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Pro-poor transport subsidies: More user welfare and faster travel ☆

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A B S T R A C T

A previous study has shown limited success of traditional fare discount subsidies in promoting public transport usage among low-income populations in Bogotá, Colombia. This paper evaluates the differential impacts of a novel demand-side subsidy, in the form of public transport vouchers, on user welfare and travel behavior. The study employs a large-scale randomized controlled trial involving 1607 frequent users of Bogotá's Integrated Public Transport System, half of whom received monthly travel vouchers on their personalized travel cards. The other half acted as a control group. A discrete choice random utility model is utilized to analyze weekly travel patterns and estimate changes in welfare in terms of consumer surplus by gender and travel purpose, based on a panel database that has information on multiple travel choices over 6 months. The results indicate a significant increase in the utility of the BRT and regular bus services for voucher recipients, leading to increased BRT usage, decreased regular bus usage, and travel time savings. The study also finds that travel vouchers notably enhance user welfare, especially for female participants and non-work-related trips, suggesting these trip purposes generate greater user benefits. The findings highlight the potential of voucher-based subsidies to induce behavioral changes and improve welfare, particularly for groups that typically depend more on public transport services.

1. Introduction

Public transport subsidies offer a valuable tool for promoting ridership and achieving broader societal goals. This policy is prevalent worldwide and governments spend vast sums on it. However, the subsidies' progressivity and redistributive effects, whether on the supply or demand side, are highly dependent on the local social context, activity location, and land use policy (Hörcher and Tirachini, 2021). Many cities, particularly in the Global North, have implemented subsidy schemes where all users benefit from the subsidy, even when they do not need it. In Latin American cities, most subsidies are provided to public transport system operators (operating expenditure), ranging between 26 % in Bogotá to 69 % in Buenos Aires (Rivas et al., 2020). However, it has been found that at least in this region, demand-side subsidies are more progressive than supply-side subsidies (Serebrisky et al., 2009).

While the general benefits of public transport usage are widely recognized (Buchanan, 2019; Noorbhai, 2022; Wang et al., 2019),

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its impacts may have different effects on users. Demand-side subsidies do not affect all users equally. Satisfaction with the transport system, gender, affordability, income level, and ease of access influence travel behavior and may affect other economic variables (Börjesson et al., 2020; Guzman et al., 2021a). Recognizing the diverse user groups and their unique needs is crucial when designing these types of measures. By carefully designing subsidy schemes, emphasizing improving experience and welfare, and adopting a data-driven approach, governments can ensure that public transport subsidies will be progressive and truly benefit society, fostering a more equitable and sustainable transport system. Understanding how subsidies affect different population groups is crucial to stimulating ridership and their impacts on welfare to guide transport policy decision-making.

Recent evidence indicates that the current demand-side subsidy scheme in Bogotá, Colombia, offering a 28 % fare discount to lower-income populations, for up to 30 trips/month, has not effectively promoted public transport use. Several factors contribute to this outcome, with the most plausible explanation being a combination of fare increases, reduced subsidy amounts, and a decrease in the number of subsidized trips since April 2017, which collectively diminished the scheme's effectiveness in encouraging ridership among users of the same socioeconomic level (Guzman and Hessel, 2022).

This paper evaluates the differential impacts of an alternative approach to delivering demand-side subsidies (i.e., public transport vouchers) to frequent users, on user welfare, measured in terms of consumer surplus. The analysis is based on a large-scale randomized controlled trial in Bogotá's Integrated Public Transport System (SITP in Spanish). We estimate the user welfare produced from their modal choices across the entire transport market, both with and without vouchers in place. We randomly selected a group of 1607 regular SITP users with personalized travel cards who did not receive any kind of subsidy, and half of them were also randomly chosen to receive the vouchers on their travel cards. The other half acts as the control group receiving nothing. The travel voucher consisted of a monthly cash transfer to their travel cards during May and August 2021. This study was conducted in collaboration with the Bogotá Transport Authority (TransMilenio S.A.), as the city has a strong interest in understanding the potential impact of the pro-poor subsidy on frequent users to improve the policy's effectiveness. This study does not aim to directly compare the two subsidy schemes (the current and the alternative).

We use detailed panel data on travel behavior during the intervention period to estimate a discrete choice random utility model. This type of model fits very well with the structure of the data collected weekly. These data are at the participant level, by week, and by mode of transport. Our experiment, which directly transferred cash to participants' travel cards, effectively reduced the costs of accessing the SITP without altering the supply side of the system. This exogenous cost variation, combined with the choice model, allows us to recover participant welfare impacts through consumer surplus changes and decompose them by participant and trip characteristics induced by the voucher. Previous research has shown that these travel vouchers increase ridership and improve user satisfaction (Guzman and Cantillo-Garcia, 2024) and also induce a net increase in weekly travel demand of between 8.0 and 8.7 % depending on the voucher value (Guzman et al., 2024).

Our focus, however, is to evaluate the welfare impacts of this new form of demand-side subsidy by determining the value that users assign to it (i.e., the welfare gains per participant). Results show that travel vouchers notably enhance user welfare by enabling access to more efficient and faster transport modes, such as the BRT. The welfare gains are particularly significant for female participants and those making non-work-related trips. These findings underscore the potential benefits of implementing a transformative policy, specifically an alternative method of delivering demand-side public transport subsidies. This approach can drive behavioral change, especially for groups that typically benefit less from public transport services, highlighting its potential to create a more equitable and efficient transport system.

The paper is structured as follows: Section 2 discusses the rationale for public transport subsidies and their general effects worldwide, highlighting the ambiguity of these policies in developing regions. The methodology section details the design and implementation of the randomized controlled trial. Subsequently, the results are presented, followed by a reflection on their practical implications and concluding remarks.

2. Public transport subsidies and welfare: an underexplored topic

Public transport subsidies play a crucial role in shaping urban mobility systems. Governments frequently allocate significant resources to support these operations, aiming to enhance accessibility, alleviate congestion, reduce emissions, and promote social equality (Robin et al., 2023). The methods for subsidizing public transport vary significantly around the world. Common approaches include direct fare subsidies, where governments or agencies cover a portion of fare costs to make travel more affordable for users (Rivas et al., 2018). Other methods involve operational subsidies, which provide funding for the infrastructure and maintenance of public transport systems. Additionally, tax-based funding is frequently employed, using dedicated taxes or levies specifically allocated to transport budgets (Ubbels et al., 2001). However, the effectiveness and welfare implications of such subsidies remain topics of debate and empirical investigation, especially in cities of the Global South.

Several studies suggest that public transport subsidies may be less effective in promoting welfare compared to alternative policies (Basso and Silva, 2014; Hörcher et al., 2020; Proost and Dender, 2008). An alternative policy, congestion pricing, could both enhance public transport ridership and agglomeration benefits, potentially leading to lower fares and increased service frequencies (Hörcher et al., 2020). However, agglomeration benefits have limitations in effectiveness (Coulombel and Monchambert, 2023). Moreover, reducing public transport fares may be politically feasible, whereas implementing congestion charges, fuel surcharges, or increasing vehicle taxes often encounters resistance. While both policies theoretically encourage a modal shift, these changes should consider their specific advantages and relevance to the unique contexts in which they're implemented. In settings like Bogotá, lowering public transport fares might be politically viable, whereas efforts to implement congestion charges, fuel surcharges, or raise vehicle taxes often face resistance. Furthermore, these issues are typically determined by a higher-level authority.

In cities and countries with low levels of car ownership, where the vast majority of people rely on public transport and active modes, it may be more important and effective to enhance the accessibility and affordability of public transport. Studies have also examined equality concerns regarding subsidies for public transport, underscoring the significance of ensuring equitable and inclusive access to these services through targeted subsidy programs (Hörcher et al., 2020; Proost and Dender, 2008). Eliminating subsidies would potentially have substantial adverse effects on transport availability (van Goeverden et al., 2006). Research in Chinese cities has suggested that transport authorities should implement special measures for frequent travelers and captive user groups (Chen and Zhou, 2022). In Santiago, Chile, it has been suggested, in light of equality considerations, that bus fares should be reduced while car taxes should be increased (Tirachini and Proost, 2021).

Focusing on the economic and distributional impacts of subsidies, a study in Washington, D.C. found that increasing public transport supply increases traveler's welfare. These benefits go to all travelers, public transport users, and even car drivers, outweighing the operating subsidies, although still significant when capital costs are taken into account (Nelson et al., 2007). In another part of the world, Stockholm, a city with congestion charges, it was seen that current bus fares and frequencies are not optimal and some adjustments could significantly improve social welfare. Specifically, lowering fares, increasing bus frequencies, and deploying larger vehicles can lead to better outcomes by reducing congestion while enhancing accessibility and convenience for passengers, particularly during off-peak hours (Börjesson et al., 2017). Since subsidies have a substantial impact on system operations and potentially on users welfare, it is crucial to adopt an appropriate subsidy scheme to maximize social welfare in public transport (Wang et al., 2024). This choice will largely depend on the specific context under study. Research conducted in several cities worldwide, particularly in developed economies, supports the effectiveness of substantial fare subsidies. Even when fares covered only a fraction of operating costs, incremental fare reductions were found to improve welfare in nearly all cases (Parry and Small, 2009).

Furthermore, other studies have investigated the impact of targeted public transport subsidies on various areas. For example, subsidies may influence labor market variables such as labor income, the likelihood of employment, and the probability of being employed (Abebe et al., 2021; Franklin, 2018; Phillips, 2014; Rodríguez et al., 2016). Additionally, Webber et al. (2020) demonstrated that public transport subsidies improved maternal care in Tanzania. Mobarak and Reimão (2020) found that transport subsidies helped reduce poverty levels among populations vulnerable to drought in Bangladesh and Indonesia. However, there are few studies examining how the fare structure design impacts the distribution of subsidy welfare across different groups.

In conclusion, the impact of subsidized public transport on welfare remains inadequately documented. Subsidies not only enhance transport affordability but also boost ridership, particularly among populations that highly value the service, since they do not have viable alternatives for transport. The literature presents mixed findings regarding the effects of subsidies on welfare and ridership (Robin et al., 2023). The welfare implications of public transport subsidies are varied and context-dependent. While subsidies can promote economic efficiency, social welfare, and equality objectives, their effectiveness depends significantly on precise policy design and implementation. Future research should continue investigating the dynamic interactions between subsidies, urban transport systems, and societal welfare to better inform evidence-based policymaking in this crucial area.

3. The Bogotá public transport system and it subsidy scheme

The public transport system (SITP) in Bogotá is widely available across the city and is the most common mode of transport for middle-low and low socioeconomic population segments. Currently, the entire system, which consists of 114 km of BRT corridors, 615 regular bus routes, and an aerial cable car, moves nearly 4.3 million passengers every day. This corresponds to 35.3 % of daily trips, while private transport (car and motorcycle) is 21.1 %, walking is 27.2 % and cycling is 7.2 %. The vast majority of SITP users, live in the lowest-income areas of the city, mostly located on the urban periphery. As a proxy for household income, Colombia classifies residential land into six categories known as socioeconomic strata (SES), which establish different rates for basic utilities. Typically, the poorest population lives in the lower SES (1 and 2) and tends to reside far from the main economic opportunities, while SES 5 and 6 correspond to the best urban conditions and wealthiest households, who are located around the highest concentrations of employment and where the transport services are best (Cantillo-García et al., 2019). Thus, the majority of SITP users, 90.1 %, live in SES zones 1 to 3.

The SITP pricing scheme consists of a flat fare, meaning the fare is independent of the trip length. In 2021, the regular fare for BRT services was 2500 Colombian pesos (COP) (about 0.67 USD), and the regular fare for regular bus services was 2300 COP (0.61 USD). Feeding services, which transport passengers from peripheral areas to the BRT trunk system, do not charge users until they enter the BRT stations. This fare scheme was originally designed to benefit poorer users, supposedly by cross-subsidizing the long trips of the poor living in the periphery with the shorter trips of the wealthy. However, lower-income users are disproportionately affected by the low affordability of the system, spending between 16 % and 25 % of their monthly income on travel (Guzman and Oviedo, 2018) and, due to the lack of viable alternatives, become captives of public transport (Guzman et al., 2021a).

Regarding demand-side subsidies, Bogotá has implemented a subsidy scheme for vulnerable populations, offering fare discounts to users who meet specific requirements. This scheme includes preferential fares for elderly individuals (over 62 years old), people with physical disabilities, and the poorest segment of the population. To identify eligible beneficiaries in the poorest segment, the city uses a social policy mechanism called SISBEN[1] (System of Identification of Social Program Beneficiaries). Established in 2013, this subsidy scheme aims to provide greater access to public transport for individuals with a low ability to pay and has changed over time.

[1] The SISBEN is an index used by the Colombian government to assess and classify households, and their members, according to socioeconomic vulnerability to identify eligible beneficiaries for social protection programs.

Currently, to access a 28 % fare discount, potential beneficiaries must have a maximum SISBEN score (originally a scale between 0 and 100) of 30.56 and be older than 16 years old, allowing for a maximum of 30 monthly trips with the fare discount.

Fares with the pro-poor benefit were 0.48 USD (1800 COP) for BRT and 0.44 USD (1650 COP) for regular buses. Additionally, it is necessary to own a personalized travel card. However, this subsidy scheme, which costs approximately 36 million USD in 2023, no longer encourages SITP use (Guzman and Hessel, 2022) and continues to be active despite the limited understanding of its effects and cost-effectiveness. Therefore, this study seeks to analyze the effects of changes in user behavior and welfare through an alternative method of delivering the public transport subsidy.

4. Experimental design and methods

This research is based on a large-scale randomized controlled trial (RCT) of Bogotá's public transport system's frequent users without any transport subsidy. From the universe of Bogotá's public transport system's frequent users (around 176,000 users),[2] we randomly selected a sample of 1607 individuals. For this sample, half was randomly assigned to a treatment group (n = 801) and the other half to a control group (n = 806). The sampling process was done using a probabilistic approach assuming a uniform distribution, guaranteeing similarity between the two groups. For four consecutive months starting in May 2021, travelers in the treatment group received a monthly cash transfer (i.e., travel vouchers) into their personalized public transport travel card, meaning that everyone in the treatment group was eligible to receive up to four vouchers, while the control group did not receive any. In turn, we divided the participants of the treatment group into two treatment arms: Treatment A, 402 participants received a monthly travel voucher of 7.5 USD (28,000 COP), equivalent to 11 trips per month. In treatment B, 399 participants received a voucher for 5.6 USD (21,000 COP), which was equivalent to 9 trips per month. As an incentive, participants from the control group received a gift voucher (7.8 USD ~ 30,000 COP) to redeem at different supermarkets at the end of the experiment.

The majority of participants (81.2 %) live in the poorest areas of the city (SES 1 and 2 zones). Their monthly household income is around 412 USD (1,540,000 COP) in a household with an average size of 3.7 people. This corresponds to 65 % of the city's average income. They make 38 trips per month on average, with an average duration of 83 min and a cost of 1.04 USD per trip, which implies that they must use transport modes outside the SITP, generally informal transport. In addition, 12 % of the participants have a car at home, 10.2 % have a motorcycle, and 27.9 % have a bicycle, while 55.8 % do not own any private vehicle. Just 41.5 % of the participants have a professional degree and work an average of 5.2 days a week for 9 h a day. As shown in Annex A, there are no significant differences between the treatment and control group characteristics and travel patterns.

4.1. Data

Before the intervention started (travel voucher delivery), participants were contacted to obtain their consent to participate, explain the experimental intervention, and validate their profile and eligibility. In summary, for this study, the collection of information was carried out in the following way:

- The application of a household survey before the first voucher delivery to capture baseline information to characterize socio-demographics, household attributes, travel patterns, and a set of attitudinal indicators (during March and April 2021). This was implemented by directly contacting each participant and implementing a personal interview (CAPI). In all cases, the questions posed to both treatment and control participants were the same.
- Weekly report on expenses and travel patterns during the intervention (from May to August 2021). This report was collected using phone calls or text messaging to all participants (CATI).
- The application of a closing survey after the RCT was concluded, collecting follow-up information like the one collected at the baseline. This stage lasted from September to November 2021. It was applied in the same way as the first household survey.

The experiment was divided into three phases: baseline (T0), intervention (T1), and closure (T2). At the baseline, the household survey was applied to all participants (N = 1607). The questionnaire included four main sections, starting with a presentation of the surveyor and the study. The second section inquired about travel patterns, main trip purposes and activities, transport modes used, travel times, average transport expenditure, and indicators of travel satisfaction. The third section collected the perception of the participants towards a set of indicators related to the quality of life, work, education, accessibility to opportunities, basic needs, and free time use. Finally, the closing survey collected the same information as the baseline survey with sociodemographic information.

The intervention phase was initiated in May 2021 after the baseline survey was collected, with the delivery of vouchers to the participants' personalized travel cards. The weekly follow-up survey was conducted among the participants during the sixteen weeks. To avoid fatigue, the monitoring questionnaire was shorter than the baseline survey, inquiring about travel patterns and expenses. The monitoring was made by chat apps and phone calls, as preferred by the participants. During this weekly follow-up survey, participants were asked about all trips made on a typical day of that week, the purposes for each trip, the transport modes used, and the travel times and costs of each trip. The average attrition rate, defined as the proportion of participants that did not respond to the closing survey (1304) to the number of participants in the baseline survey (1607), was 18.8 %, which is considered low compared to the existing

[2] Own a personalized travel card and nine or more monthly trips during a typical work day in the time-slot between 4:00 and 9:00*h*.

literature (Abebe et al., 2021; Brough et al., 2022).

The experimental intervention did not affect the operating conditions of the SITP, so participants faced the same operating conditions and, in addition, the regular system fares. We use the data collected, particularly, the weekly survey as the source to get a comprehensive view of the consumer surplus changes produced by the travel voucher. The weekly follow-up survey provides information on travel alternatives that are not restricted to the public transport system.

4.2. Empirical strategy

As mentioned above, we want to estimate the effects of this new form of subsidy delivery on behavioral change and welfare among the recipients. We integrate experimentally identified changes in travel behavior induced by the subsidy with a structural discrete choice model, allowing us to study welfare changes induced by the travel voucher. Data collected provide us with a panel data set with variation in all transport choices across time for participants during the intervention allowing us to use random utility theory to model discrete choice travel demand.

However, a standard conditional logit model has limitations when estimating travel demand: it does not allow for random taste variation across individuals for correlation in unobserved factors over time. It also imposes the assumption of the independence of irrelevant alternatives, which means that the choice between two alternatives does not change if a third alternative is introduced (IIA) (Train, 2009). Further discussion on this restriction and how the variation of the choice sets helps us to understand first and second-hand decisions can be found below. We can relax these assumptions by using a mixed logit model since in addition to a Gumbel iid component, correlation and/or heteroskedasticity can be modeled (McFadden and Train, 2000). The mixed logit model allows for random taste variation, enabling us to estimate individual-level coefficients, avoid violating IIA assumptions, and recover the full distribution of the benefits (utility function) in the participants (León and Miguel, 2017). The mixed logit model allows us to do this, taking full advantage of the panel structure of the data with multiple observations per participant. By estimating the utility function changes, we calculate welfare gains measured as the Consumer Surplus (*CS* henceforth).

The first part of the proposed empirical strategy consists of analyzing how the random allocation of travel vouchers affects the modal choice. We model the participant's i decision to use a transport alternative j, with J being a set of finite discrete transport alternatives composed of five alternative transport modes ($j \in J$): walking, private transport (car and motorcycle), taxi, BRT, and regular bus, covering the whole transport market in the city. Walking is defined then as the 'outside good' of the transport alternatives. That is, if participants do not have access to any vehicle or service, they walk.

Participant i's benefit from choosing transport mode j at period t (each period t corresponds to a calendar week), is related to a utility function U_{ijt} with the structure of Eq. (1), where V_{ijt} is the observed utility and ε_{ijt} is the random error associated with the unknown component of the utility. This represents the net influence of all unobserved or not explicitly included characteristics of the individual or the alternative that affect the utility (Ortúzar and Willumsen, 2011):

$$U_{ijt} = V_{ijt} + \varepsilon_{ijt} \tag{1}$$

$$V_{ijt} = \beta c_i \bullet C_{jt} + \beta t_i \bullet T_{ijt} + \beta v_j \bullet \textit{treat}_i + \beta_j' \bullet X_{ij} \tag{2}$$

The observed utility is specified as a linear combination of a vector of parameters and observed attributes (Eq. (2). βc_i and βt_i are individual random coefficients for travel cost and travel time per participant, respectively; while βv_j and β_j' are fixed-among-individuals coefficients for each transport mode j. $treat_i$ is a *dummy* variable equal to 1 if participant i was assigned to one of the two treatment groups, 0 otherwise. X_{ij} is a vector of observable attributes: age, gender, household size, private vehicle ownership, and security perception[3] in the neighborhood (with a scale where 5 strongly agree and 1 corresponds to strongly disagree). These variables may affect the use of certain transport modes (Ortúzar and Willumsen, 2011). In summary, Eq. (2) was implemented for each transport alternative. The travel and cost coefficients (βc_i and βt_i) are the same for all transport modes of the same participant, while are different between participants. This proposed model configuration allows the changes in *CS* due to the use of the travel voucher to be estimated at the individual level.

A leading concern in discrete choice models is omitted variable bias. For example, the motorcycle is often quite fast, while it is also quite unsafe, noisy, and polluting. On the other hand, while the car is an expensive option, it might also be perceived by some to be the most "high-status" alternative (Soza-Parra and Cats, 2023). For its part, public transport is crowded and perceived as unsafe, particularly by women, but it is cheaper than cars and can be much faster (especially the BRT). Thus, alternatives with desirable characteristics usually have higher costs because their attributes are expensive or because many commuters want to use them. Not considering the correlation between price and mode-specific attributes can bias the coefficient estimates. Bottom line, there is a need to account for commuters' perceptions of the available transport modes' multiple attributes, beyond travel time and costs.

To address this concern, individual and mode-specific variables are included as control variables. These are represented by the vector of coefficients β_j' from Eq. (2). This specification allows for stable coefficients, which are also reinforced by the random allocation of the travel voucher that generates exogenous variation in the participant's effective costs of accessing the SITP by supplementing their monthly income. Using the postulate that a one-unit reduction in costs equals a one-unit increase in income (Train, 2009), the random provision of the travel voucher generates exogenous variation to uniquely identify the coefficient of the price (βc_i).

[3] This perception of security refers to how safe participants feel when walking alone in their neighborhoods (Likert scale).

Moreover, the panel data structure strengthens our empirical strategy by controlling for all time-invariant unobservable characteristics among participants that could affect their modal choice. Having travel records for participants allows us to use variation in decisions under different choice sets.

Assuming that ε_{ijt} follows and iid type I extreme value distribution the probability that participant i will choose alternative transport mode j in period t is given by:

$$P_{ijt} = \int \prod_{t}^{T} L_{ijt}(B) \bullet f(B|\zeta) dB \tag{3}$$

where $f(B|\zeta)$ is a density function that depends on parameters ζ. Eq. (3) highlights that the probabilities of a mixed logit model are the weighted average of the observed part of the utility evaluated at different values of B. Weights are assigned by the distribution $f(B|\zeta)$ (widely known in the literature as the mixing distribution). $L_{ijt}(B)$ is the logit probability evaluated at parameters B:{ βc_i, βt_i, βv_j, β_j'} as is shown in Eq. (4). The unobserved part of the utility (ε_{ijt}) is independent over time, so it is not included here.

$$L_{ijt}(B) = \frac{exp(V_{ijt})}{\sum_{k \in J} exp(V_{ikt})} \tag{4}$$

We use a triangular distribution in the estimates since this distribution has desirable characteristics, such as continuity and symmetry. Also, a triangular distribution implies the estimation of a single ζ parameter for each random variable, making the estimation computationally feasible. The distribution is also characterized by the lack of broad tails, a main feature of other distributions (normal and lognormal). Given that the model estimates random and fixed effects, the mixing distribution for the random coefficients corresponds to the triangular distribution, but fixed estimates use a degenerate distribution (i.e., they are a constant with probability 1). Moreover, by using a mixed logit model we can allow for random taste variation across individuals for correlation in unobserved factors over time and relax the independence of irrelevant alternatives (IIA) assumption (Train, 2009).

Using the utility functions defined in Eq. (2), the second step of the empirical strategy is to estimate the change in *CS* as our measure of welfare before and during the intervention. To convert the utility into monetary units, we use the estimated coefficient of travel cost βc_i (Eq. (2)) because of its equivalent relationship with income. Conventionally, the parameter associated with income is used as the estimate for the marginal utility of income, allowing it to translate utility levels into monetary terms. Therefore, one monetary unit increase in income is equivalent to a one monetary unit decrease in costs, as consumers internalize both effects as one in the budget constraint (Train, 2009). The *CS* is defined as the welfare gain, in monetary terms, that a participant i perceives given their decision to choose alternative j. The CS_{it} per participant i in period t can be estimated using Eq. (5):

$$CS_{it} = \frac{1}{\beta c_i}(U_{ijt}) \tag{5}$$

where βc_i is the marginal utility of income of participant i, estimated from the model from Eq. (2). However, since U_{ijt} is not completely observed, the observable part of the utility, V_{ijt}, and the assumptions around the error ε_{ijt} term are used. Thus, assuming that utility is linear in income, the *CS* is defined as (Small and Rosen, 1981):

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

C is an unknown constant related to the fact that the absolute utility cannot be measured (Williams, 1977). Eq. (6) describes the average *CS* for the population that has the same utility as participant i. Therefore, *CS* for the whole population is estimated as the weighted sum of Eq. (6), where the weights reflect the number of people who have the same utilities as the participants in the experiment. Empirically, this is approximated as the marginal of a uniform distribution.

To estimate welfare changes generated by the travel vouchers we can compare changes in *CS* before and during the intervention (Eq. (7)):

$$\Delta E(CS_{it}) = \left[\frac{1}{\beta c_i} ln\left(\sum_{j=1}^{J} e^{V_{ijt}}\right)\right]^{During} - \left[\frac{1}{\beta c_i} ln\left(\sum_{j=1}^{J} e^{V_{ijt}}\right)\right]^{Before} \tag{7}$$

We can further analyze these results, by regressing the individualized CS_{it} according to the participant characteristics, as is shown in Eq. (8):

$$log(E(CS_{it})) = \beta_{at}A + \beta_{bt}B + X_i\overline{\beta}_x + \epsilon_{it} \tag{8}$$

This approach allows us to understand the impacts on *CS* by participant socioeconomic characteristics and period. Note this simplifies the comparisons, as a direct comparison of the coefficients from the utility model is not a straightforward task given the non-linearity and the changes in the coefficients over time. Because the dependent variable is the result of an estimation, the standard errors are calculated using bootstrap methods.

Finally, estimations of Eq. (7) for the average treatment effect on the treated (ATT) will yield a biased estimator of the effect of the interventions. Staggered treatment adoption leads to multiple erroneous definitions of the comparison group, rendering it impossible to meet the parallel trend assumption in differences in differences model. To obtain unbiased estimates, we use two stages of differences-in-differences estimator presented in Gardner (2022). This estimator addresses staggered treatment adoption concerns present in the literature (Athey and Imbens, 2022; Goodman-Bacon, 2021; Sun and Abraham, 2021) while implementing a two-stage regression analysis. The estimator states that under the parallel trends' assumption: the group and time-fixed effects are identified from the untreated/not-yet-treated subsample, allowing to estimate an unbiased ATT of the intervention. The estimator follows two steps of regression analysis (see Annex B for a complete description of this estimator).

4.3. Behavioral changes

Treatment effects do not focus solely on behavioral changes related to modal choice due to a cost reduction induced by the travel voucher. We are also interested in whether potential changes in modal choice additional consequences have, such as changes in travel times. However, under a discrete choice framework, we are not able to measure changes in travel times induced by the intervention. To identify the potential effects on travel times, it would be possible to compare the average travel times of treated and control participants, given the exogenous variation in the random treatment assignment.

To achieve this, we propose a different empirical strategy using a reduced-form regression analysis. Given the structure of the intervention, with the delivery of the travel voucher at different times, we implement an event study specification using Eq. (9). In this setting, the event is represented as the first time a participant, assigned to either the A or B treatment group, uses the travel voucher.

$$TT_{it} = \delta_i + \varnothing_t + \sum_{s \neq -1}^{S} \tau_s \bullet treat_{its} + X'_{it}\omega + \vartheta_{it} \tag{9}$$

where TT_{it} is the travel time, given the transport mode chosen by participant i in period t.[4] $treat_{its}$ is a *dummy* variable equal to 1 if in period t, participant i used the voucher in event s, 0 otherwise. δ_i and $\varnothing_t$ are fixed effects per participant and period, respectively. Thus, τ_s allows us to recover the effect of the intervention on travel times in terms relative to the treatment adoption. Negative values of s refer to surveys before the first activation of the voucher. Thus, $s = 0$ indicates the instantaneous effect of the voucher on travel time (basically by a change in modal choice). Positive values of s refer to treatment effects of treatment on travel times. X'_{it} is a vector of controls that includes the cost of travel, day of the week, and transport mode and varies by participant i and period t (vector ω).

5. Results

In terms of the experimental design, control, and treatment participants statistically differ only in treatment eligibility and adoption. There are no differences in the participants' socioeconomic characteristics and weekly trips, before the intervention between the treatment and control groups. There are no statistically significant differences between the control and treatment groups that could affect the outcome variables. The control and treatment groups only differ in terms of the intervention (the vouchers). This means that there is a balance in the sample as is shown in Annex A. Below are the results of our RCT, separating them into the results of the proposed modeling framework and user welfare.

5.1. Modeling results

Table 1 shows the results for the random coefficients from the mixed logit model[5]: travel time (opportunity costs), and travel cost (monetary costs). Note these coefficients are constant across transport modes for each participant and differ among participants. The results for these participant-level coefficients are shown by average trips, trip purpose, and before and during the intervention. The estimated coefficients are significant at a 95 % significance level, except for trips whose purpose is other than work. Columns (4) and (5) report significantly lower estimates of the marginal utility of trip costs for the sample before the intervention (−0.461) and the sample during the intervention (−0.237). This implies a decrease in the cost sensitivity of travel monetary costs before and during the intervention. Note this decrease is associated with the travel voucher delivery to the participants.

The control coefficients by age, gender, household size, vehicle ownership, and perception of safety in the neighborhood (SP), are presented in Fig. 1. Point estimates for each alternative and the 95 % standard error graphed for each alternative are shown here. As the random utility model reports relative-risk ratios, we transform the coefficients to obtain the percent change in the odds ratios according to *100 %*×*[*exp*(β)-1]*.

Results from Fig. 1 show that for treatment group A, the utility for using the BRT increases by 106.5 % (*100 %*×*[*exp*(0.7249)-1]*) relative to the control group, while the regular bus utility increases by 27.8 %. The right panel shows the coefficients (odd ratios) for the control variables. In addition, results also show that once the travel voucher is delivered to treatment group A, a marginally

[4] The period t in this case, may be different for each participant, since they do not answer the weekly surveys at the same time. This temporal variation is accounted in the model.

[5] Average coefficients for the sample.

Table 1
Cost and time coefficient estimations from the mixed logit model.

Coefficients	Dependent variable: Transport alternative chosen				
	Total sample	Trip purpose		Timeline	
		Work trips	Other trips	Before	During
	(1)	(2)	(3)	(4)	(5)
Travel costs (βc_i)	−0.259***	−0.997***	−0.0544	−0.461***	−0.237***
	(0.0326)	(0.0885)	(0.0390)	(0.0786)	(0.0374)
Travel time (βt_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
Control variables	Yes	Yes	Yes	Yes	Yes
Standard Errors	Participant	Participant	Participant	Participant	Participant
Log-likelihood	−13,861	−6737	−5588	−3663	−9958
Number of participants	1564	1396	1282	1455	1345
Number of trips	14,753	9818	4935	3993	10,760

Note: This table presents the estimates of the mixed logit model. The data come from the baseline survey and the follow-up surveys. The estimates correspond to the regressions of the indicator variable for modal choice on total costs, treatment group assignment, and control variables. The table presents only the estimates of the random coefficients of travel cost and travel time. The random coefficients are estimated using a triangular distribution. Clustered standard errors at the person level are shown in parentheses. Significance level: ***p < 0.001 **p < 0.01 *p < 0.05.

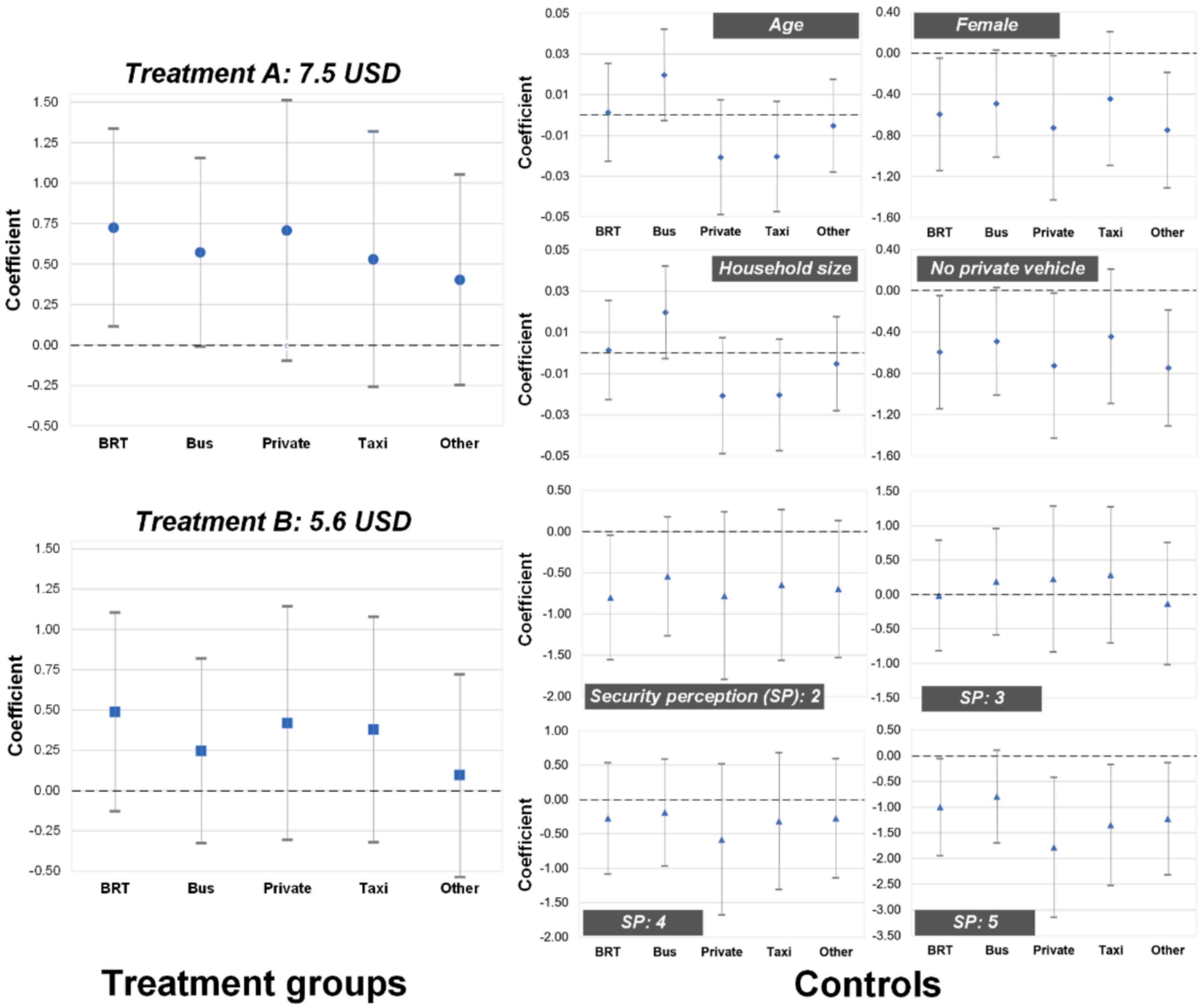

Fig. 1. Control variable estimations from the mixed logit model Note: The figure shows estimates of the coefficients from Eq. (2) and ratios with their respective 95 % confidence interval. For the treatment variables, it shows the change in the odds ratio of the treatment relative to the control group. No private vehicle is an indicator variable equal to 1 if the household does not have any car, motorcycle, or bicycle, and 0 otherwise.

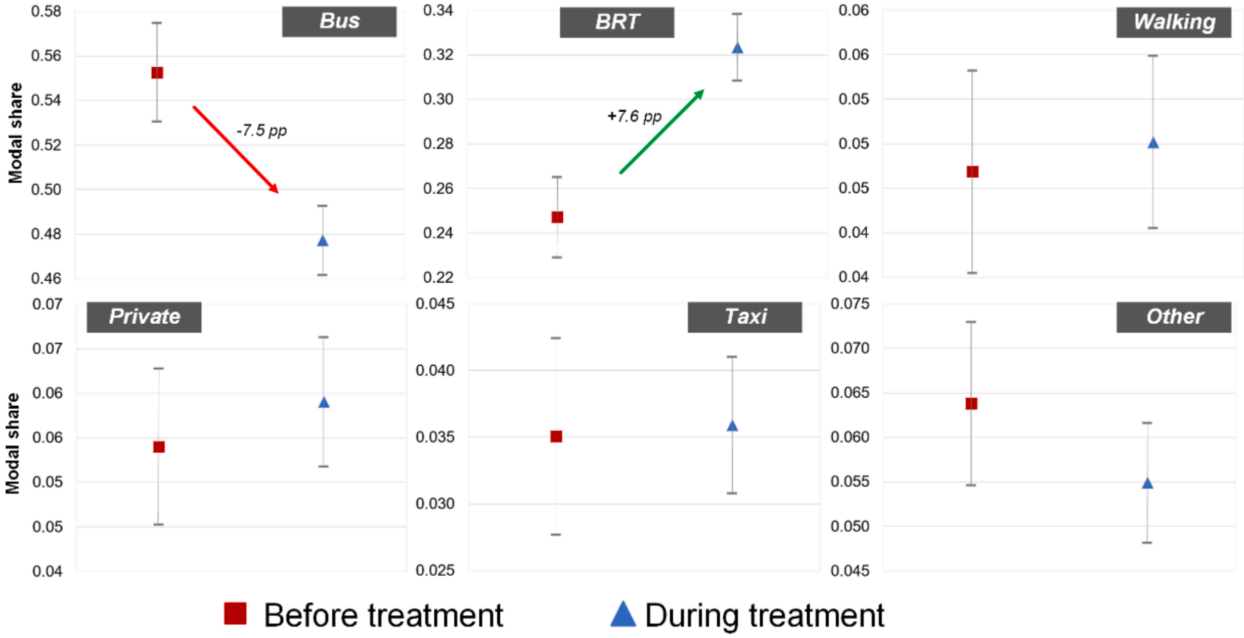

Fig. 2. Modal share before and after the voucher.

significant effect in encouraging regular bus ridership is produced. Treatment group B participants do not exhibit treatment effects on modal shift at the 95 % significance level. However, at 90 % of the significance level, participants in treatment group B significantly increases BRT demand. That is, the voucher also increases the utility of the BRT. The voucher produces an increase in ridership and most of those additional trips go to the BRT.

5.2. *Welfare determinants*

Using the full results of the choice model (Table 1 and Fig. 1), the modal shift before and during (with the voucher in place), for the complete sample are shown in Fig. 2. The figure shows that the voucher had an impact on the modal choice of the participants. During the intervention, the modal share of the regular bus share decreased by 7.5 percentage points (pp) compared to the period before the voucher delivery. At the same time, BRT increased by 7.6 pp (see panels *Bus* and *BRT* from Fig. 2, respectively). For the other modal alternatives, no significant differences in modal shifts were found before and during the intervention. In this case, we are discussing the treatment coefficients for each transport mode compared to walking. These results suggest that the voucher generates a reconfiguration of participants' travel preferences, causing them to use more of the BRT that is more efficient (faster), but also has a higher fare.

From the choice model we also have obtained two groups of coefficients: 1) the first group of coefficients varies between participants and is fixed across transport alternatives, and 2) fixed coefficients across participants, and vary between transport alternatives. With this, it is possible to estimate the derived-from-travels utility that every participant made by week during the intervention. Specifically, we estimate the *CS* produced from the modal chosen by each participant on each trip. Knowing that the travel voucher induces participants to use the SITP more compared to the base transport mode (walking), particularly the BRT component, we estimate the welfare gains, in terms of *CS* on treated participants. We approximate welfare using *CS* specification in Eq. (7).

Table 2 shows the determinants of *CS* at the individual level, as a function of the participants' characteristics (according to Eq. (8)). The dependent variable is Log(*CS*) for each participant and is estimated using the coefficients presented in Table 1. *CS* is defined in monetary units per person. Table 2 also presents the results progressively estimating the effect of different variables. Column (1) examines the effect of the travel voucher random assignment. In column (2) it was added trip purpose, gender, and its interaction. Column (3) included household income. Column (4) includes the distance from the participants' households and the closest BRT station. Column (5) includes a dummy variable for trip start time within time slots. Finally, column (6) includes all previously mentioned variables.

We observe a negative and significant relationship between *CS* and women (columns 2 and 6). However, the overall effect of being women on *CS* should consider the coefficient of the interaction of trip purpose and gender, as women produce more non-work-related trips than men. This interaction implies a net negative effect of −0.176 (0.0072), which implies that women benefit less from the use of public transport than men. Also, in columns (2) and (6) it can be seen that trips whose purpose is other than work, significantly increase *CS* (+0.016). Regarding the trip start time, the range between 4:00 and 8:00 h (morning peak time related to mandatory trips) is used as a base. Thus, compared to this time slot, trips between 9:00 and 16:00 h significantly increase *CS*. This effect can be attributed to the high levels of congestion and long travel times during the morning peak hour (Guzman et al., 2020). Column (6) shows the determinants of *CS* including all variables. In this case, except for the coefficients of trip purpose and gender that change in magnitude,

Table 2
Determinants of CS at the individual level.

	Dependent variable: Log(*CS*)					
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment A	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	0.112***	0.112***	0.111***	0.113**	0.113***	0.097***
	(0.0050)	(0.0046)	(0.0054)	(0.0052)	(0.0050)	(0.0053)
Log(household monthly income)			0.032***			0.016***
			(0.0040)			(0.0042)
SITP quality perception (1–10 scale)						−0.0025**
						(0.0012)
Transport expenses satisfaction						0.003***
						(0.0011)
Distance to closest BRT station (Km)				−0.012***		−0.014***
				(0.0019)		(0.0020)
Household size						0.051***
						(0.0015)
Age						0.004***
						(0.0002)
Other trip purpose (other than work)		0.016**				0.0131
		(0.0070)				(0.0087)
Female		−0.198***				−0.174***
		(0.0045)				(0.0056)
Other trip purpose *x* Female		0.022***				0.0044
		(0.0082)				(0.0091)
Trip start time: 00:00–04:00					−0.009	−0.0095
					(0.0066)	(0.0072)
Trip start time: 09:00–12:00					0.029***	0.0140*
					(0.0060)	(0.0074)
Trip start time: 13:00–16:00					0.044***	0.041***
					(0.0074)	(0.0089)
Trip start time: 17:00–20:00					0.026***	0.0143
					(0.0098)	(0.0108)
Trip start time: 21:00–24:00					0.073***	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
R2	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

The standard errors obtained by a bootstrap process with 1000 random samples are presented in parentheses. Significance level: ***p < 0.001 **p < 0.01 *p < 0.05.

the other coefficients remain stable, with increases in the *CS* of the participants. Moreover, columns (3) and (6), show estimates of the income elasticity of *CS*, presenting a significant positive coefficient of less than 1. Thus, differences in perceptions, age, distance to the nearest BRT station, income, and so on, partly explain (around 40 % of the observed variation) the differences in *CS* from modal choices.[6] The bottom line is that the voucher increases the *CS* of all participants. Nevertheless, older people, those closer to a BRT station, individuals with larger households, and those with higher incomes benefit the most from their modal choices.

The vouchers (in both treatment groups A and B), produce a sizable increase in *CS*. With a higher effect for the treatment A group. Note that the effect is about twice the size of the treatment B group and that both are consistent among the different versions of the regressions (see Table 2 column (1) 0.201 and 0.112, respectively). To obtain a better measurement of the positive change in *CS*, we employ the methods devised in the previous section (see Eq. (8)). Table 3 shows the results of the two-stage Gardner (2022) estimator in a *CS* monthly variation before and during having received the voucher. This methodology implements in two stages a difference-in-differences estimator that allows us to obtain unbiased results of treatment adoption on the *CS* variation.

These results indicate a large impact of the new scheme of delivering subsidies. For the treatment groups, the monthly *CS* of participants increased on average by 12.8 USD (3.1 % of the average household income of our sample) compared to the control group. Disaggregating the results by treatment group, participants assigned to group A present monthly increases in average *CS* of 15.6 USD (3.8 % of average household income), while treatment group B increases their average monthly *CS* by 10.2 USD (2.5 % of average household income) compared to the control group. These differences between treatment groups can be largely attributed to the heterogeneous effects present in the voucher value, the increased use of the BRT, and the travel time changes.

[6] However, it is not possible to fully determine the determinants of *CS* by trip purpose, opening the research agenda for the future.

Table 3
Monthly consumer surplus change (ΔCS) per treatment group and segment.

Treatment groups	Monthly welfare change [USD]				
	Complete sample	Trip purpose		Gender	
		Work trips	Non-work trips	Female	Male
(1)	(2)	(3)	(4)	(5)	(6)
Complete sample	12.8***	5.6***	26.7***	21.2***	16.6***
	[11.4, 14.3]	[3.9, 7.3]	[24.2, 29.3]	[19.8, 22.6]	[14.3, 18.9]
Treatment A: 7.5 USD	15.6***	7.9***	30.8***	24.7***	18.5***
	[13.9, 17.2]	[6.0, 9.8]	[28.0, 33.6]	[23.1, 26.3]	[15.8, 21.3]
Treatment B: 5.6 USD	10.2***	3.4***	22.5***	17.5***	14.9***
	[8.5, 11.9]	[1.4, 5.4]	[19.8, 25.1]	[15.9, 19.1]	[12.2, 17.5]

Significance level: ***$p < 0.001$ **$p < 0.01$ *$p < 0.05$.
[95 % confidence intervals].

Results in Table 3 also show heterogeneous effects by gender and trip purpose. Men benefit more from their modal choices, meaning they have a higher utility. However, in the sample population, when given the voucher, women benefit more than men, as their utility increases more. Columns (5) and (6) indicate that, on average, women have a higher monthly *CS* gain than men, with an average difference of 4.6 USD. Although women benefit less from their modal choices, they gain more from the travel voucher. Moreover, columns (3) and (4) show a monthly and positive change in *CS* for work trips (5.6 USD or 1.4 % of average household income), which is statistically lower than the *CS* for other trips (26.7 USD or 6.5 % of average household income). This difference represents about 5 times the effects produced by work trips. In this case, the baseline (Table 2) indicates that these other trip purposes also have associated higher *CS*. That is, non-work-related trips that were newly generated or that changed their transport mode due to the voucher, have a higher impact on positive changes in *CS*. The value that participants give to their non-work trips is higher than that of their work trips.

Besides results from Table 2, one of the channels that could be inducing *CS*-enhancing from the travel vouchers is the reduction in

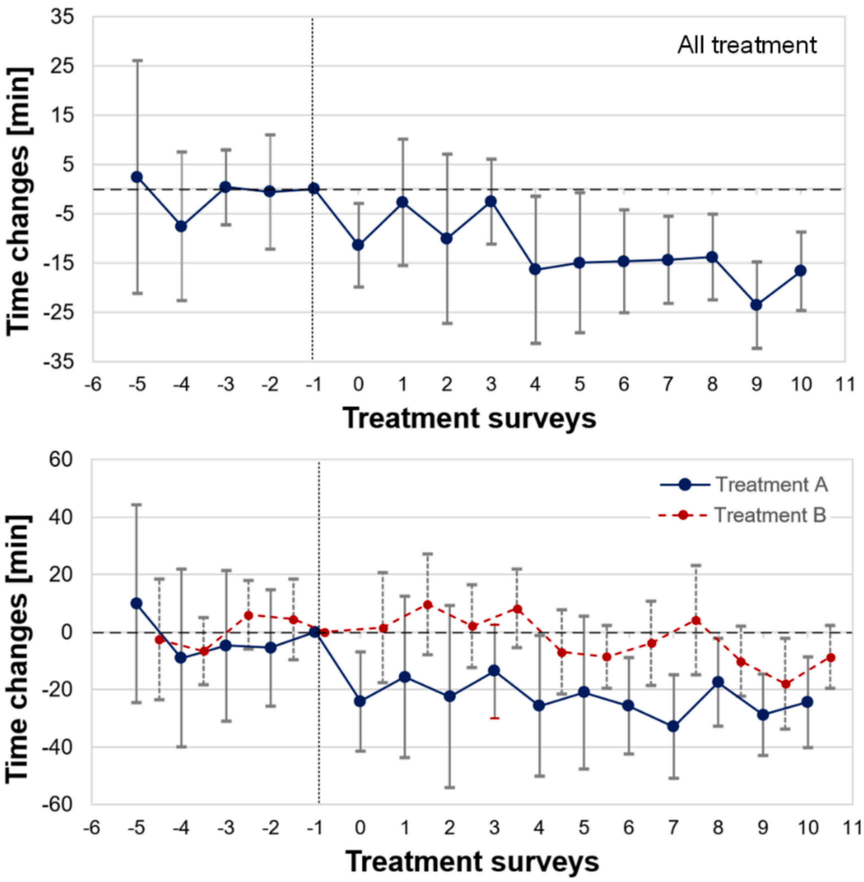

Fig. 3. Travel time changes.

travel time since participants choose faster transport alternatives (remember that the transport supply did not change during the intervention). To provide evidence in this line, Fig. 3 shows the effects of the travel voucher on travel time changes according to the number of weekly surveys each participant has responded to. Negative values on the Y-axis represent travel time savings due to the travel voucher compared to the travel time reported in the baseline survey. The top graph shows the estimates of Eq. (9) for the aggregate treatment, while the bottom graph shows estimates according to each treatment group. The dotted vertical line represents the week before the delivery of the travel vouchers (start of treatment).

These results show a clear trend toward decreased travel times for participants in the treatment group. In the first week of follow-up, after activating the travel voucher, a reduction in travel times is observed by 10 min on average per trip (significant at 95 %), representing a travel time decrease of 10.1 % compared to the average travel time of the control group. Although it is observed that during the first three weeks, following the start of the voucher delivery (mid-May), there is no significant travel time reduction effect, from that point on the effect becomes significant and is maintained during the remaining intervention period, reaching a decrease of 22 min in average per trip in the 9th week (significant at 95 %). This represents travel time savings of up to 24 % compared to the control group. On the other hand, participants assigned to treatment group reduced their travel time according to their exposure to the voucher. The greatest decrease in travel time is found in the 7th week for treatment group A, with a reduction of 32 min on average (−34.2 %) compared to the control group. Conversely, for treatment group B the story is different: There is no evidence of a significative effect on travel time reduction.

Notice that during the experiment, the supply of public transport did not change (routes, frequencies, and average travel speeds remained the same for all participants). Therefore, these changes in travel times are not due to improvements in service provision but to a modal shift: trips that were previously made on regular buses, which share the road with mixed traffic and suffer from high levels of congestion, were now made on BRT, thanks to the travel voucher. BRT buses operate in exclusive lanes, resulting in faster trips, and are preferred for longer trips (Guzman et al., 2021b). When people change their mode of transport, their travel times decrease because they stop using regular buses and switch to the BRT, which is also more expensive. Additionally, and quite importantly, the voucher had a greater impact on women, a group that typically benefits less from the use of public transport compared to men. The voucher produced changes that reduced the gap between men and women in their ability to benefit from transport decisions.

6. Practical implications

In the context of the Global South, communication between academia and decision-makers is not as fluid as desired. However, studies of this type are essential for promoting more sustainable mobility in our cities and encouraging the use of public transport. To move from theory to practice, it is crucial to determine if these types of policies are beneficial for citizens and cities. For example, is it worth implementing these measures from the users' perspective?

The results of our experiment demonstrate that by changing the method of subsidy delivery, the policy can become more progressive and, eventually, socially profitable. Delivering subsidies in the form of a voucher has several advantages: First, because users must have a personalized transport smart card, the value delivered in each voucher can be variable, offering greater benefits to more vulnerable groups, such as women, caregivers, or people seeking employment. Second, the money given in the vouchers returns entirely to the system. They can also be free vouchers, which can have financial effects to investigate, though this is beyond the scope of this study. Third, a significant part of the welfare produced is due to the time savings from the modal shift. This greatly benefits a population (our sample) whose average travel time is 83 min per trip and also spends 1.6 times the average fare cost per trip.

From the city's perspective, would it be worth implementing this policy? We don't know yet, but our hypothesis is yes. Our results would allow an evaluation of the cost-effectiveness of the policy by estimating and comparing the benefits to users with the cost of the vouchers. As a first contribution in that regard, it must be noted that the consumer surplus generated from the subsidy is higher the the nominal costs of the voucher. Additionally, the proposed scheme is more advantageous for the city, as mere fare discounts do not achieve the same increases in demand as the voucher does, particularly in areas where users are inelastic to fare increases (Guzman et al., 2024). This underscores that the distributional profile of public transport subsidies depends on the fare schemes and on where high- and low-income groups live, in the city center or peripheries. Transport policies must be flexible and adaptable over time, to be able to easily adapt to changes in travelers' behavior and their travel patterns. This is a key determinant of the distribution of subsidies.

In other contexts, it has been observed that differentiated fares are resisted due to the argument that they would have regressive distributional effects (Börjesson et al., 2020). The main results of this study show that for Bogotá a carefully designed differentiated fare can benefit specific population segments: the voucher scheme had a higher benefit to women and not-related work trips in our sample. Indeed, our robust findings have been adopted by the city. So much so that in the new 2024–2027 administration, the city council approved the City Development Plan, which serves as the city's navigation chart for the next four years. This plan includes the implementation of public transport subsidies for vulnerable groups in the voucher form. Article 74 of the approved text states: "Transport subsidies for extremely poor people, moderately poor people, people with disabilities, elderly people, and poor or vulnerable students. These people will be entitled to a transport subsidy in the SITP of the city of Bogotá D.C., in proportion to their economic capacity." Paragraph 2 further specifies: "The subsidy will operate through the delivery of vouchers that may be differentiated.". In fact, starting in February 2025, the city implemented the subsidy scheme proposed in this study, replacing fare discounts with focused free vouchers.

In cities of the Global South, and potentially in any urban area, implementing well-designed and targeted public transport subsidies can enhance users' welfare and transport satisfaction, providing a sustainable solution. It is important to note that the value delivered through these vouchers must be carefully studied according to the objective to be achieved. These limits will also depend on the available budget, technology, and political will in each case.

7. Conclusions

Using a controlled experiment in the public transport system in Bogotá, we randomly assigned 1607 frequent users to either a treatment group or a control group. Travelers in the treatment group received four monthly travel vouchers loaded onto their personalized public transport travel cards. We aimed to study behavioral responses and evaluate the differential impacts of the vouchers on changes in modal choice and welfare among the recipients. We found strong responses in the treatment group to the travel vouchers. For the average treated participant in our study, the travel voucher increased the utility of BRT by 107 % compared to walking and the control group, while the utility of the regular bus increased by 28 %. This implied an increased BRT use and a decrease in regular bus use, with no significant changes in other transport modes. This modal change represents travel time savings of up to 22 min compared to the control group. Additionally, the vouchers produced a sizable increase in user welfare in terms of consumer surplus, with a higher effect for the treatment A group.

The benefits of affordable public transport services are particularly significant for groups that typically benefit less from public transport, such as women. We found that the effects on SITP utilization and the associated consumer surplus change are stronger among female participants. Additionally, we observed that non-work-related trips have a greater impact on increasing participants' welfare than work trips. We have found that providing vouchers induces behavioral changes, altering transport choices. These behavioral changes yield greater benefits when the trips are not work-related. This may encourage other trip purposes, such as leisure and recreation, which generate greater benefits for users (Guzman et al., 2023).

These results provide evidence that, in developing country cities like Bogotá, individuals benefit more when the cost of public transport services decreases and they are not close to satiating their travel demand, particularly for non-work-related trips. This has important implications for policymakers, suggesting that improvements in public transport services and more flexible, better-targeted subsidy schemes could substantially increase mobility, enhance user welfare, and potentially mitigate transport externalities in cities like Bogotá. In summary, our study provides strong evidence to justify shifting from the current pro-poor subsidy scheme (fare discount) to a voucher-based scheme.

Finally, the results presented in this research should be considered within the following limitations. First, due to its experimental approach, the results cannot be directly extrapolated to different contexts or non-experimental conditions. Second, the empirical strategy used does not account for general equilibrium effects in large-scale transport subsidy programs. Therefore, the impacts of subsidy programs may involve a variety of variables outside the scope of this study.

CRediT authorship contribution statement

Luis A. Guzman: Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Jorge Luis Ochoa:** Formal analysis, Data curation, Conceptualization. **Santiago Gómez Cardona:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization. **Ignacio Sarmiento-Barbieri:** Writing – review & editing.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Balanced sample

According to the summary statistics of the sample shown in Table A1, there are no previous differences between the treatment and control groups. The control and treatment groups only differ in terms of the intervention (the vouchers).

Table A1
Summary statistics and balance between treatment and control groups.

Variable	Control [Std. Dev.]	Treatment [Std. Dev.]	Mean difference (p-values)
Transport modes used to the main activity	1.79	1.76	−0.03
	[0.790]	[0.760]	(0.480)
Journey time (trip yesterday)	89.4	87.3	−2.11
	[80.51]	[69.95]	(0.610)
Journey time (regular trip)	99.4	90.7	−8.72

(continued on next page)

Table A1 (*continued*)

Variable	Control [Std. Dev.]	Treatment [Std. Dev.]	Mean difference (p-values)
	[104.33]	[59.98]	(0.200)
Distance to transport – minutes	7.97	7.92	−0.05
	[7.390]	[7.640]	(0.910)
Distance to transport – blocks	4.3	4.6	0.30
	[3.830]	[4.560]	(0.210)
Waiting time	12.8	12.4	−0.41
	[9.99]	[8.91]	(0.450)
Fare price paid (trip yesterday) COP	3150	3225	74.94
	[4034.7]	[3747.8]	(0.740)
Weekly trips to the main activity	4.7	4.8	0.09
	[1.92]	[1.75]	(0.380)
Transport cost (all transport modes) to the main activity in COP	3912	4020	107.43
	[2683.72]	[2460.21]	(0.610)
Household size	3.6	3.8	0.16
	[1.45]	[1.51]	(0.030)
Age	43.8	43.3	−0.45
	[11.84]	[11.81]	(0.450)
Married	0.22	0.23	0.01
	[0.42]	[0.42]	(0.590)
Women	0.72	0.72	0.00
	[0.45]	[0.45]	(0.890)
Current worker	0.88	0.90	0.010
	[0.32]	[0.30]	(0.360)

Fig. A1 shows weekly trips between treatment and control groups before, during, and after treatment. There was no statistically significant difference between the control group and the treatment group (p-value = 0.5) before treatment started. These results indicate that the treatment groups and the control group are balanced and that the control group is correctly identified as a comparison group. This allows us to recover the causal effect of the transport voucher.

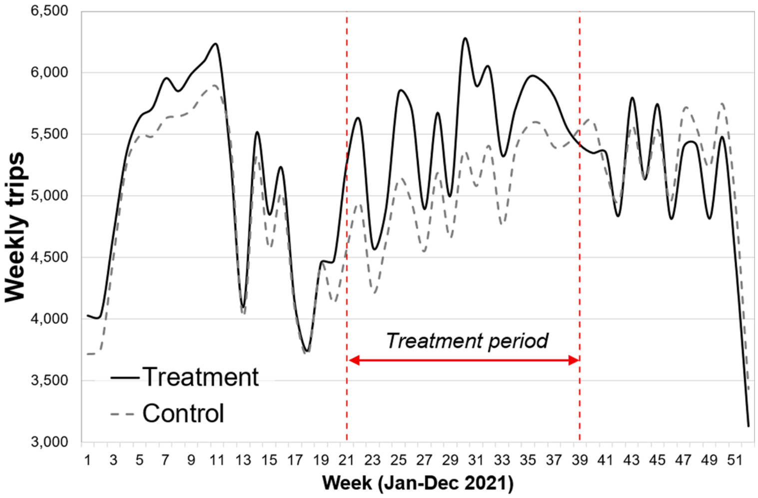

Fig. A1. Weekly trips of the entire sample

Appendix B. The gardner estimator

In the first step, cohort and time effects are identified for the control group participants using the model of Eq. (B1):

$$y_{igt} = \mu_g + \eta_t + \varepsilon_{igt} \tag{B1}$$

where μ_g is defined as the cohort of treatment adoption, and ηt is the week t (baseline or follow-up). D_{gt} is defined as 1 for participants with treatment adoption on cohort g in week t, 0 otherwise. Using the untreated/not-yet-treated subsample (defined by the treatment variable $D_{gt} = 0$), we estimate the group-fixed effects (μg) and the time-fixed effects (ηt).

In the second step, we regress the adjusted outcomes $\widetilde{y_{igt}} \equiv y_{igt} - \widehat{\mu_g} - \widehat{\eta_t}$ on treatment variable D_{gt} in the full sample, to estimate the ATT coefficient τ. The second stage regression is as shown in Eq. (B2):

$$\widetilde{y_{igt}} = \tau D_{gt} + \vartheta_{igt} \tag{B2}$$

These estimators produce unbiased effects of the causal effect of the transport subsidies on welfare if the parallel trends assumption holds. To see why this two-stage estimator works, the parallel trends assumption implies:

$$y_{igt} = \mu_g + \eta_t + \tau_{gt} D_{gt} + \varepsilon_{igt}$$
$$= \mu_g + \eta_t + \overline{\tau} D_{gt} + \left(\tau_{gt} - \overline{\tau}\right) D_{gt} + \varepsilon_{igt} \tag{B3}$$

Where τ_{gt} is the difference in potential outcomes, conditional on the observed staggered treatment adoption times, and $\overline{\tau}$ is the overall average treatment effect. Under parallel trends, we rearrange to get:

$$y_{igt} - \mu_g - \eta_t = \overline{\tau} D_{gt} + \left(\tau_{gt} - \overline{\tau}\right) D_{gt} + \varepsilon_{igt} \tag{B4}$$

Thus, Eq. (B4) describes the need for a two-stage regression analysis, given that μg and ηt are not observed. Finally, under parallel trends, τ is an unbiased estimator of the ATT.

Data availability

Data will be made available on request.

References

Abebe, G., Caria, A.S., Fafchamps, M., Falco, P., Franklin, S., Quinn, S., 2021. Anonymity or distance? Job Search and Labour Market Exclusion in a Growing African City. Rev. Econ. Stud. 88, 1279–1310. https://doi.org/10.1093/restud/rdaa057.

Athey, S., Imbens, G.W., 2022. Design-based analysis in Difference-In-Differences settings with staggered adoption. J. Econom. 226, 62–79. https://doi.org/10.1016/j.jeconom.2020.10.012.

Basso, L.J., Silva, H.E., 2014. Efficiency and substitutability of transit subsidies and other urban transport policies. Am. Econ. J. Econ. Policy 6, 1–33. https://doi.org/10.1257/pol.6.4.1.

Börjesson, M., Eliasson, J., Rubensson, I., 2020. Distributional effects of public transport subsidies. J. Transp. Geogr. 84, 102674. https://doi.org/10.1016/j.jtrangeo.2020.102674.

Börjesson, M., Fung, C.M., Proost, S., 2017. Optimal prices and frequencies for buses in Stockholm. Econ. Transp. 9, 20–36. https://doi.org/10.1016/j.ecotra.2016.12.001.

Brough, R., Freedman, M., Phillips, D.C., 2022. Experimental evidence on the effects of means-tested public transportation subsidies on travel behavior. Reg. Sci. Urban Econ. 96, 103803. https://doi.org/10.1016/j.regsciurbeco.2022.103803.

Buchanan, M., 2019. The benefits of public transport. Nat. Phys. 15, 876. https://doi.org/10.1038/s41567-019-0656-8.

Cantillo-García, V., Guzman, L.A., Arellana, J., 2019. Socioeconomic strata as proxy variable for household income in transportation research. Evaluation for Bogotá, Medellín, Cali and Barranquilla. DYNA 86, 258–267. https://doi.org/10.15446/dyna.v86n211.81821.

Chen, R., Zhou, J., 2022. Fare adjustment's impacts on travel patterns and farebox revenue: an empirical study based on longitudinal smartcard data. Transp. Res. Part A Policy Pract. 164, 111–133. https://doi.org/10.1016/j.tra.2022.08.003.

Coulombel, N., Monchambert, G., 2023. Diseconomies of scale and subsidies in urban public transportation. J. Public Econ. 223, 104903. https://doi.org/10.1016/j.jpubeco.2023.104903.

Franklin, S., 2018. Location, Search Costs and Youth Unemployment: Experimental Evidence from Transport Subsidies. Econ. J. 128, 2353–2379. https://doi.org/10.1111/ecoj.12509.

Gardner, J., 2022. Two-stage differences in differences.

Goodman-Bacon, A., 2021. Difference-in-differences with variation in treatment timing. J. Econom. 225, 254–277. https://doi.org/10.1016/j.jeconom.2021.03.014.

Guzman, L.A., Arellana, J., Alvarez, V., 2020. Confronting congestion in urban areas: developing Sustainable Mobility Plans for public and private organizations in Bogotá. Transp. Res. Part A Policy Pract. 134, 321–335. https://doi.org/10.1016/j.tra.2020.02.019.

Guzman, L.A., Arellana, J., Oviedo, D., Castaño Herrera, D., Sarmiento, O.L., 2023. Lifting urban mobility for the poor: cable-cars, travel satisfaction and subjective well-being. Transp. Res. Part D Transp. Environ. 119, 103765. https://doi.org/10.1016/j.trd.2023.103765.

Guzman, L.A., Beltran, C., Bonilla, J., Gomez Cardona, S., 2021a. BRT fare elasticities from smartcard data: spatial and time-of-the-day differences. Transp. Res. Part A Policy Pract. 150, 335–348. https://doi.org/10.1016/j.tra.2021.06.018.

Guzman, L.A., Cantillo-Garcia, V.A., 2024. Exploring the effects of public transport subsidies on satisfaction and ridership. Res. Transp. Bus. Manag. 56, 101168. https://doi.org/10.1016/j.rtbm.2024.101168.

Guzman, L.A., Cardona, S.G., Ochoa, J.L., 2024. Increased ridership and improved affordability: Transforming public transport subsidies in developing contexts. Res. Transp. Econ. 108, 101492. https://doi.org/10.1016/j.retrec.2024.101492.

Guzman, L.A., Hessel, P., 2022. The effects of public transport subsidies for lower-income users on public transport use: a quasi-experimental study. Transp. Policy 126, 215–224. https://doi.org/10.1016/j.tranpol.2022.07.016.

Guzman, L.A., Oviedo, D., 2018. Accessibility, affordability and equity: assessing 'pro-poor' public transport subsidies in Bogotá. Transp. Policy 68, 37–51. https://doi.org/10.1016/j.tranpol.2018.04.012.

Guzman, L.A., Oviedo, D., Arellana, J., Cantillo-García, V., 2021b. Buying a car and the street: transport justice and urban space distribution. Transp. Res. Part D Transp. Environ. 95, 102860. https://doi.org/10.1016/j.trd.2021.102860.

Hörcher, D., De Borger, B., Seifu, W., Graham, D.J., 2020. Public transport provision under agglomeration economies. Reg. Sci. Urban Econ. 81, 103503. https://doi.org/10.1016/j.regsciurbeco.2019.103503.

Hörcher, D., Tirachini, A., 2021. A review of public transport economics. Econ. Transp. 25, 100196. https://doi.org/10.1016/j.ecotra.2021.100196.

León, G., Miguel, E., 2017. Risky transportation choices and the value of a statistical life. Am. Econ. J. Appl. Econ. 9, 202–228. https://doi.org/10.1257/app.20160140.

McFadden, D., Train, K., 2000. Mixed MNL models for discrete response. J. Appl. Econom. 15, 447–470. https://doi.org/10.1002/1099-1255(200009/10)15:5<447::AID-JAE570>3.0.CO;2-1.

Mobarak, A.M., Reimão, M.E., 2020. Seasonal poverty and seasonal migration in Asia. Asian Dev. Rev. 37, 1–42. https://doi.org/10.1162/adev_a_00139.

Nelson, P., Baglino, A., Harrington, W., Safirova, E., Lipman, A., 2007. Transit in Washington, DC: current benefits and optimal level of provision. J. Urban Econ. 62, 231–251. https://doi.org/10.1016/j.jue.2007.02.001.

Noorbhai, H., 2022. Public transport users have better physical and health profiles than drivers of motor vehicles. J. Transp. Heal. 25, 101358. https://doi.org/10.1016/j.jth.2022.101358.

Ortúzar, J. de D., Willumsen, L.G., 2011. Modelling Transport, 4th Editio. ed. Wiley, Chichester.
Parry, I.W.H., Small, K.A., 2009. Should urban transit subsidies be reduced? Am. Econ. Rev. 99, 700–724. https://doi.org/10.1257/aer.99.3.700.
Phillips, D.C., 2014. Getting to work: experimental evidence on job search and transportation costs. Labour Econ. 29, 72–82. https://doi.org/10.1016/j.labeco.2014.07.005.
Proost, S., Dender, K.V., 2008. Optimal urban transport pricing in the presence of congestion, economies of density and costly public funds. Transp. Res. Part A Policy Pract. 42, 1220–1230. https://doi.org/10.1016/j.tra.2008.03.009.
Rivas, M.E., Brichetti, J.P., Serebrisky, T., 2020. Operating Subsidies in Urban Public Transit in Latin America: A Quick View. Inter-American Development Bank, Washington D.C. doi: 10.18235/0002911.
Rivas, M.E., Serebrisky, T., Suárez-Alemán, A., 2018. How Affordable is Transportation in Latin America and the Caribbean? Washington, D.C. doi: 10.18235/0001530.
Robin, L., Ioannis, T., Hassett, K., 2023. Distributional effects of urban transport policies to discourage car use (No. Environment Working Paper No. 211). doi: 10.1787/8bf57103-en.
Rodríguez, C., Gallego, J.M., Martinez, D., Montoya, S., Peralta-Quiros, T., 2016. Examining Implementation and Labor Market Outcomes of Targeted Transit Subsidies: Subsidy by Sistema Nacional de Selección de Beneficiarios for Urban Poor in Bogotá, Colombia. Transp. Res. Rec. J. Transp. Res. Board 2581, 9–17. https://doi.org/10.3141/2581-02.
Serebrisky, T., Gómez-Lobo, A., Estupiñán, N., Muñoz-Raskin, R., 2009. Affordability and subsidies in public urban transport: what do we mean, what can be done? Transp. Rev. 29, 715–739. https://doi.org/10.1080/01441640902786415.
Small, K.A., Rosen, H.S., 1981. Applied welfare economics with discrete choice models. Econometrica 49, 105. https://doi.org/10.2307/1911129.
Soza-Parra, J., Cats, O., 2023. The role of personal motives in determining car ownership and use: a literature review. Transp. Rev. 1–21. https://doi.org/10.1080/01441647.2023.2278445.
Sun, L., Abraham, S., 2021. Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. J. Econom. 225, 175–199. https://doi.org/10.1016/j.jeconom.2020.09.006.
Tirachini, A., Proost, S., 2021. Transport taxes and subsidies in developing countries: the effect of income inequality aversion. Econ. Transp. 25, 100206. https://doi.org/10.1016/j.ecotra.2021.100206.
Train, K.E., 2009. Discrete Choice Methods with Simulation, Discrete Choice Methods with Simulation, second ed. Cambridge University Press, Cambridge. doi: 10.1017/CBO9780511805271.
Ubbels, B., Nijkamp, P., Verhoef, E., Potter, S., Enoch, M., 2001. Alternative ways of funding public transport. Eur. J. Transp. Infrastruct. Res. 1, 73–89. https://doi.org/10.18757/EJTIR.2001.1.1.2629.
van Goeverden, C., Rietveld, P., Koelemeijer, J., Peeters, P., 2006. Subsidies in public transport. Eur. Transp. Trasp. Eur. 5–25.
Wang, Q., Ma, S., Xu, G., Yan, R., Wu, X., Schonfeld, P.M., 2024. Enhancing financial viability and social welfare in public transportation: a study of subsidy schemes for urban rail transit systems. Comput. Ind. Eng. 193, 110313. https://doi.org/10.1016/j.cie.2024.110313.
Wang, X., Rodríguez, D.A., Sarmiento, O.L., Guaje, O., 2019. Commute patterns and depression: evidence from eleven Latin American cities. J. Transp. Heal. 14, 100607. https://doi.org/10.1016/j.jth.2019.100607.
Webber, G., Chirangi, B., Magatti, N., 2020. Experiences of a multiple intervention trial to increase maternity care access in rural Tanzania: focus group findings with women, nurses and community health workers. Women's Heal. 16. https://doi.org/10.1177/1745506520969617.
Williams, H.C.W.L., 1977. On the formation of travel demand models and economic evaluation measures of user benefit. Environ. Plan. A 9, 285–344.