidies, suggesting that these do not fully satisfy their demand for transport services. This implies that improvements in public transport service provision can increase demand for the system and decrease negative externalities such as congestion and emissions.

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APPENDIX:

A TABLES

Table A.1: Determinants of CS at the individual level

	Dependent variable: *Log(Consumer Surplus)*					
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment A: $COP28.000	0,201	0,205	0,203	0,201	0,201	0,209
	(0,0046)	(0,0044)	(0,0051)	(0,0049)	(0,0047)	(0,0053)
Treatment B: $COP21.000	0,112	0,112	0,111	0,113	0,113	0,0967
	(0,0050)	(,,0046)	(0,0054)	(0,0052)	(0,0050)	(0,0053)
Log(Household montly income)			0,032			0,0161
			(0,0040)			(0,0042)
SITP quality perception (1-10 scale)						-0,0025
						(0,0012)
Transport expenses satisfaction						0,0032
						(0,0011)
Minimum distance to closest BRT station (Km)				-0,0119		-0,0140
				(0,0019)		(0,0020)
Number of persons in the household						0,0508
						(0,0015)
Age						0,0039
						(0,0002)
Reason for trip: Other trips		0,016				0,0131
		(0,0070)				(0,0087)
Gender: Female		-0,198				-0,174
		(0,0045)				(0,0056)
Reason for travel: Other trips *times* Gender: Female		,,022				0,0044
		(0,0082)				(0,0091)
Trip start time: 00:00 - 04:00					-0,0092	-0,0095
					(0,0066)	(0,0072)
Trip start time: 09:00 - 12:00					0,0288	0,0140
					(0,0060)	(0,0074)
Trip start time: 13:00 - 16:00					0,0440	0,0409
					(0,0074)	(0,0089)
Trip start time: 17:00 - 20:00					0,0255	0,0143
					(0,0098)	(0,0108)
Trip start time: 24:00 - 21:00					0,0732	0,0030
					(0,0194)	(0,0206)
Intercept	2,395	2,523	1,938	2,415	2,384	1,944
	(0,0031)	(0,0041)	(0,0569)	(0,0049)	(0,0038)	(0,0641)
Observations	14.753	14.753	12.631	13.672	14.753	10.349
R^2	0,159	0,262	0,164	0,160	0,162	0,354
Survey fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Alternative fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents regression estimates using as dependent variable the logarithm of the CE presented in equation 6 equation using estimates in column 1 of Table A.2. Controls are progressively introduced in the columns until column 6 where the estimates with all dependent variables are presented. The standard errors obtained by a bootstrap process with 1,000 random samples are presented in parentheses.

Table A.2: Transport Decisions - Mixed Logit Model Estimates

	Dependent variable: *Chosen alternative*									
	Complete sample		Trip motive				Intervention timing			
			Work trips		Other trips		Before		During	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Random coefficients										
Monetary costs (θ_i)	-0,263	-0,259	-1,011	-0,997	-0,0622	-0,0544	-0,457	-0,461	-0,246	-0,237
	(0,0327)	(0,0326)	(0,0886)	(0,0885)	(0,0400)	(0,0390)	(0,0664)	(0,0786)	(0,0366)	(0,0374)
Opportunity cost (β_i)	-0,0269	-0,0272	-0,0378	-0,0369	-0,0297	-0,0300	-0,0255	-0,0250	-0,0338	-0,0330
	(0,0018)	(0,0018)	(0,0050)	(0,0037)	(0,0025)	(0,0024)	(0,0034)	(0,0034)	(0,0022)	(0,0019)
Observations	88.842	88.518	59.112	58.908	29.730	29.610	24.246	23.958	64.596	64.560
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Standard Errors	Participant	Participant	Participant	Participant	Participant	Participant	Participant	Participant	Participant	Participant
Log-likelihood	-14.118	-13.861	-6.868	-6.737	-5.705	-5.588	-3.809	-3.663	-10.109	-9.958
Number of participants	1.598	1.564	1.419	1.396	1.294	1.282	1.489	1.455	1.346	1.345
Number of trips	14.807	14.753	9.852	9.818	4.955	4.935	4.041	3.993	10.766	10.760
Mean CS (***COP***)	12.095	12.311	6.455	6.893	27.761	32.015	9.232	9.383	12,091	13.005
Percentile 5	8.479	7.411	5.022	4.250	12.759	11.502	6.838	6.176	7.526	7,024
Percentile 95	16.074	17.439	8.130	9.685	44.960	55.067	11.770	12.641	17.333	19.398

Note: This table presents the estimates of the mixed logit model. The data come from the follow-up survey and the follow-up surveys. The estimates correspond to the estimates of the regressions of the indicator variable for mode choice on total costs, treatment group assignment and control variables. The control variables correspond to age, gender, number of people in the household, presence of a vehicle in the household, and perceptions of safety in the sector where they live (with a scale where 5 is strongly agree and 1 is strongly disagree). The table presents only the estimates of the random coefficients for trip price and trip time. The random coefficients are estimated using a triangular distribution, while the other coefficients are presented in the Figure B.5 and are assumed fixed for each alternative. The CE presented corresponds to the estimate of the figure 6. Clustered standard errors at the person level are shown in parentheses.

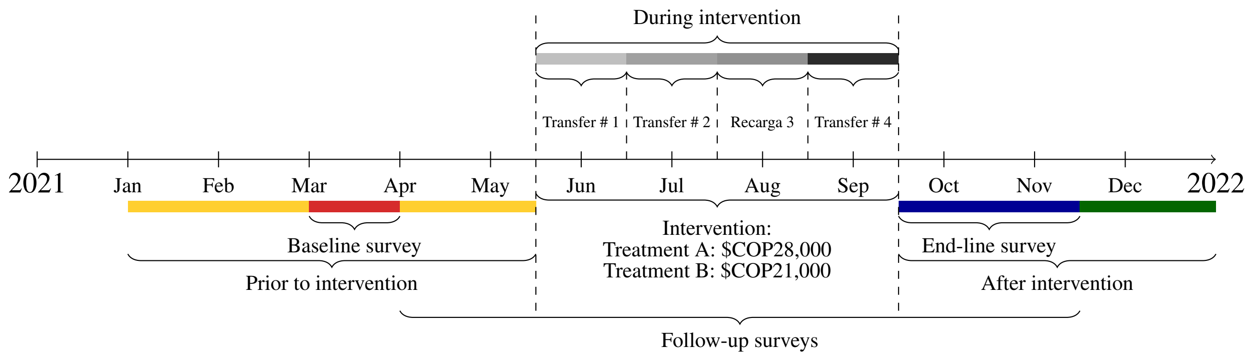
Table A.3: Descriptive statistics

	Treatment groups								
	Complete sample		Control		Treatment		Difference		
	(N = 1,607)		(N = 806)		(N = 801)		(N = 1,607)		
	Mean	Stand. Dev.	Mean	Stand. Dev.	Mean	Stand. Dev.	Value	Stand. Error	P-value
Panel A. Socioeconomic characteristics									
Number of persons in the household	3,7162	1,4827	3,6378	1,4473	3,7953	1,5143	0,1576	0,0739	0,0332
Age	43,5470	11,8235	43,7692	11,8421	43,3233	11,8080	-0,4459	0,5820	0,4500
Study	0,0311	0,1737	0,0397	0,1954	0,0225	0,1483	-0,0172	0,0087	0,0467
Female	0,7175	0,4504	0,7159	0,4513	0,7191	0,4497	0,0032	0,0225	0,8861
Married	0,2265	0,4187	0,2209	0,4151	0,2322	0,4225	0,0114	0,0210	0,5865
Own household	0,6167	0,4864	0,6216	0,4853	0,6117	0,4877	-0,0099	0,0243	0,6848
SISBEN 3 Score	56.59718	14.2971	56.5094	14.4722	56.6744	14.1274	0,1650	0,7149	0,8175
Work	0,8668	0,3399	0,8586	0,3487	0,8752	0,3307	0,0166	0,0170	0,3279
Household monthly income ($COP)	1.537.632	1.205.005	1.583.710	1.371.663	1.494.635	1.024.546	-89.074,56	66.836	0,1829
Days worked per week	5,2457	1,2600	5,2029	1,3107	5,2875	1,2080	0,0846	0,0674	0,2097
Hours worked per day	9,0587	2,4409	8,9797	2,4642	9,1360	2,4171	0,1563	0,1306	0,2319
Work from home	0,0585	0,2348	0,0633	0,2436	0,0537	0,2255	-0,0096	0,0117	0,4130
Education: High School	0,8339	0,3723	0,8412	0,3657	0,8265	0,3790	-0,0147	0,0186	0,4282
Education: Undergraduate	0,4144	0,4928	0,4342	0,4960	0,3945	0,4891	-0,0397	0,0246	0,1061
Education: Graduate School	0,0330	0,1787	0,0409	0,1983	0,0250	0,1561	-0,0160	0,0090	0,0731
Panel B. Transport characteristics									
Number of modes of transport	1,7710	0,7737	1,7860	0,7860	1,7562	0,7616	-0,0298	0,0418	0,4767
Usual trip travel time (min)	95,082	85,5161	99,3639	104,3293	90,6459	59,9787	-8,7180	6,8610	0,2043
Distance to main transport mode (min)	7,9428	7,5145	7,9680	7,3905	7,9186	7,6380	-0,0493	0,4330	0,9093
Distance to main transport mode (blocks)	4,4465	4,2182	4,2931	3,8337	4,5946	4,5572	0,3015	0,2430	0,2149
Waiting time - main transport mode	12,5960	9,4500	12,8074	9,9880	12,3929	8,9060	-0,4146	0,5440	0,4462
Travel cost - usual trip ($COP)	3.188	3.890	3.150	4.035	3.225	3.748	74,9398	225,0901	0,7392
Weekly commutings	4,7483	1,8364	4,7034	1,9184	4,7926	1,7520	0,0892	0,1021	0,3823
SITP perception (1-10 scale)	5,5669	2,2322	5,4863	2,3094	5,6479	2,1502	0,1616	0,1113	0,1469
SITP validations - February	6,7393	5,6351	6,6219	5,6829	6,8575	5,5877	0,2356	0,2817	0,4030
Motive: work trips	0,8669	0,33986	0,8586	0,34870	0,8752	0,3307	0,0166	0,0170	0,3279
Motive: study trips	0,0311	0,1737	0,0397	0,1953	0,0225	0,1483	-0,0172	0,0087	0,0467
Motive: other trips	0,4493	0,4976	0,4442	0,4972	0,4544	0,4982	0,0103	0,0248	0,6794
Weekly SITP validations	7,3716	7,5660	7,1446	7,4030	7,6006	7,7244	0,4558	0,3781	0,2282

Note: This table presents the mean and standard deviation of the mean for different sample groups. Columns 1 and 2 present the mean and standard deviation for the full sample respectively. Columns 3 and 4 present the mean and standard deviation for the sample of participants in the experiment who were assigned to the control group. Within this subsample are 806 people. Columns 5 and 6 present the mean and standard deviation for the participants assigned to the treatment group. This treatment group is comprised of individuals in both treatment group A 28,000 and treatment B 21,000. Within this subsample there are 801 individuals. Columns 7, 8 and 9 present the mean difference, standard error of the mean difference and p-value associated with a test of mean difference respectively between the control (column 3) and treatment (column 5) groups. Panel A of the table shows the statistics of the socio-demographic variables collected for the sample, while panel B presents the statistics of the transportation/mobility variables of the sample.

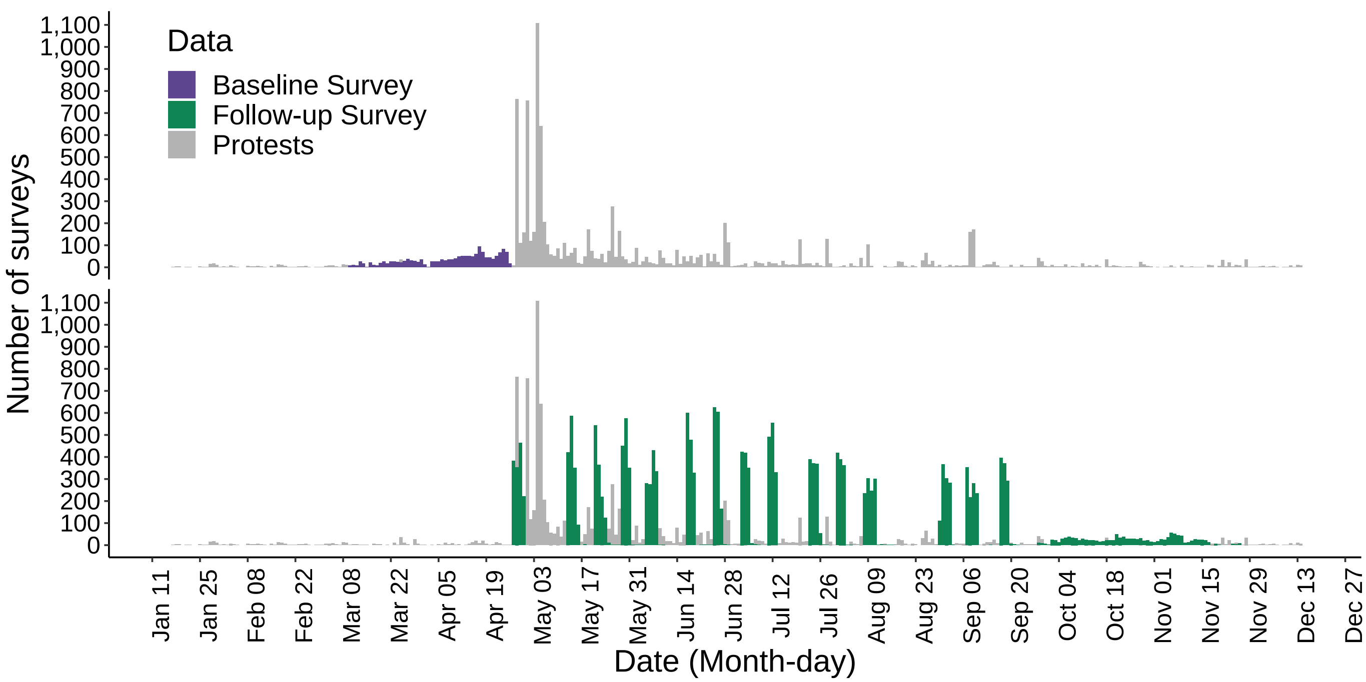
B.2 Figures

Figure B.1: Intervention's timeline



Note: This figure shows the timing of data collection along three periods in experiment: baseline, follow-up and end-line. It also shows the monthly periods of subsidy transfers and their implementation during the intervention.

Figure B.2: Surveys and demonstrations

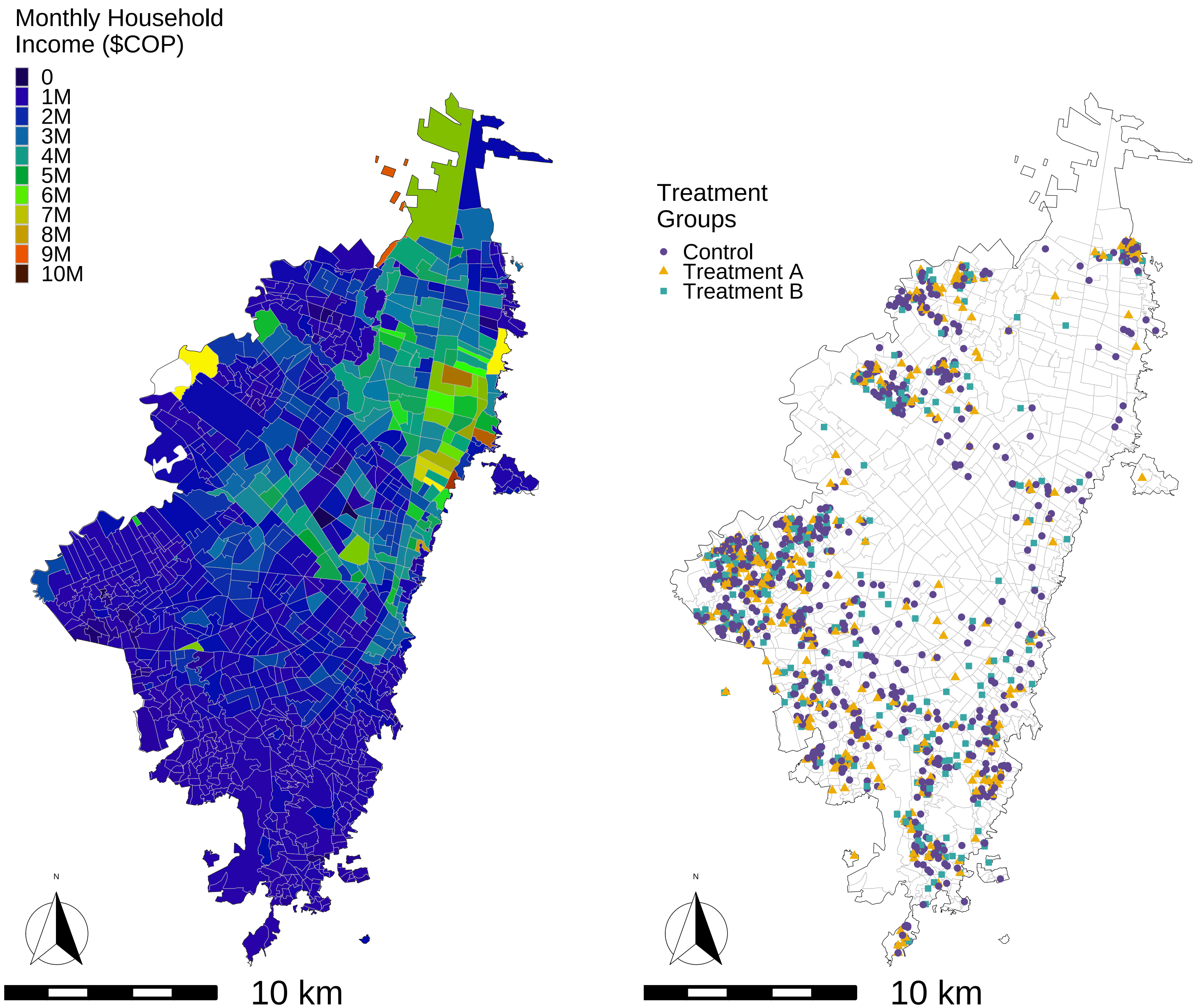


Note: This figure shows the number of recollected baseline and follow up surveys and the total number of reported protest/happenings in the city.

Figure B.3: Income and residential spatial distribution of participants

(a) Spatial distribution of household income

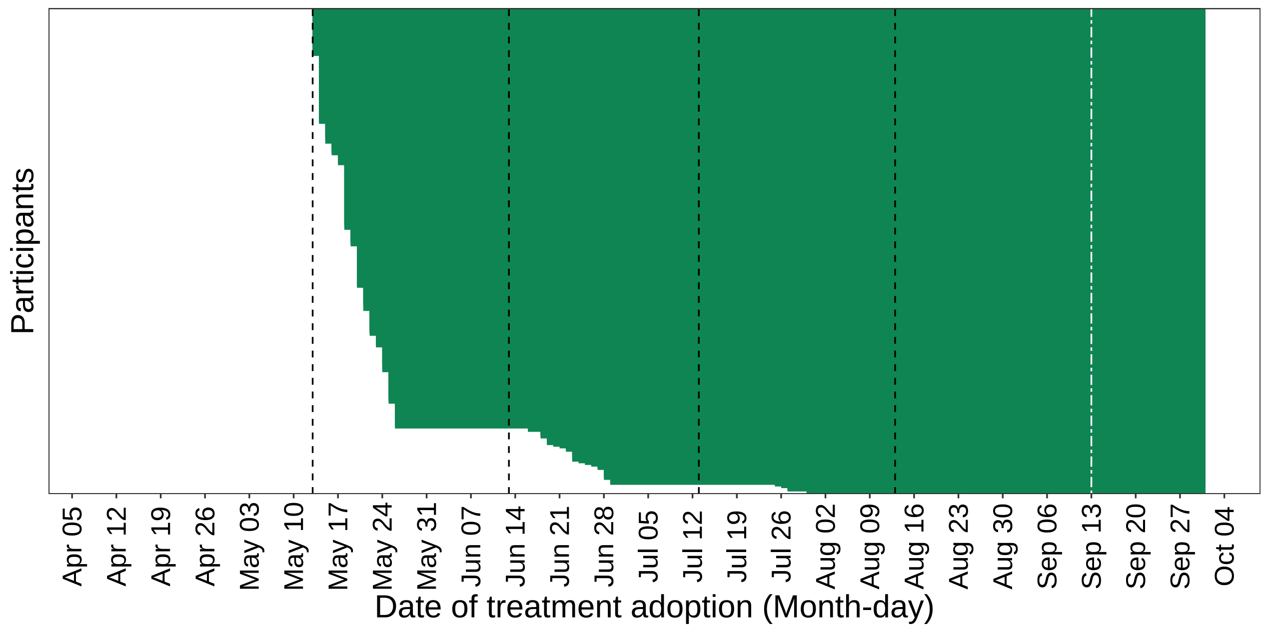
(b) Spatial distribution of households



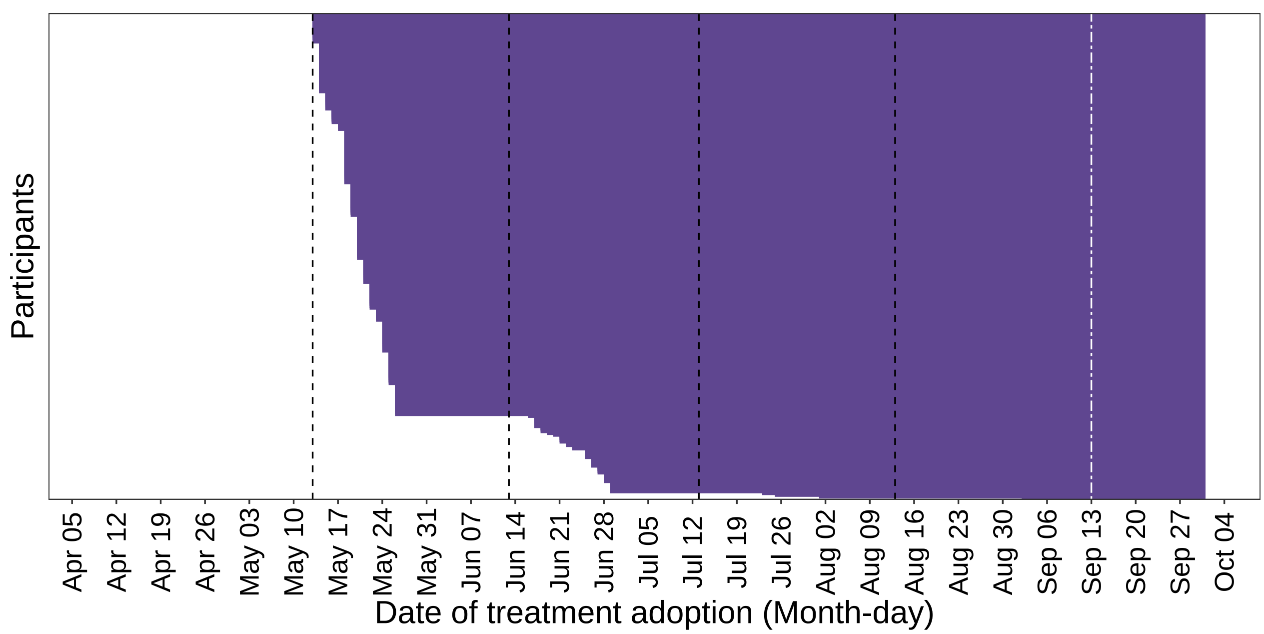
Note: This figure shows 1) the average monthly household income reported in the 2021 "*Encuesta Multipropósito*" at the neighborhood level, and 2) the residential spatial distribution of participants reported in the baseline survey. The sample is composed of participants in the control group (N=806) and treatment group (N=801), for a total of 1,607 people.

Figure B.4: Staggered adoption of the treatment

(a) Treatment A



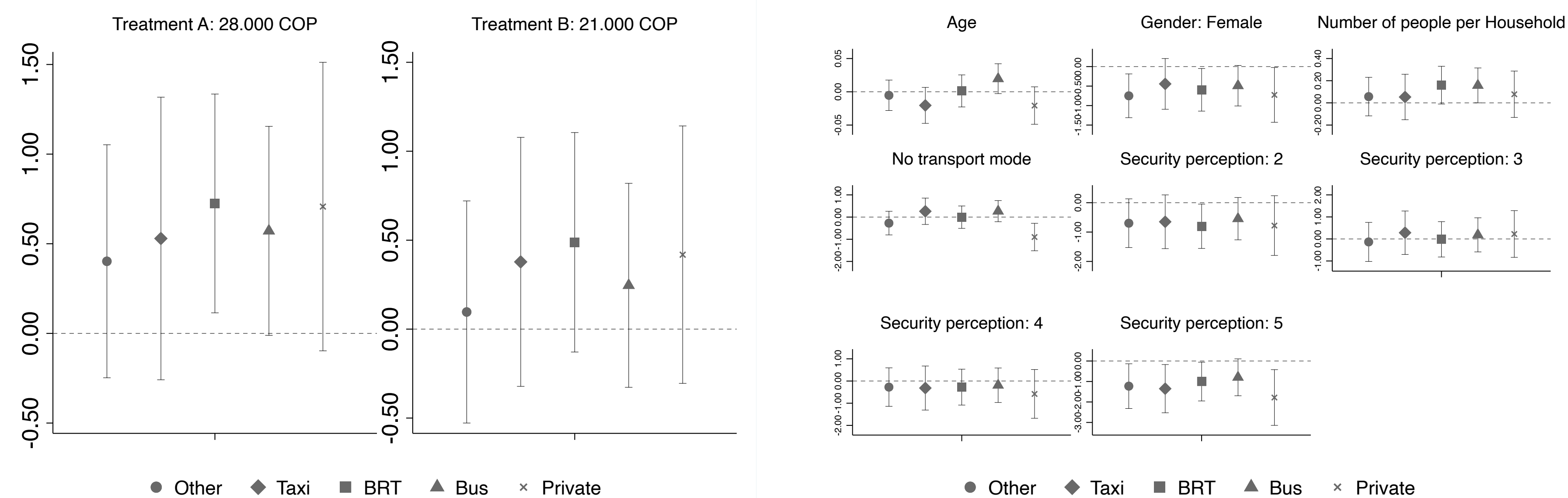
(b) Treatment B



Note: This figure presents the staggered adoption of treatment in the experiment per treatment group. The date of adoption of the treatment is the date when a participant first claimed the subsidy at one of the recharge points through the city. X axis represents time, while the y axis identifies each of one the participants, per treatment group, that use the provided subsidy. The black dashed lines represent the moment in time where each of the 4 monthly subsidy periods were available for use. The white dashed-dotted lines represent the last day the $4^{t}h$ subsidy was available for treated participants. Panel B.4a shows the staggered treatment adoption for participants assigned to the treatment group A, while panel B.4b shows staggered treatment adoption for treatment group B.

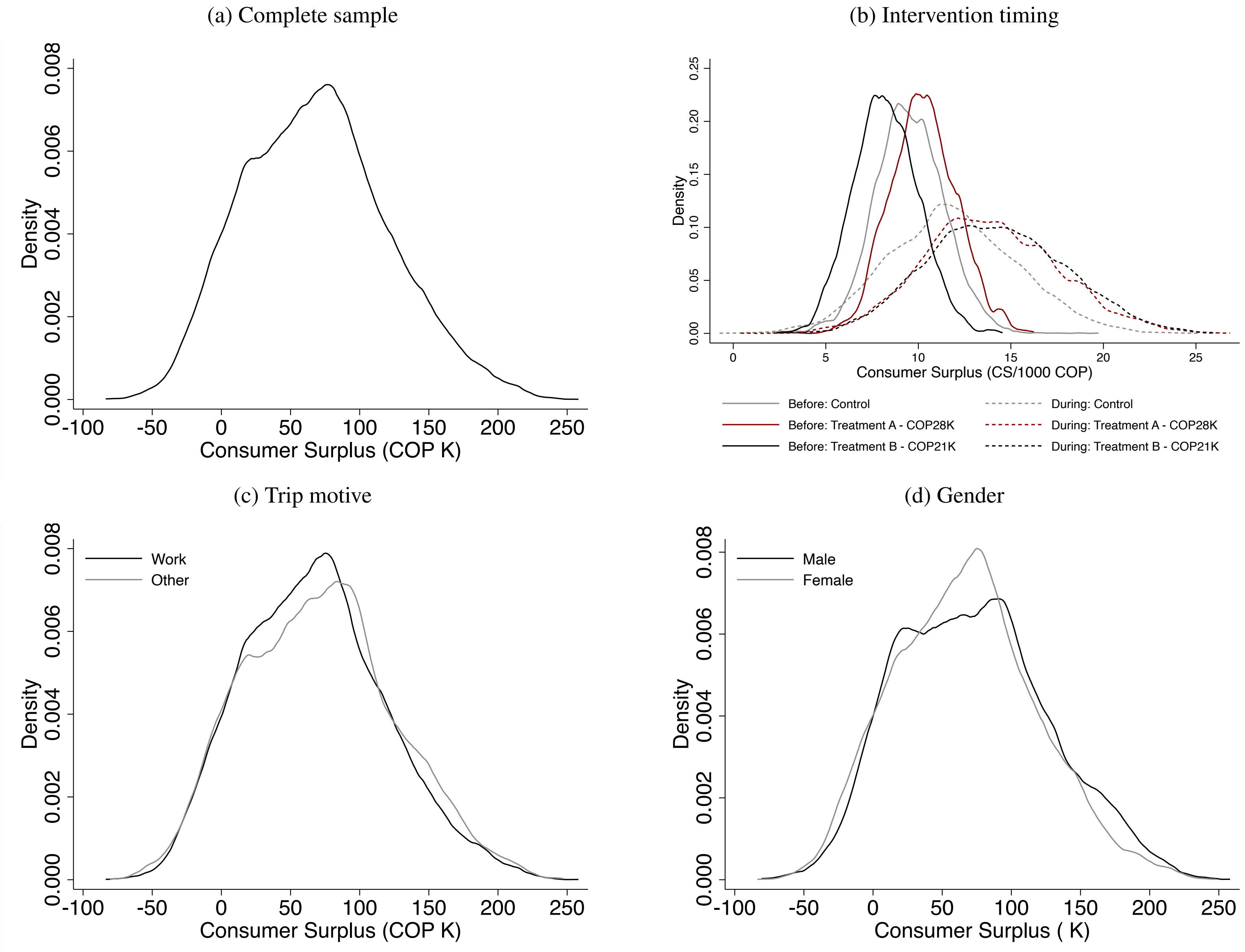
Figure B.5: Mixed Logit coefficients - Complete sample

(a) Treatment Groups (b) Controls



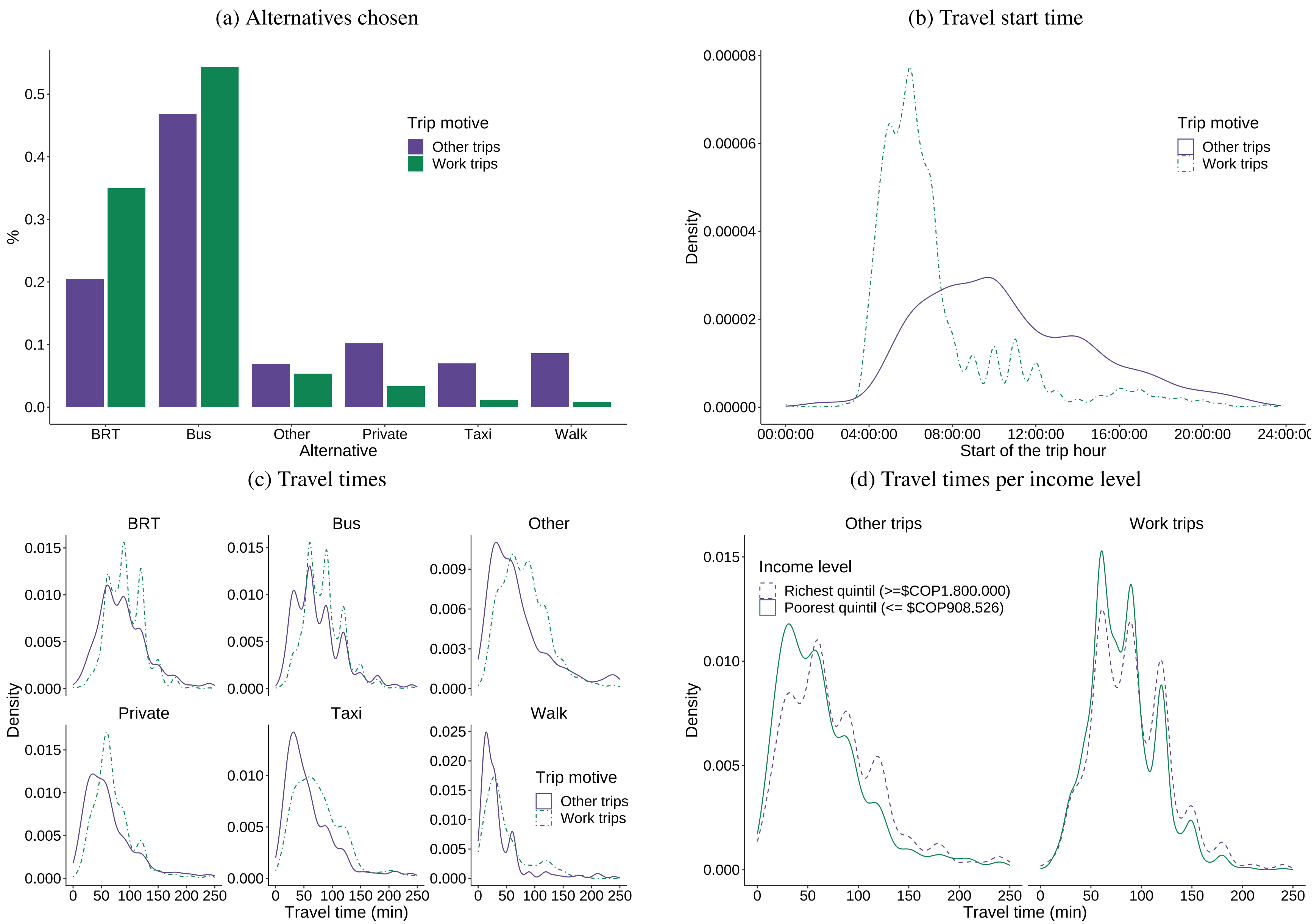
Note: This figure presents the estimates of the preferred mixed logit model presented in the Table A.2. Figures correspond to the fixed coefficients per alternative specified in equation 2. Panel a shows the coefficient estimates of the assignment to treatment groups A and B, while panel b corresponds to the characteristics of the individuals included as controls. The variable security corresponds to the perception of the level of security reported in the area of residence using a scale where 5 is strongly agree and 1 is strongly disagree. The estimates presented correspond to the *relative-risk* ratio reported by Stata relative to the “outside” alternative, in this case walking.

Figure B.6: Distribución mensual del Excedente del Consumidor



Note: This figure presents the distribution of the CS presented in equation **??** using estimates in column 1 of Table A.2. Estimates use random coefficients of total costs, assuming a triangular distribution. Distributions presented correspond to Kernel density estimates of the CS. Panel a presents the full distribution of the CS. Panel b presents the distribution before and during treatment for each treatment group in the sample. Panel c shows the distribution of CS by trip motive. Finally, panel d shows the distribution of CS by gender.

Figure B.7: Observable differences between reasons for displacement



Note: This figure presents in panel a the percentage of times the alternative was chosen dividing the sample by trip purpose. Panel b shows the Kernel distribution of travel start time dividing the sample by trip purpose. Panel c shows the Kernel distributions of travel times by alternative used dividing the sample by trip reason. Finally, panel d shows the Kernel distributions of travel times by dividing the sample between households with lower income (monthly income less than $COP908,526) and high income (greater than $COP1,800,000) by trip purpose.