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The effects of fare-free transit on the travel behavior of older adults

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A B S T R A C T

Transit fare subsidies can be justified as a second-best policy to address automobile-related externalities. Yet, evidence of fare subsidy effectiveness in shifting users from cars to transit, particularly in low- and middle-income contexts, remains limited. This study leverages a large-scale quasi-natural experiment in Brazil, a developing country with high public transit usage, to evaluate the causal effects of a full fare subsidization on travel behaviors among older adults. Utilizing a regression discontinuity design based on age-based eligibility thresholds that vary by sex and city, we analyze data from 11 household travel surveys covering seven metropolitan areas and approximately 25 % of the Brazilian population. By comparing individuals just above and below eligibility thresholds, we assess changes in trip frequency, duration by transport mode, and vehicle ownership. Results indicate fare-free transit eligibility increases older adults' public transit ridership by approximately 7.1 %, with transit trips becoming 7.3 % shorter. However, the rise in transit use predominantly reflects substitution away from walking, which decreased by 8.2 %. Importantly, we find no significant impacts on car usage or vehicle ownership, suggesting that fare-free transit policies may have limited effectiveness in reducing automobile use and related externalities in such contexts.

1. Introduction

Transit fare subsidies are often justified by a second-best economic argument (Serebrisky et al., 2009): by lowering transit fares, negative externalities—such as congestion and pollution—can be mitigated through an induced shift from private vehicles to public transit. This rationale underpins various structural models suggesting that transit fares should be subsidized to some extent. In fact, several studies propose that, under specific conditions, the optimal policy may involve fully subsidizing transit (i.e., free-fare) (Basso and Silva, 2014; De Borger and Proost, 2015; Parry and Small, 2009; Proost and Van Dender, 2008; Tscharaktschiew and Hirte, 2012). However, the effectiveness of fare reductions in promoting a transport mode shift depends on the actual substitutability between private cars and public transit (Fearnley, 2013).

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Recent evidence indicates that substitution from cars to public transit due to fare subsidies is minimal or even nonexistent (Borck, 2019; Andersson et al., 2023; Brough et al., 2022; Bull et al., 2021; Hall et al., 2021; Dai et al., 2021; Matas et al., 2020; Ortega and Link, 2025; Webster, 2024; Yang and Tang, 2018; Albalate et al., 2024). Moreover, fare reductions may inadvertently lead to environmentally undesirable outcomes by inducing users of active transportation modes, such as walking and cycling, to switch to transit (Keblowski, 2020; Cats et al., 2017; Pesola et al., 2022; Storchmann, 2003). Nonetheless, the effectiveness of transit subsidies in inducing environmentally desirable mode shifts depends significantly on context. Evidence suggests that fare reductions might be particularly beneficial in cities characterized by high population density, substantial transit dependency (Basnak and Giesen, 2023; Shin, 2021; Offiaeli and Yaman, 2023; Liang and Wang, 2025), and pronounced affordability issues among lower-income populations (Vasudevan et al., 2021; Guzman and Hessel, 2022). Given that these characteristics typically define urban areas in Low- and Middle-Income Countries (LMICs)—which account for an increasing share of the global population (World Bank, 2020)—understanding the actual impact of fare-free policies in such contexts is critical for both welfare improvements and environmental policy goals.

Nevertheless, rigorous empirical research on how fare-free policies influence travel behavior in this type of context, particularly regarding mode substitution, remains scarce. Existing studies are limited because they either: (a) rely on data that cannot adequately capture mode substitution effects; (b) focus on short-term interventions or experimental settings unlikely to reflect sustained behavioral changes; or (c) investigate contexts that significantly differ from urban areas in LMICs, which typically feature high transit reliance and a large proportion of lower-income residents.[1]

In this study, we provide novel evidence on individuals' behavioral responses to fully subsidized transit fares in low-income urban settings where public transit constitutes a significant share of overall mode choice. We analyze a national policy in Brazil that grants fare-free transit to older adults based on an age threshold that varies by sex and by city. Using household travel survey data covering 0.6 million adults across seven metropolitan regions (representing 25 % of the Brazilian population), we employ a Regression Discontinuity Design (RDD) to estimate the causal effects of free-fare transit eligibility on travel behavior. By comparing individuals just above and below the policy's age threshold, we assess the impact of the fare-free policy on changes in transit use, mode substitution, and vehicle ownership. Additionally, we leverage S ão Paulo's distinct eligibility threshold as an additional validity check of our results.

Our findings indicate that the fare exemption eligibility increases transit ridership among older adults by approximately 7.1 %. However, this increase primarily reflects a substitution from short walking trips rather than a shift from private vehicle use or an increase in overall mobility. We find no evidence that the policy affects vehicle ownership rates.

This study contributes to the literature on transit fare subsidies by providing robust causal evidence on a permanent free-fare policy's impact on travel behavior. Using multi-city data from a middle-income country where public transit affordability is a key concern, we show that even in contexts favoring strong policy effects, the impact on mode substitution remains minimal.

Finally, our paper contributes to the broader public debate on fare-free transit policies, which is gaining traction in various countries (Carr and Hesse, 2020; Keblowski, 2020; Saphores et al., 2020; Basnak and Giesen, 2023; Straub et al., 2023; Ortega and Link, 2025). In Brazil, the discussion on fare-free transit has gained further momentum following a 2022 ruling by the Supreme Court, which mandated that all municipalities provide free fare transit on election days (Pereira et al., 2023). Moreover, there is a growing concern that government expenditure to cover free transit for older adults will rise substantially due to expected demographic changes (Pereira et al., 2015), unless eligibility rules are modified. Compelled by this scenario, policymakers have begun debating the need to change the eligibility criteria for transit fare exemptions.[2] The results from this paper are timely and important to inform such policy debates.

2. The fare-free transit policy for older adults in Brazil

The Brazilian National Constitution mandates all urban transit services to be free of charge for individuals above the age of 65 years old.[3] Eligible individuals can board any transit vehicle for free by simply presenting an identification document that displays their date of birth. This document can be shown to the bus driver, ticket collector, or subway personnel at the station entrance. In many cities, seniors can also obtain a special transit card, which can be used on automated ticketing systems, eliminating the need to carry identification.

The fare exemption for individuals above 65 years old is valid throughout the country, but local governments can extend the benefit to individuals younger than the national age threshold. For example, in 1993, the city of São Paulo extended fare exemption eligibility on municipal buses to women aged 60 – 64 (Municipal Law n° 11.381 of June 17, 1993). In 2013, São Paulo further extended the fare exemption at age 60 for males and to other transit modes.[4] In the rest of the São Paulo Metropolitan Region and in most cities in Brazil, including the other cities in our sample — Belo Horizonte, Bras'ilia, Rio de Janeiro, Salvador, and Fortaleza—both men and women are eligible for fare-free transit only upon turning 65.[5]

[1] See Table A.1 in Appendix for a summary of the empirical literature on the effects of fare pricing on travel behavior.

[2] https://www.camara.leg.br/noticias/1015874-comissao-aprova-assistencia-financeira-federal-para-garantir-transporte-publico-gratuito-a-idosos/.

[3] According to Article 230 of the Federal Constitution of Brazil, available at: https://www.senado.gov.br/atividade/const/con1988/CON1988_05.10.1988/art_230_.asp.

[4] Municipal Law n° 15.912 of December 16, 2013 and State Law n° 15.187, of October 29, 2013.

[5] Bras'ilia - DF also reduced the minimum age for fare exemption in the public urban transport system to 60 years in 2023 (District Law n^{r}c. 7298 of July 24, 2023). However, our main analysis in this paper considered only the information available for Bras'ilia - DF in 2000. Consequently, it is not affected by this later policy change.

Table 1
Brazilian household travel surveys included in the study.

City/year	Individuals		Trips		Fare-free	
	All adults	Older adults	All adults	Older adults	threshold age	
	(18+ yo)	(60–69 yo)	(18+ yo)	(60–69 yo)	Male	Female
Belo Horizonte-MG						
2002	86,782	7613	55,939	2889	65	65
2012	77,707	8860	50,724	4461	65	65
Campinas-SP						
2003	22,896	2172	16,808	920	65	65
Bras'ilia-DF						
2000	38,276	2343	25,929	852	65	65
Rio de Janeiro-RJ						
2003	73,866	7848	40,108	2844	65	65
Salvador-BA						
2012	48,346	5077	35,848	2872	65	65
S ao Paulo-SP						
1997	67,218	5580	52,519	2802	65	60/65
2007	72,191	7903	59,691	5126	65	60/65
2012	18,912	2108	16,078	1362	65	60/65
2017	69,597	9531	56,754	6484	60	60
Fortaleza-CE						
2019	54,014	7019	40,424	4268	65	65
TOTAL	629,805	66,054	450,822	34,880	–	–

Note: The table presents the unweighted number of individuals and trips recorded in each household travel survey included in our analysis, both for the whole adult population (18+ years old) and for the specific subset of older adults between 60–69 years old, which is the most relevant subgroup for our analyses. Trips are defined as journeys that start at someone's residence.

Table 1 shows the fare exemption criteria by age and gender for the cities included in our analysis. Moreover, we note that the fare cost also varies little across cities. Table B.1 in the appendix lists the inflation adjusted baseline transit fare in each city from our study. Throughout the period of analysis, these transit fare costs remained relatively stable, between 0.3 % and 0.5 % of the minimum salary. Finally, the proportion of family income allocated to urban public transit was fairly similar across metropolitan areas. In the years 2002 and 2017, across all cities in our analysis, families in the 5th income decile spent on average approximately 10 % of their household income on public transit, while this percentage stayed between 11 % and 18 % among the poorest (Pereira et al., 2021).

3. Data—household travel surveys

To analyze individual travel behavior, we rely on a set of household travel surveys from 7 of the largest Brazilian metropolitan areas (see Table 1). These surveys were designed to be representative of all trips made by the population of each metro area on a regular working day. Respondents were asked to report all trips taken on the weekday immediately before the interview, providing information about trip purpose, transportation modes, time of departure and arrival, and geocoded origins and destinations. Additionally, the surveys also include a rich compilation of respondents' socioeconomic characteristics such as age, sex, educational attainment, income, employment, and vehicle ownership.

Combined, the 11 surveys used in our study include 629,805 adults who reported information on 450,822 home-based trips. However, our analysis focuses on the travel behavior of individuals who are close to the age threshold for fare exemption, which is 65 years old in most cities. Because of that, we also present in Table 1 the sub-sample of 66,054 individuals in each survey who were between 60 and 69 years old, and who reported a total of 34,880 home-based trips. This sub-sample of older individuals near the age threshold for fare exemption represents the most relevant population segment for our estimations.

It is important to note that, from 1993 to 2013, the fare-free threshold age for women in São Paulo was 60 years. This exemption applied only to municipal buses, while the threshold for other modes, such as subway and rail, remained at 65 years. Since municipal buses account for about two-thirds of all public transit trips and their network coverage overlaps with virtually all other public modes, individuals in São Paulo could substitute nearly any subway or rail trip with a bus trip. For this reason, we treat women's eligibility for fare exemption at age 60 during this period as effectively equivalent to a general free-fare eligibility across all modes of public transportation. Beginning in 2013, the fare-free eligibility age was standardized at 60 years across all modes for both men and women.

Finally, we also note that we chose to restrict our main analyses to home-based trips under the assumption that these trips are less constrained in terms of mode choice and, therefore, more likely to respond to the free-fare policy. Nonetheless, we conducted a robustness exercise in Section 4 re-estimating our models without imposing any trip-origin restriction, observing no significant changes in our main results.

Next, Table 2 presents the basic descriptive statistics of individuals included in the data, highlighting again the older adult population around the policy threshold age. Overall, seniors close to the policy age limit present similar characteristics to the general population in terms of gender distribution, household vehicle ownership and travel times. However, older adults have slightly lower educational attainment, are less likely to be employed and make fewer trips.

Table 2
Descriptive characteristics of individuals observed in our sample.

Variable	Mean	
	All adults (18+ yo)	Older adults (60–69 yo)
Sex (%)		
Male	46.6	44.3
Female	53.4	55.7
Educational attainment (%)		
Below secondary	50.3	62.5
Secondary or higher	49.7	37.5
Vehicle ownership (%)		
Owns car	49.8	51.5
Owns moto	10.8	7.6
Employment status (%)		
Employed	54.3	25.0
Retired	14.1	45.8
Other	31.6	29.2
Number of trips per day		
Private vehicle	0.21	0.18
Public transit	0.23	0.15
Walking	0.17	0.12
All modes	0.71	0.52
Travel time (*minutes*)		
Private Vehicle	26.61	28.63
Public Transit	57.30	53.21
Walking	23.18	22.94
All modes	38.71	35.31

Note: This table presents the means of observable characteristics for the 629,805 adults and 66,054 older adults from the sample of individuals in the 11 household travel surveys included in our study. Sex, educational attainment, employment status and number of trips are directly measured at the individual level. Mean travel time is calculated based on individuals who make at least one trip by the corresponding mode. Vehicle ownership is calculated at the individual level based on household ownership of private motorized vehicles.

4. Methods

4.1. Research design

We employ a regression discontinuity design (RDD) to identify how fare-free transit eligibility affects the travel behavior of individuals. The main advantage of this methodological approach is that the underlying assumptions needed for the internal validity of results are relatively weak. It only requires the unobserved characteristics that affect travel behavior to be similar for individuals just above and just below the policy threshold and for the relationship between the running variable (age), and dependent variable (number of trips) to be described by a continuous function. That is, people who are just slightly younger and slightly older than the policy age threshold should have a very similar travel behavior. If these assumptions hold, then any discontinuities in the dependent variable at the threshold age could only be attributed to the policy effect.

Panel A on Fig. 1 presents graphical evidence about the continuous relationship between age and number of trips in our sample. From the figure, there does not seem to exist any major discontinuities between the two variables for the adult population. The average number of trips made by individuals in our sample peaks at age 18 and remains relatively constant until the age of 38, after which it declines almost linearly.

As discussed in Section 2, the fare-free eligibility is not homogeneous within our sample. While most individuals are eligible for the fare exemption at 65 years old, women in São Paulo and men after the year 2013 were eligible at 60 years old. To deal with this variation, we estimate our model using the Regression Discontinuity estimator with multiple cutoffs from Cattaneo et al. (2020), where treatment effects are calculated for each cutoff using traditional regression discontinuity methods (Calonico et al., 2014) and the global average policy effect is calculated by weighting the cutoff-specific effects by the number of individuals within the bandwidth used in each cutoff specific estimation.

Our treatment effects are calculated as described above with cutoff-specific estimations. Nonetheless, in order to visualize the effect of free transit eligibility on key patterns of travel behavior across several cities and years, we also construct a pooled sample by re-centering the running variable according to the threshold age for each individual. That is, we calculate:

$$d_i = age_i - age_i^o \tag{1}$$

Where age_i is the age of individual i, age_i^o is the age threshold for fare exemption eligibility for that particular individual, and d_i is the difference between these values. From the normalized running variable, the treatment status T_i in the pooled sample is then defined as:

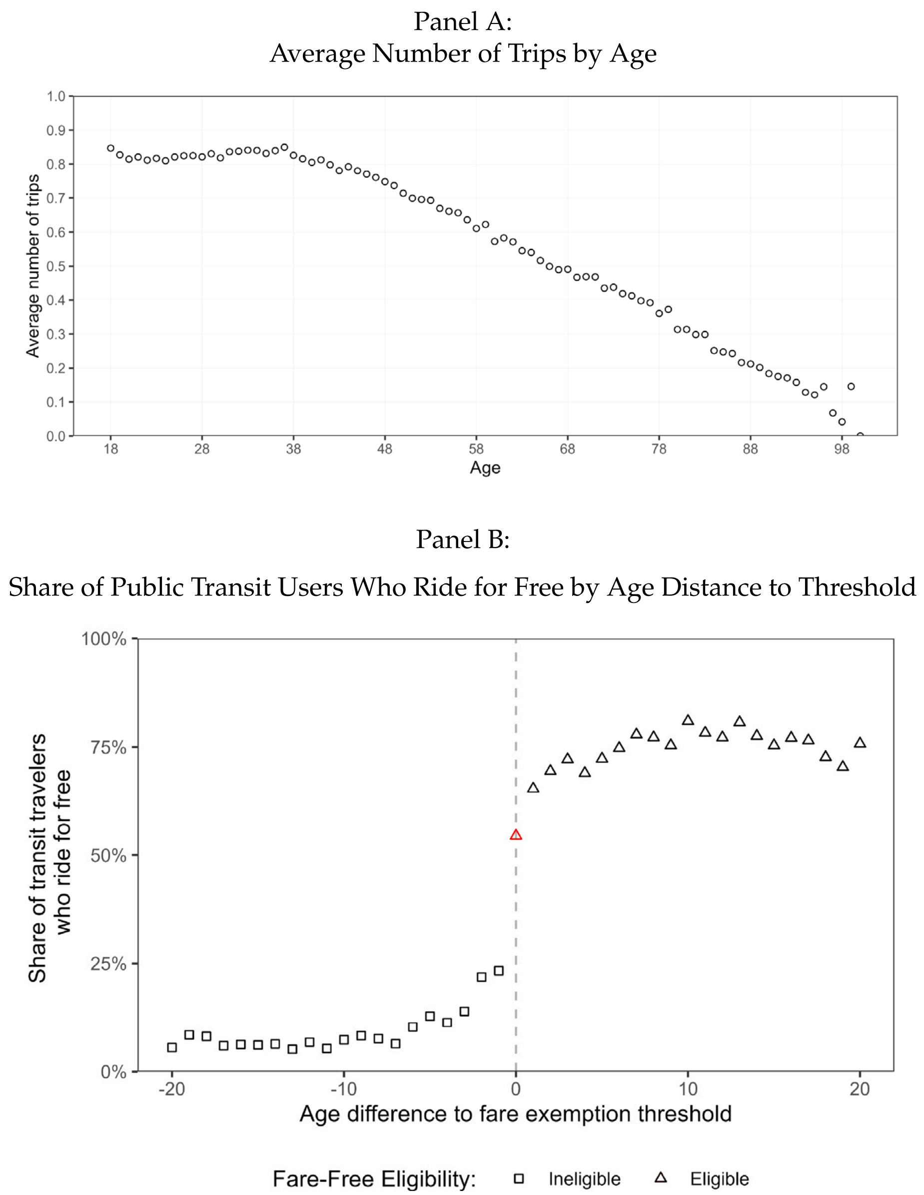


Fig. 1. Travel behavior by age. *Note.* For **Panel A**, sample size includes all 629,805 individuals from the 11 household travel surveys used in our study. Each dot represents the average number of trips made by individuals of each year of age. Trips are defined as journeys that start at someone‘s residence. For **Panel B**, the sample used to construct the figure includes all individuals from the São Paulo travel surveys who reported public transit trips. Each dot represents the average number of trips made by individuals of each age-distance in years to the age-exemption threshold.

$$T_i = 0 \quad if \quad d_i < 0 \qquad\qquad T_i = 1 \quad if \quad d_i \geq 0 \tag{2}$$

Using this normalized running variable, we first show in Panel B on Fig. 1 the share of transit travelers in São Paulo who reported riding for free by age distance relative to the age eligibility threshold.[6] The figure clearly shows that individuals who become eligible for free transit due to the age criteria are much more likely to make free transit trips than those who are below the age threshold. For individuals below the age threshold, only about 10 % of trips are fare-free. However, that share goes up to more than 70 % for those above the threshold age. From this figure, it is important to note that there are individuals younger than the threshold age who ride for free, and there are people above the threshold age but who pay for their trips. The first case can be explained by other fare exemption rules such as for school students, individuals with physical disabilities and for some groups of workers such as policemen, firefighters and mailmen. As for the seniors who are eligible for a fare exemption but who pay for the transit fare, possible explanations include

[6] The information about who paid for each trip is only available in the São Paulo travel surveys.

a lack of awareness about the benefit (Neri et al., 2007), difficulties in providing a valid ID or some unwillingness to be seen as a welfare beneficiary. Still, the discontinuity in the probability of riding for free around the policy threshold age supports the validity of using such threshold as a valid strategy to identify the causal the effects of transit fare-exemption on travel behavior.

One final important element observed in Panel B in Fig. 1 is the abnormal behavior of individuals who are exactly at the exemption-age threshold. Although this group is eligible for the fare exemption, they report a much lower percentage of transit trips made for free. These individuals may either be misclassified or may not be using their benefit due to a lack of information. Either way, in all the following analyses, we exclude this group. In particular in regression discontinuity designs, this type of exclusion is recommended in cases with uncertain treatment status for observations that are extremely close to the threshold (Barreca et al., 2011). We follow this recommendation in our main analyses because the lower compliance rate of individuals exactly at the threshold is associated with systematic heaping in self-reported age. In particular, there is an over representation of respondents reporting ages that are multiples of 5 or 10,[7] a phenomenon commonly observed in survey data (Barreca et al., 2011). This creates a potential bias if part of the heaping comes from individuals younger than the rounded age, who would then be incorrectly classified as treated in our setting, biasing the RD estimates toward zero. Still, in Section 5.3, we also present robustness analyses re-estimating all main specifications while including individuals exactly at the policy threshold age. The results remain qualitatively unchanged, although point estimates become slightly smaller in magnitude, which is consistent with misclassifications of treatment status near the discontinuity.

Next, we begin to analyze the relationship between the running and the dependent variables of our study. Fig. 2 is divided into three vertical panels. In all panels, the x-axis is the age distance to the fare exemption threshold in years. Panel A shows the average number of trips for different modes. It shows that the number of trips consistently decreases with age for all transport modes. However, there is a small discontinuity at the cutoff for public transit, with a small increase in the number of transit trips right after the threshold. Next, Panel B presents the average travel time by transport mode for all trip purposes. Again, all series are decreasing with age. Once again, the patterns for transit trips present some discontinuity right after the policy threshold, with a drop in average travel times once individuals become eligible for free transit. Finally, Panel C presents the relationship between vehicle ownership and age. The plot shows a similar pattern, with lower car ownership rates as individuals grow older. Nonetheless, here there is no clear discontinuity at the cutoff. Together, these results suggest that the fare-free policy increases the use of public transit while reducing the travel time of transit trips, with no effect on car ownership rates. In the next section we examine this graphical evidence with an empirical statistical strategy.

4.2. Empirical strategy

To formally estimate the size and significance of the observed discontinuities, we follow Cattaneo et al. (2020) and estimate a non cumulative multiple RD model, where each cutoff specific estimation is described by the following equation:

$$y_{im} = \beta_{0\ m} + \beta_{1\ m} f_m(d_i) T_i + \beta_{2\ m} f_m(d_i)(1 - T_i) + \beta_{3\ m} T_i + \gamma_m X + \varepsilon_{im} \tag{3}$$

Where the outcome variable y_{im} is either the number of trips made by individual i using mode m, the average travel time of trips made by mode m, or the number of vehicles owned by the individual's household i. The transport modes considered in our analyses include three aggregated categories: public transit (bus, train, subway, etc.), private vehicle (driving automobile, passenger of automobile, taxi, ride-hailing, etc.) and walking.[8] Therefore, our analyses consist of results for nine distinct dependent variables: four results related to the number of daily home-based trips by transport mode (all modes, public transit, private vehicle and walking), four other dependent variables related to the travel time of home-based trips by transport mode, and a ninth dependent variable which is vehicle ownership.

Moreover, $f_m(d_i)$ is a continuous function that describes the relationship between the running variable d_i and the dependent variable. Furthermore, X_i is a vector of controls that includes gender, city of residence, income, vehicle ownership, employment and retirement status as well as eligibility for social security collection. Finally, ε_{im} is a noise term that captures all other unobservables.

The main coefficient of interest is $\beta_{3\ m}$, which describes, for each mode, and each cutoff, the discontinuity in the outcome variable at the policy age cutoff. Under the assumption of continuity of y_{im} on d_i at $d_i = 0$, β_3 is equivalent to the policy eligibility average treatment effect at the threshold (Imbens and Lemieux, 2008) or the Intention-To-Treat (ITT of free-fare). The cutoff specific estimates are then averaged using weights defined by the population within the selected bandwidths for each cutoff.

In all the results presented in the next section, we divide the estimated treatment effect coefficient by the projected dependent variable mean from the left of the cutoff. This allows all results to be interpreted as relative effects, enabling direct comparisons irrespective of differences in the levels between the dependent variables included in the analysis.

In our baseline RD estimation, we use a linear approximation of $f_m(d_i)$ and we subset the estimation to a neighborhood of observations around the threshold using the non-parametric minimum square error optimization procedure suggested by Calonico et al. (2014). Observations within the selected bandwidth are weighted using a triangular kernel and standard errors are clustered by age, gender and metro area.

Due to imperfect compliance, as shown in Fig. 1, Panel B, all of our main results are intention-to-treat effects of free-fare rather than treatment effects for compliers. We note that the reduced-form policy ITT effect is valuable in its own right, as eligibility for

[7] In Appendix C , we analyze the density smoothness of the running variable and document the presence of age heaping. However, we show that this age heaping does not reflect manipulation of the running variable to gain access to the fare exemption, as similar patterns are observed at ages not associated with any benefits. Apart from the concentration at round ages, our analysis indicates that the age distribution is otherwise smooth across the policy threshold.

[8] We exclude from our analyses other active modes such as bicycles, cargo vehicles and extremely rare modes.

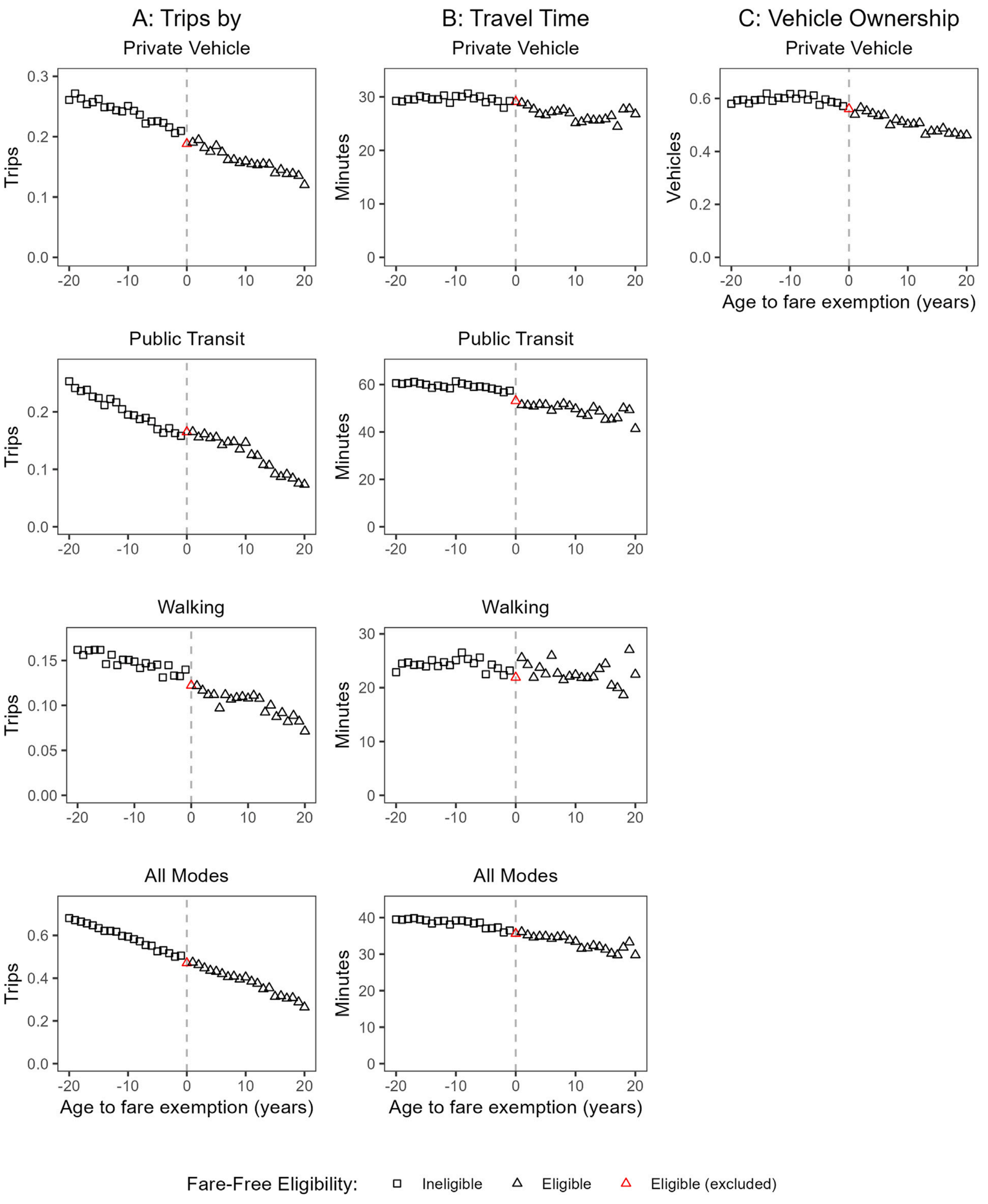


Fig. 2. Average number of trips (A), travel time (B) and vehicle ownership (C) by age-distance to fare exemption age-threshold. *Note.* The sample for all plots includes all 243,700 individuals who are between 20 years below and 20 years above the corresponding fare exemption age threshold, except for individuals who are exactly at the threshold age, who are excluded from the analysis as their de facto treatment status is uncertain (see Fig. 1, Panel B). Each dot represents the average for each variable by relative age.

the free fare is the policy lever most directly under policymakers' control. Understanding these first-stage effects is therefore highly informative for policy analysis.

Still, estimating the average treatment effect (ATE) of free-fare would also be of interest for broader comparisons and could be achieved in a Fuzzy RD design. Unfortunately, compliance information is available exclusively for São Paulo, and only for the subset of individuals from the 2007 and 2017 survey waves who reported traveling by public transportation and were asked to report the details about their fare payments. As a result, policy ATEs can be estimated only from a smaller sample and are further limited to variables with sufficient variation within the subset of public transit users. The variables for which we can estimate policy ATEs include travel time for transit trips, the sub-mode split within public transportation, and the departure hour of transit trips. The results for such estimations are presented in Section 5.5. The ATE for other variables of interest, such as private vehicle use or walking, cannot be estimated because there is no meaningful variation for these variables among individuals who use public transit at least once and who were requested to answer the survey question about transit fare payments.

5. Results

5.1. Main results

Panel A on Fig. 3 shows the results for the averaged global effect of the fare exemption on the nine different dependent variables that we analyzed. In our preferred specification, using robust and bias-corrected estimates, we find three significant results. First, we estimate that the policy leads to a 7.1 % increase in public transit trips and an 8.2 % reduction in walking trips. Given that the total number of trips and trips by private vehicle remain largely unaffected, these results suggest that the main policy effect is a substitution from walking trips to public transit. Additionally, we find that public transit trips become 7.3 % shorter after individuals become eligible for riding for free, which supports the mode substitution hypothesis.

For all other variables, estimates are not significant, suggesting that there are no observable changes in the total number of trips, on trips made by private vehicles or in vehicle ownership as a consequence of the fare exemption. The null result is particularly precise in the case of vehicle ownership.

In summary, our main results suggest that the exemption for public transit for older adults causes people to use public transit more and walk less. These new transit trips are shorter and appear to be induced by trips that otherwise would have been made by walking. We find no significant policy effects on private vehicle trips or on vehicle ownership.

5.2. Other discontinuities at the policy threshold

The main threat to the validity of our estimates is the potential presence of unobserved shocks that could influence travel behavior and be correlated with the age threshold that defines the eligibility for the fare exemption. This issue is particularly relevant in our

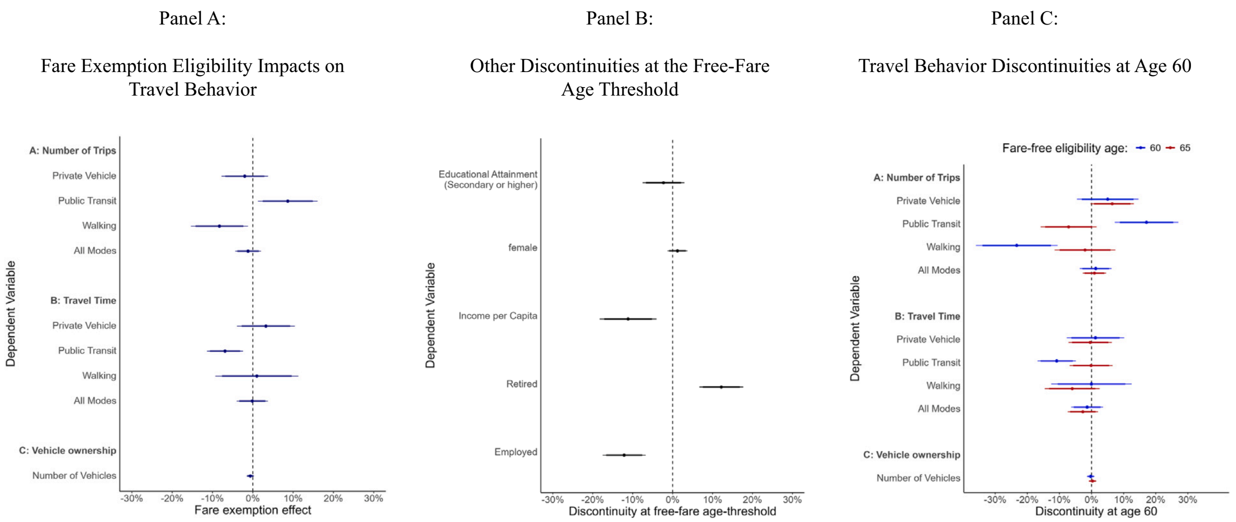


Fig. 3. Regression discontinuity results. *Note.* All estimates were calculated using the rdmulti package (Cattaneo et al., 2020) to handle multiple cutoffs. Thicker horizontal bars represent 90 % confidence intervals of estimates, thinner bars represent the 95 % confidence intervals. Estimation procedures include Robust Bias-Corrected and Conventional methods (Calonico et al., 2014). Detailed Regression outputs are presented in Appendix B, Tables E.1 – E.3. For **Panels A and B**, the cutoffs are: (1) 60 years old for women from São Paulo in all surveys and for men from São Paulo in 2017; (2) 65 years old for men from São Paulo in 1997, 2007 and 2012, and for all individuals from other cities throughout all years. For **Panel C**, results for variables in group A are re-estimated for two groups assigning the age of 60 as the threshold age for treatment in both cases. The first group, for which results are shown in blue, includes all individuals who truly receive the fare exemption benefit at age 60, that is, women from São Paulo in all surveys and men from São Paulo in the 2017 survey. The second group, for which results are displayed in blue, includes the individuals who receive the fare exemption benefit at age 65, hence the estimated policy effects displayed in the plot represent a placebo effect at age 60 for this group.

empirical setup because the age cutoffs for fare exemption eligibility coincide with those used for other policies and benefits targeting older adults. Some examples include the minimum age for collecting social security benefits in Brazil (60 years for women, 65 for men),[9] preferential service lines in public offices, banks and other services (60 years),[10] priority parking slots (60 years),[11] and priority seats on public transit (60 years).[12] If eligibility for these other benefits were to affect the demand for transit and other modes, then our baseline RD estimates would reflect the combined impact of multiple policies rather than isolating the causal effect of fare exemption policy eligibility.

To address this issue, we first examine whether age-related discontinuities exist in other observed variables that are unlikely to be caused by the fare exemption policy. We do this by estimating a similar model to the one employed in the previous session, but instead of looking at travel behavior effects, we analyze discontinuities at the policy threshold on observed characteristics such as working status, educational attainment, place of residence, and household income. Panel B in Fig. 3 presents the results of these regressions, showing significant discontinuities associated with the employment and retirement status of individuals at the age threshold for transit fare exemption. These results are not surprising because the Brazilian minimum age for workers to start collecting social security benefits coincides with the fare exemption threshold for a large portion of our sample. For the other variables included in the analysis, the discontinuities are negligible.

In our main analysis, the potential bias that would be caused by these discontinuities is mitigated because we control for income, employment, retirement status and for social security eligibility.[13] Still, the existence of these other discontinuities at the policy threshold raises concern about the possibility of other coincident and unobserved shocks that could affect the internal validity of our main estimates on travel behavior, particularly given the existence of the other benefits that individuals become eligible for at age 60.

Therefore, to assess the potential bias from such unobserved shocks, we conducted a placebo-type test with the following steps. First, we split our sample into two groups: individuals who receive the fare exemption at age 60 and those who only get it at age 65. For each group, we estimate a set of traditional RD estimations using 60 years old as the age threshold. For the first group, individuals are truly treated at the regression threshold, so we expect results to be similar to the ones observed in our main analysis. However, for the second group, the regression threshold does not coincide with the fare-free eligibility, so results should all be null unless shocks other than the fare exemption were causing the changes in travel behavior.

The results of this placebo exercise are presented in Fig. 3 Panel C. For the first group of truly treated individuals, effects are shown in blue, and are in line with the results from our main model. Public transit trips increase by almost 20 % while walking trips decrease by a similar amount. These point estimates are roughly twice as large as those from the full-sample results. Although the differences are not statistically significant, the larger effects may reflect the fact that São Paulo, where all individuals treated at age 60 are located, has higher income and better accessibility by public transportation, and, as shown in our heterogeneity analysis in Section 5.4, wealthier regions with better accessibility are more responsive to the policy. In addition, the duration of public transit trips is reduced by approximately 10 %.

Meanwhile, for the second group, composed of individuals who do not have fare exemption, the placebo effects at age 60 are shown in red, indicating that discontinuous changes in travel behavior at that age are not significant. Furthermore, the point estimates are significantly different from the results for the first group precisely for the variables for which a significant effect is observed for the latter. For the case of transit trips, the discontinuity at age 60 among non-treated individuals is only marginally significant at the 90 % confidence interval, and the point estimate is negative. This suggests that, in the absence of the fare exemption, individuals would actually make fewer transit trips at that age, thus indicating that our main estimate of the policy's impact on transit take up could be slightly downward biased by unobserved shocks that affect travel behavior at the threshold age of 60. Overall, the results from this exercise suggest that it is very unlikely that other shocks at the threshold age could be biasing up our main results.

5.3. Robustness

Next, we carry out two distinct exercises to evaluate the robustness of our main results. First, we verify the robustness of results to alternative choices of parameters in the regression discontinuity estimation, including the type of polynomial fit, the running variable bandwidth choice, the weighting kernel over the running variable, the inclusion of covariates, the exclusion of the observations that are exactly at the threshold age, and the inclusion of trips that do not necessarily start at home. For this first exercise, similar estimates to our baseline suggest robust findings with respect to the choices of parameters.

The results of the first exercise are presented in Fig. 4. In general, results using alternative specifications are similar to our preferred baseline estimations. Except for some extreme choices of parameters, such as a very short fixed bandwidths, our main significant results remain significant and of similar magnitude throughout all specifications. No null results become significant with any alternative choice of parameters. We also note that including individuals exactly at the threshold age and using an origin-unrestricted definition of trips, all point estimates decrease in magnitude, though they remain statistically indistinguishable from those in the main specification. This effect attenuation is to be expected given the heaping observed in the distribution of the running variable, and considering that home-based trips are indeed more likely to be impacted by the free-fare policy as we originally assumed.

[9] http://www.previdencia.gov.br/servicos-ao-cidadao/todos-os-servicos/aposentadoria-por-idade/.

[10] http://www.planalto.gov.br/ccivil_03/leis/2003/L10.741.htm.

[11] http://www.prefeitura.sp.gov.br/cidade/secretarias/transportes/autorizacoes_especiais/index.php?p = 21225.

[12] http://www.planalto.gov.br/ccivil_03/leis/L10048.htm.

[13] Appendix D presents a detailed discussion about the overlapping cutoffs between social security and free-fare eligibility and how controlling for such facts impacts our results.

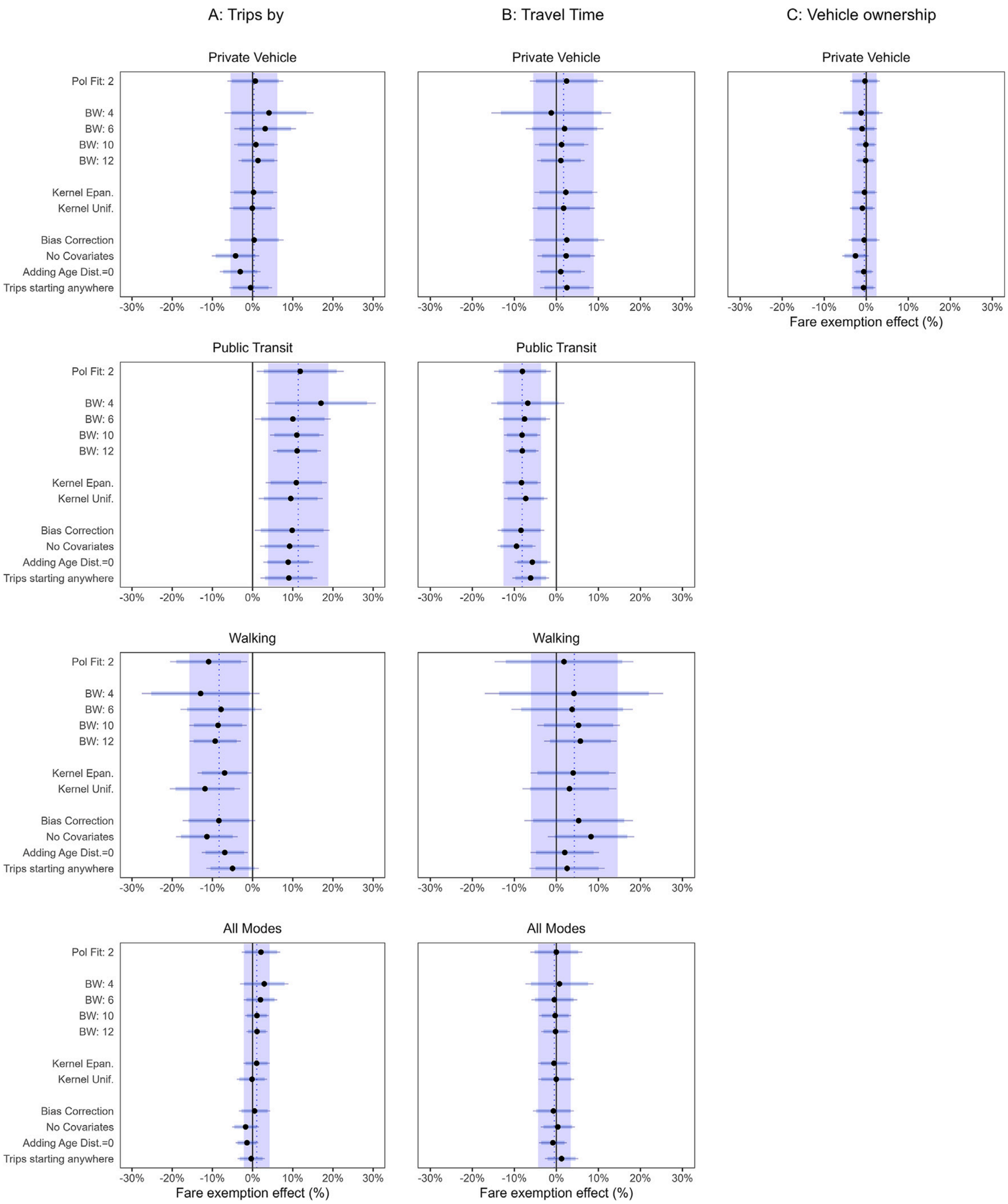


Fig. 4. robustness of results: RD estimates using alternative parameters. *Note.* All results were calculated using the rdmulti package by Cattaneo et al. (2020) for Regression Discontinuities with multiple noncumulative cutoffs. As in our main results the cutoffs are: 1) 60 years old for women from São Paulo in all surveys and for men from São Paulo in 2017; 2) 65 years old for men in São Paulo before 2017 and for all individuals from other cities. Each plot includes alternative calculations of the main effect for each of the nine dependent variables from our main analysis. All reported results are robust and bias corrected estimates and horizontal lines represent 90 % and 95 % confidence interval of point estimates. Each element in the y-axes represents a change in one of the parameters for the main RD estimation. The blue shaded area represents the 95 % confidence interval from our baseline result reported on Fig. 3, Panel A. Pol. Fit 2. substitutes the polynomial fit used for the RD estimation to a second degree polynomial. BW 4 – 12 substitutes the optimal bandwidth calculated in the baseline result to fixed bandwidth of age. Kernel Epan. amd Unif. are alternative weightings of observations based on age distance to policy threshold (baseline = triangular). City/Year Clust. SE cluster standard errors by survey instead of by survey/gender/year-of-age. No Covariates remove all covariates from each cutoff-specific RD estimation. Adding Age Dist. = 0 adds back the individuals whose age is exactly at the exemption threshold, assuming that this individuals are treated. Finally, “Trips starting anywhere” looses the definition of trips to include any journey reported in the household travel surveys, regardless of origin.

Meanwhile, with respect to the choice of focusing on home-based trips in our main specification, we note that point estimates for significant outcomes—such as the share of trips by public transportation, walking, and the duration of public transportation trips—were slightly smaller in magnitude when we consider all types of trips regardless of origin, thus supporting our assumption of more pronounced policy impacts on home-based trips.

Next, we re-estimate our main model defining placebo ages for the fare exemption threshold. The idea of this exercise is to compare the magnitude of identified discontinuities with the discontinuities observed in other parts of each dependent variable series. Here, significant results should only be observed at the true threshold. The results for the placebo tests are presented in Fig. 5. The results for public transit, both for the number of trips and for the travel time, are largest at the true age-threshold suggesting that results are unlikely to be explained by typical unobserved shocks in the running variable series. However the results for the reduction in walking trips are not as consistent. As shown in Fig. 5, Panel A, the estimated policy impact at the true eligibility threshold (threshold shift equal to zero) is negative and statistically significant. Yet, similar effects are also observed at placebo thresholds—shifting the cutoff by one, two, three, or four years, which could result from declining physical activity at older ages. This pattern suggests that the observed reduction in walking trips at the policy threshold is not distinguishable from reductions occurring at older ages unrelated to the policy, thereby casting doubt on the robustness of this particular effect.

5.4. Treatment effect heterogeneity

We also investigate the heterogeneity of treatment effects for different groups of individuals. We run a series of estimations using different subsets of the population. Ideally, we would like to estimate the average treatment effects for all relevant combinations of individual characteristics. However, one of the main limitations of the regression discontinuity design is that the effective sample is restricted to the neighborhood of the running variable threshold, limiting the statistical power of estimations (Angrist and Pischke, 2009), therefore meaningful inference for small subsets of the population is not feasible. Given this limitation, we estimate a series of models using different partitions of our total sample. We estimate the policy effects for subsets of the total population defined in terms of employment status, period of the day, sex, educational attainment, vehicle ownership, household income and neighborhood accessibility.[14]

As presented in Fig. 6, few major differences are observed between subgroups. The reduction in walking trips and the increase in public transit trips are more pronounced among wealthier individuals. For low-income individuals, public transit use also rises significantly, but no meaningful change is observed for middle-income groups. We interpret these patterns as evidence that the mechanisms driving the increase in transit use differ across income levels. In low-income neighborhoods, where opportunities are more dispersed, fare exemption appears to generate new and shorter trips, as suggested by the positive effect on the total number of trips across all modes and the stronger reduction in average transit trip duration. In high-income neighborhoods, where opportunities are more concentrated and often accessible on foot, individuals appear to substitute walking with transit once it becomes free, consistent with the observed decline in walking trips among wealthier individuals and in areas with higher accessibility. By contrast, the absence of additional transit trips among middle-income individuals may reflect that fare exemption alone is insufficient to stimulate new trips and that transit service quality in these areas is not high enough to induce substitution from other modes.

We also find that travel time reductions in public transit trips are larger for individuals who are still working, traveling during peak hours, of lower income and education, without access to a private vehicle, and living in low-accessibility neighborhoods. Taken together, these results suggest that the policy has an important effect in creating a set of shorter public transportation trips for less privileged individuals. Still, we acknowledge that these findings are less precise and may partly reflect multiple testing and the loss of statistical power when splitting the sample into subgroups. Additional analyses using alternative datasets and methodological approaches would be required to better understand the heterogeneity of policy impacts across population segments.

5.5. Fuzzy RD results for the ATE of free-fare on the characteristics of public transit trips

Here we report the results of the fuzzy RD estimation focused on public transit users from São Paulo who reported the details about fare payment in the Surveys of 2007 and 2017. While all of our previous results referred to the effects of fare exemption eligibility on travel behavior, the results from this section indicate the actual policy impacts on compliers, i.e., individuals who shift from paying for the fare to riding for free once becoming eligible for the fare exemption. The treatment status within the fuzzy RD design is defined by the response of travelers to the question about who paid for the transit fare. If the traveler reported riding for free, treatment status is 1. For all other responses, a value of zero is assigned to the treatment status.

Fig. 7 presents the estimated ATEs in green and compares such results with the equivalent ITT of free-eligibility that is comparable to the previous results presented until now. First, it is important to note that estimates are much less precise than our main results given the substantially smaller sample size. None of the results are significant at a 90 % confidence level. Still, point estimates of ATEs are about twice as large as ITT coefficients, consistent with the increase of about 50 % in the probability of riding public transit for free observed in Fig. 1, Panel B. The results for public transit trip duration, although not significant, are in the same direction

[14] The urban landscape in Brazil follows a common pattern across major cities. Central and more traditional areas concentrate most economic activity and benefit from denser public transportation networks, while peripheral regions, where much of the lower-income population resides, face limited economic opportunities and sparse transit coverage. As a result, public transportation accessibility is significantly higher in central, wealthier neighborhoods and considerably lower in the urban periphery (Pereira et al., 2019).

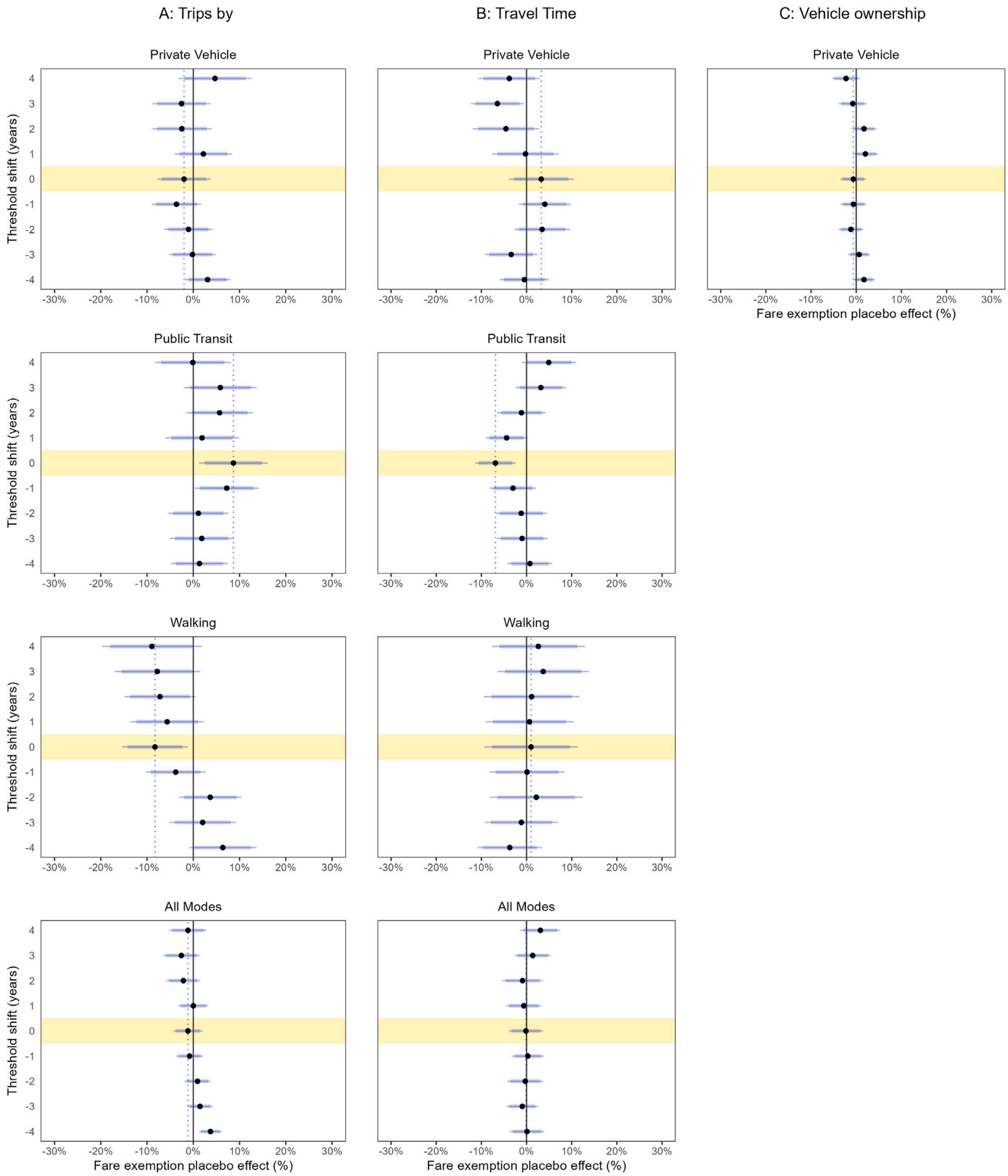


Fig. 5. RD estimates using placebo threshold ages. *Note.* All results were calculated using the rdmulti package by Cattaneo et al. (2020) for Regression Discontinuities with multiple noncumulative cutoffs. As in our main results the cutoffs are: (1) 60 years old for women from São Paulo in all surveys and for men from São Paulo in 2017; (2) 65 years old for men in São Paulo before 2017 and for all individuals from other cities. Each plot reports the robust and bias corrected estimates for the global weighted treatment effect for each one of the nine dependent variables of the analyses. Each element in the y-axes represents a shift in the definition of the policy eligibility for all individuals. For example, a value of 4 indicates an estimation assuming that individuals become eligible to fare exemption 4 years after the true eligibility threshold. Horizontal bars represent 90 % and 95 % confidence interval of point estimates.

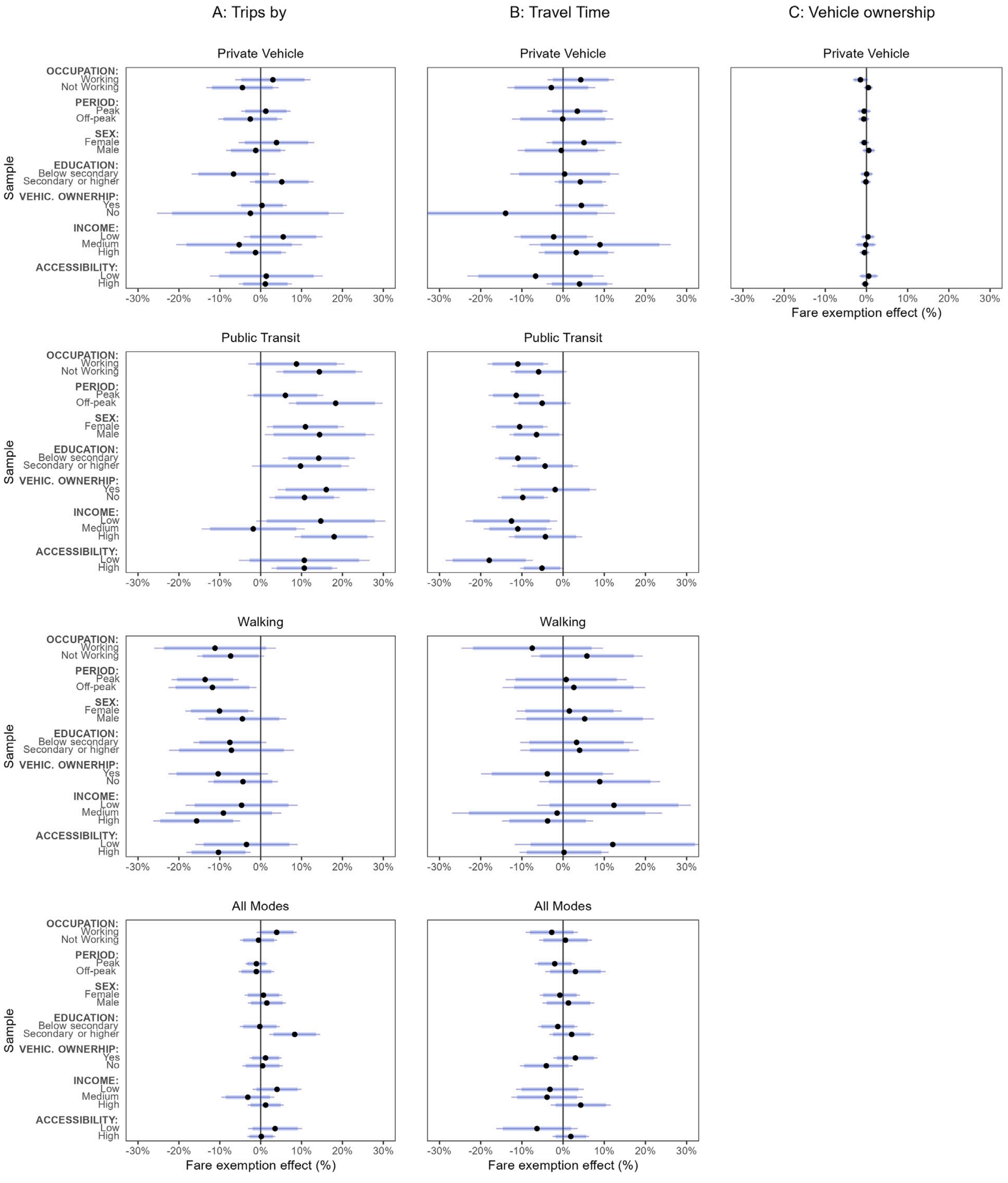


Fig. 6. RD Estimates of fare exemption impacts for partitions of the main sample. *Note.* All results were calculated using the rdmulti package by Cattaneo et al. (2020) for Regression Discontinuities with multiple noncumulative cutoffs. As in our main results the cutoffs are: (1) 60 years old for women from São Paulo in all surveys and for men from São Paulo in 2017; (2) 65 years old for men in São Paulo before 2017 and for all individuals from other cities. All reported results are robust and bias corrected estimates and horizontal lines represent 90 % and 95 % confidence interval of point estimates. Each element in the *y*-axes represents the weighted RD result for a partition of the total sample used for estimating the main result according to characteristics of trips or of individuals.

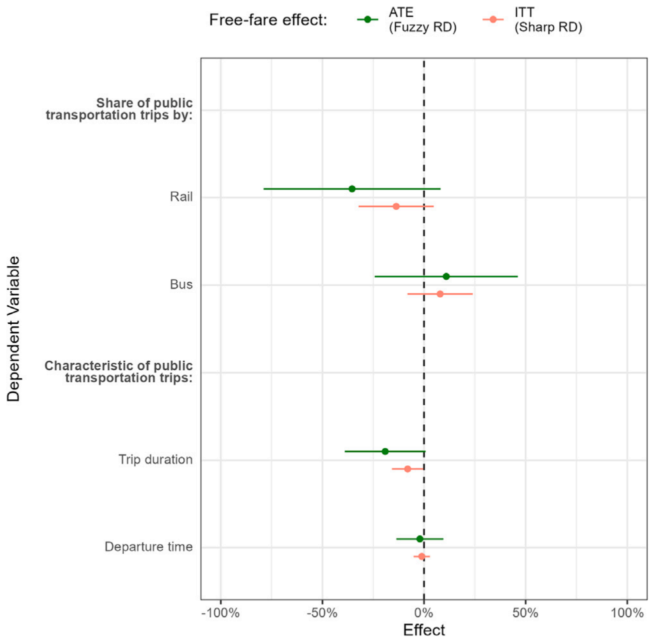


Fig. 7. ITT and ATE of fare exemption on public transit trips characteristics. *Note.* All estimates were calculated using the rdmulti package (Cattaneo et al., 2020) to handle multiple cutoffs. The treatment status within the fuzzy RD design is defined by the response to the question about who paid for the transit fare. If the traveler reports riding for free, the treatment status is defined as 1. For all other responses, a value of zero is assigned to the treatment status. Horizontal bars represent 90 % confidence intervals of point estimates. Estimation are Robust and Bias-Corrected (Calonico et al., 2014). The sample of all regressions includes is restricted to 20,993 public transit trips trips from the São Paulo surveys of 2007 an 2017. The policy cutoffs are: (1) 60 years old for women in both surveys and for men in 2017; (2) 65 years old for men from 2007.

and magnitude as the equivalent result presented in our main estimation, indicating a reduction in the duration of trips by public transportation.

6. Conclusion

From a policy perspective, our results show that fare-free transit policies may not effectively shift behavior toward more sustainable transportation modes and away from private vehicle use, even in contexts with high public transit use. The absence of any measurable reduction in automobile use implies that the fare-free policy, while potentially enhancing affordability and social inclusion for older adults, is ineffective as a standalone instrument for mitigating car-related externalities such as congestion, emissions, and traffic accidents. On the contrary, they may inadvertently reduce physical activity by replacing walking trips with transit use. These findings add further evidence that such policies appear insufficient as standalone measures for addressing congestion, emissions, and other negative externalities associated with car use. From an economic efficiency perspective, this suggests the policy is sub-optimal if its primary justification rests on environmental or congestion-relief grounds, as it fails to induce the intended substitution from private vehicles to public transit. Cities aiming to achieve these goals should, therefore, combine fare policies with other measures that directly target car usage, such as congestion pricing, parking restrictions, or improvements in transit quality and connectivity. These conclusions align with the recommendations of Storchmann (2003), who argued that automobile externalities are best addressed by directly internalizing external costs, rather than through transit fare subsidies.

Our results contrast with evidence from settings such as Seoul, South Korea, where fare-free transit for seniors effectively reduced automobile use and ownership (Shin, 2021), and from the cases of England and Finland, where the policy increased active travel behavior (Coronini-Cronberg et al., 2012; Pesola et al., 2022). Some of these divergent results could be due to different methodological approaches used to measure trips by active transportation modes (Pesola et al., 2022). Nonetheless, our findings are in line with most of the empirical evidence, which suggests that different fare-free transit experiences have helped increase the share of transit trips at the expense of reducing walking trips with negligible if any effect on driving. Overall, though, these discrepancies in the literature highlight the context-dependent nature of fare-subsidy policies and underscore the need to identify factors that explain their success in some places but not in others. We hypothesize that urban density, transit quality, reliability, and safety are critical factors that may account for observed differences in the environmental impact of fare-free policies. For instance, Christensen et al. (2024) demonstrates that transit comfort mediates substitution effects resulting from e-hailing price shocks in Cairo, Egypt.

Although our empirical approach credibly identifies the causal impact of fare-free policies on travel behavior, it lacks the statistical power to determine which specific factors drive the observed mode shifts. Future research should employ complementary methods and richer datasets to examine the broader impacts of fare-free policies on trip generation, social participation, and accessibility—among not only older adults, but broader demographics across diverse urban contexts. In particular, further work should investigate the extent to which variables such as urban density, public transportation quality and reliability, and overall accessibility mediate the effects of transit subsidies, as well as the magnitude of these mediating channels.

CRediT authorship contribution statement

Renato Vieira: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Rafael H. M. Pereira:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Resources, Project administration, Methodology, Conceptualization. **Lucas Emanuel:** Writing – review & editing, Writing – original draft, Validation, Resources, Methodology, Conceptualization. **Pedro Jorge Alves:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of generative AI and AI-assisted technologies

During the preparation of this work the authors used ChatGPT to review grammar and language editing. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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. Summary of empirical literature on the effects of free- or reduced-fare on travel behavior and emissions

See Table A.1.

Table A.1
Comparison between this study (Vieira et al., 2025) and similar empirical analyses.

Paper	Location	Transit mode share[1]	Income per Capita[2] (USD 2023)	Outcomes				Method
				transit ridership	active travel	car usage	other	
Permanent free or lower fare								
Vieira et al. (2025)	7 major Brazilian Metro Areas	40%	10,294	+	−	0		RDD - senior free-fare
Andrews et al. (2012)	England	24%	49,463	+			+ wellbeing	On-board bus survey
Cats et al. (2017)	Tallin, Estonia	40%	30,133.3	+	−	ambiguous		Before-and-after comparisson free-fare adoption
Coronini-Cronberg et al. (2012)	England	24%	49,463	+	+			Before-and-after comparisson free-fare adoption
Guzman & Hessel (2022)	Bogotá, Colombia	40%	6,947.4	+				RDD - lower fare to low-income residents
Offiaeli & Aman (2023)	London, UK	45%	49,463	+				RDD - lower fare to low-income residents
Pesola et al. (2022)	Finland	28%	52,925.7		ambiguous			DiD comparisson city with/without free-fare
Shin. (2021)	South Korea	66%	33,121.4	+	+	−	−	RDD - senior free-fare
Storchmann. (2003)	Templin, Germany	24%	54,343.2	+	−	−		Before-and-after comparisson of fare reduction
Whitley et al. (2020)	England	24%	49,463	+			+ wellbeing	DiDiD of senior fare eligibility changes
Yang & Tang (2018)	Beijing, China	33%	12,614.1	+			+ emissions (short run)	Synthetich Control and DiD fare hike
Temporary free- or lower fare								
Andersson (2023)	Stockholm, Sweden	28%	55,516	+	0			Experiment: short-term free fare passes
Brough et al. (2022)	Seattle, USA	5%	82,769.4	+	0			Experiment: short-term free fare passes to low-income residents
Bull et al. (2021)	Santiago, Chile	40%	17,067.8	+	0			Experiment: short-term free-fare passes to workers
Dai et al. (2021)	3 Chinese cities	46%	12,614.1	+				Synthetic Control - before and after comparisson
Gohl & Schrauth (2024)	Germany	24%	54,343.2				− emissions	DiD fare reduction
Hall et al. (2021)	Vancouver, Canada	20%	54,343.2	+		−	− emissions	Experiment: short-term free fare passes to hotel workers
Ortega & Link (2025)	Germany	24%	54,343.2		0	0		Before-and-after comparisson of fare reduction
Pereira et al. (2023)	Brazil	40%	10,294				0 election turnout	DiD free-fare adoption
Webster (2024)	Colorado, USA	5%	82,769.4	+			0 emissions	Synthetich Control and DiD Colorado free-fare policy

Note: 1: Transit mode share estimates from Prieto-Curiel and Ospina (2024); 2: Income per capita estimates from World Bank (2025).

Appendix B. Public transit fares in different metropolitan areas

See Table B.1.

Table B.1
Inflation adjusted public transit fares in the metropolitan areas included in the study.

Metro area	Year	Fare (R$)	Adjusted fare (R$ 2025)
Belo Horizonte[1]	2002	1,15	4,53
	2012	2,65	5,57
Campinas[2]	2003	1,60	5,37
Rio de Janeiro[3]	2003	1,30	4,36
Salvador[4]	2012	2,80	5,88
São Paulo[5]	1997	0,90	4,66
	2007	2,30	6,32
	2012	3,00	6,30
	2017	3,80	5,74
Fortaleza[6]	2019	3,40	4,77
Brasília[7]	2000	0,50	2,27

Notes: Adjusted values based on IPCA from IBGE. Sources: [1] https://prefeitura.pbh.gov.br/sites/default/files/estrutura-de-governo/bhtrans/2025/historico_de_tarifas-convencional.pdf; [2] https://www.transurc.com.br/informacoes/historico-da-tarifa/; [3] https://www1.folha.uol.com.br/folha/cotidiano/ult95u60552.shtml; [4] https://web.archive.org/web/20160415181744/http://www.setps.com.br/sistema_transporte/evolucao_tarifa.asp; [5] https://www.sptrans.com.br/tarifas; [6] https://www.fortaleza.ce.gov.br/noticias/etufor-divulga-novos-valores-da-tarifa-de-onibus-em-fortaleza; [7] https://dflegis.df.gov.br/ato.php?p=decreto-20496-de-13-de-agosto-de-1999.

Appendix C. Running variable density: heaping, treatment status misclassification and manipulation

Fig. C.1 shows the density of the running variable for (A) all individuals in our sample, regardless of free-fare eligibility age; (B) individuals who become eligible for free fare at 60; and (C) at 65. In all three plots we notice the phenomenon of age heaping, with an overrepresentation of observations declaring ages that end either in 5 or in 0. It seems unlikely that such heaping is caused by any type of manipulation in the running variable with the objective of becoming eligible for the free-fare. (1) The survey response has no direct connection with actual eligibility; (2) the heaping occurs in ages that end in either 0 or 5 regardless of free-fare eligibility age at each specific threshold.

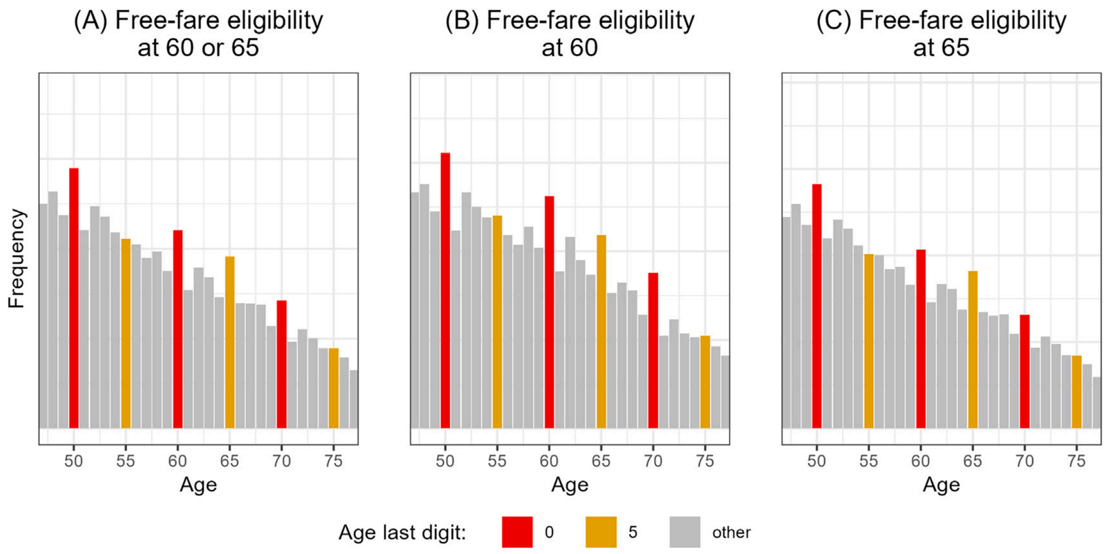
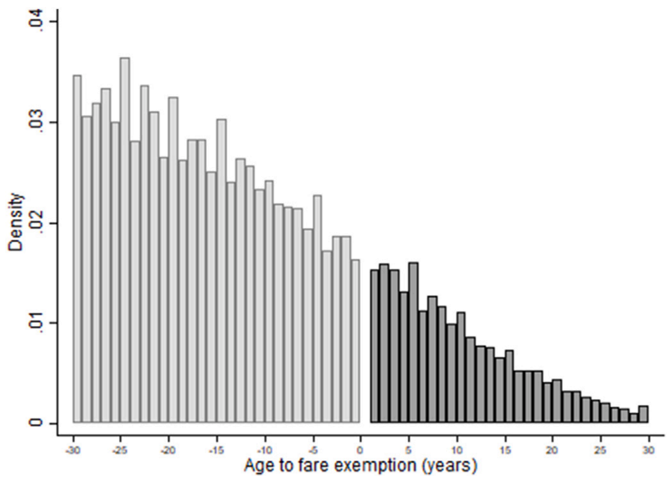


Fig. C.1. Running variable density by free-fare eligibility age. *Notes*. Panel (A) includes all individuals in our sample, Panel (B) is restricted to the individuals who become eligible for free-fare at age 60 (women from São Paulo in all years and men from São Paulo in 2017), and Panel (C) is restricted to the individuals who become eligible for free-fare at age 65. Bars indicate the frequency of observation at each year of age. Red bars indicate ages that end in 0, and golden bars the ages that end in 5.

Consistent with the RD identifying assumption, we apply the McCrary (2008) test. Fig. C.2 shows the distribution of the running variable-age relative to the eligibility threshold-and implements a McCrary-type density test. Panel (a) shows the histogram within ±20 years of the cutoff. Panel (b) reports the estimated log-density jump at the threshold, $\theta = 0.004$ (s.e. = 0.004), so we fail to reject continuity of the density at conventional levels. This provides no evidence of manipulation or sorting around the threshold in our preferred RD estimates where we exclude observations exactly at the cutoff (a “doughnut” RD) to minimize potential treatment-status misclassification exactly at the threshold.

(a) Distribution



(b) Density Continuity Test

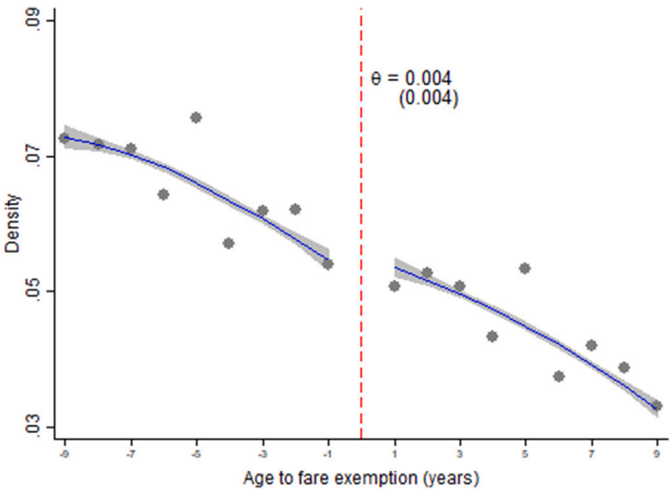


Fig. C.2. Distribution of age to fare exemption and density continuity test. *Notes*. Panel (a) plots the histogram of the running variable—age minus the eligibility threshold (in years)—for individuals within ±20 years of the cutoff. Panel (b) reports a McCrary-type density continuity test estimated with a local-polynomial density (triangular kernel). In our preferred RD estimates, we exclude individuals exactly at the threshold because of treatment-status misclassification caused by age heaping at round values which coincide with free-fare eligibility thresholds.

Appendix D. Controlling for social security eligibility

As we have discussed in Section 5.2, the main threat to the internal validity of our results is the potential existence of other unobserved shocks coinciding with the free-fare policy thresholds. Although we do include retirement status, income and employment status as covariates in our main specification, there could exist other unobserved shocks affecting travel behavior at the age-threshold and not related to the free-fare eligibility.

In our main analysis, presented in Section 5.1, we deal with this issue by exploring the different age cutoffs for free-fare eligibility within our sample, showing that travel behavior discontinuities at age 60 are only observed for individuals who are eligible for free-fare, and no significant discontinuities at age 60 are observed for individuals who only got the free-fare benefit at an older age, thus suggesting that other non-observed shocks coinciding with the policy cutoff age do not seem to be significant.

However, unobserved shocks can also differ by age, with some individuals being impacted at the lower age threshold and others at the higher age threshold. One example is the minimum age for social security collection, which, during the period analyzed in our study, was 60 years old for women and 65 years old for men in Brazil. Indeed, this age threshold heterogeneity by gender coincides

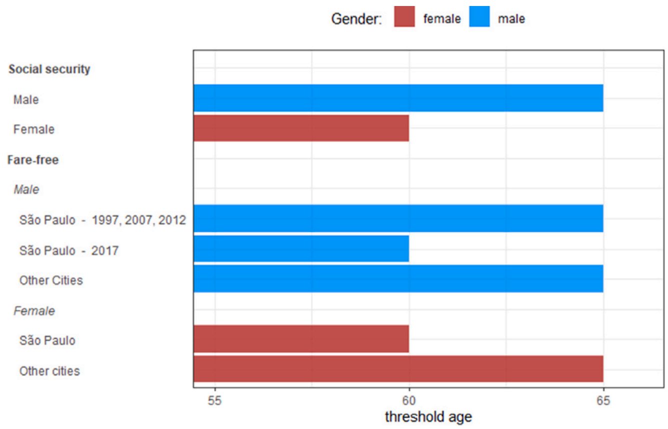


Fig. D.1. Age thresholds for fare-free and for social security by gender, by city and by year.

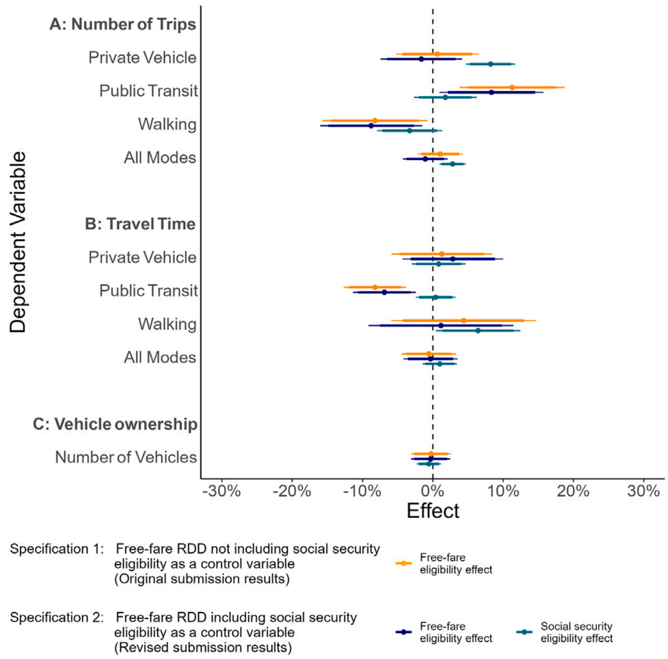


Fig. D.2. Free fare and social security eligibility effects on travel behavior.

with the different fare-free thresholds in some cities. Fig. D.1 summarizes the social security and free fare-policy age thresholds within our sample by city and by gender.

For women from São Paulo and for men from all cities, except from São Paulo-2017, the fare-free age threshold coincides with the social security minimum age. Thus, the effect observed in our original estimations could indeed be biased if social security eligibility also had an effect on travel behavior not captured by the other control variables that were included in the estimation (individual income, working and retirement status).

To address this issue, we also include in our main analysis the social security eligibility status of each individual as a control variable to explicitly account for any travel behavior effect due to such condition. Fig. D.2 summarizes the impacts of controlling for this variable on our main results. None of the main travel behavior effects change significantly, and all significant effects remain so, although the magnitude of point estimates decreases both for public transit usage and public transit travel time reduction, thus indicating some degree of complementarity between both policies, even though social security eligibility effects are only identified as significant for the use of private vehicles and for the total number of trips.

Appendix E. Detailed tables of main results

See Tables E.1–E.3.

Table E.1
Regression discontinuity results: fare exemption eligibility impacts on travel behavior.

Dependent variable	Cutoff	Policy effect [1] (s.e. in parenthesis)	Outcome mean at cutoff [2]	Relative effect [1]/[2]	Bandwidth		Obs	
					Left	Right	Left	Right
Number of trips								
	60	−0.0171 (0.0219)	0.5605	−0.0305	9	9	18,011	14,098
	65	−0.0040 (0.0126)	0.5466	−0.0074	9	9	38,835	26,902
	Weighted	−0.0083 (0.0111)	0.5605	−0.0149	9	9	56,846	41,000
	Pooled	−0.0138 (0.0111)	0.5466	−0.0253	10	10	76,866	50,819
Number of trips by private vehicle								
	60	−0.0106 (0.0185)	0.2399	−0.0443	8	8	18,011	14,098
	65	−0.0020 (0.0100)	0.2320	−0.0088	9	9	44,564	29,337
	Weighted	−0.0046 (0.0090)	0.2399	−0.0193	9	9	62,575	43,435
	Pooled	−0.0079 (0.0091)	0.2320	−0.0340	10	10	67,682	46,526
Number of trips by public transit								
	60	0.0320 (0.0128)	0.1594	0.2007	10	10	23,216	17,046
	65	−0.0032 (0.0092)	0.1710	−0.0185	8	8	33,578	24,091
	Weighted	0.0113 (0.0075)	0.1594	0.0708	9	9	56,794	41,137
	Pooled	0.0115 (0.0079)	0.1710	0.0675	8	8	51,181	38,177
Number of trips by walking								
	60	−0.0401 (0.0129)	0.1537	−0.2609	9	9	20,187	15,341
	65	−0.0006 (0.0082)	0.1379	−0.0047	10	10	50,322	31,775
	Weighted	−0.0126 (0.0069)	0.1537	−0.0817	10	10	70,509	47,116
	Pooled	−0.0158 (0.0071)	0.1379	−0.1143	10	10	67,682	46,526
Number of vehicles								
	60	−0.0093 (0.0045)	0.5683	−0.0163	14	14	33,357	21,309
	65	0.0018 (0.0045)	0.5544	0.0032	10	10	44,564	29,337
	Weighted	−0.0029 (0.0032)	0.5683	−0.0052	11	11	77,921	50,646
	Pooled	−0.0138 (0.0115)	0.5544	−0.0249	8	8	56,866	41,012
Travel time								
	60	−0.3167 (1.1547)	35.4293	−0.0089	12	12	15,876	8876
	65	0.0133 (1.2888)	35.7705	0.0004	8	8	19,663	10,912
	Weighted	−0.1343 (0.8798)	35.4293	−0.0038	10	10	35,539	19,788
	Pooled	0.3412 (0.8859)	35.7705	0.0095	9	9	36,540	20,205
Travel time by private vehicle								
	60	−0.0250 (1.5128)	28.2107	−0.0009	8	8	3944	2726
	65	1.7327 (1.7959)	29.2204	0.0593	9	9	8035	4340
	Weighted	1.1171 (1.2816)	28.2107	0.0396	8	8	11,979	7066
	Pooled	1.0096 (1.1592)	29.2204	0.0346	9	9	13,131	7652
Travel time by public transit								
	60	−5.9899 (2.2320)	56.0354	−0.1069	11	11	5338	3402
	65	−2.3172 (2.2389)	51.1670	−0.0453	8	8	6123	3634
	Weighted	−4.0526 (1.5834)	56.0354	−0.0723	9	9	11,461	7036
	Pooled	−4.8684 (1.5921)	51.1670	−0.0951	9	9	11,946	7111
Travel time by walking								
	60	−0.9217 (1.2830)	22.2614	−0.0414	10	10	2802	1532
	65	1.2537 (2.1344)	25.4781	0.0492	9	9	5288	2981
	Weighted	0.5056 (1.4683)	22.2614	0.0227	9	9	8090	4513
	Pooled	3.2167 (1.7213)	25.4781	0.1263	8	8	7082	4239

Notes: Fig. 3, Panel A, presents the “relative effects” from the “weighted” estimations from this table. For each variable and cutoff, we conducted robust and bias-corrected RD estimations (Calonico et al., 2014). The rows labeled “Weighted” report the aggregation of cutoff-specific results following Cattaneo et al. (2020), while the rows labeled “Pooled” report the mean RD estimates without any weighting of cutoff-specific results. For all specifications, a common MSE-optimal bandwidth was selected on both sides of the cutoff. The size of each bandwidth, in years, is reported in the columns under the “Bandwidth” header, and the sample sizes within the each side of the selected cutoff-specific bandwidths are reported in the rightmost columns of the table.

Table E.2
Regression discontinuity results: other discontinuities at the policy exemption threshold age.

Dependent variable	Cutoff	Policy effect [1] (s.e. in parenthesis)	Outcome mean at cutoff [2]	Relative effect [1]/[2]	Bandwidth		Obs	
					Left	Right	Left	Right
Educational attainment (Secondary or higher)								
	60	0.0277 (0.0223)	0.3711	0.0747	6	6	10,863	9652
	65	−0.0303 (0.0152)	0.3646	−0.0830	5	5	24,784	19,326
	Weighted	−0.0119 (0.0125)	0.3711	−0.0320	5	5	35,647	28,978
	Pooled	−0.0064 (0.0094)	0.3646	−0.0177	9	9	59,386	42,675
Employed								
	60	−0.0126 (0.0212)	0.2977	−0.0423	5	5	10,863	9652
	65	−0.0377 (0.0111)	0.2606	−0.1446	7	7	29,815	22,163
	Weighted	−0.0306 (0.0100)	0.2977	−0.1027	6	6	40,678	31,815
	Pooled	−0.0371 (0.0104)	0.2606	−0.1424	7	7	43,038	33,332
Female								
	60	0.0226 (0.0162)	0.5708	0.0397	6	6	13,223	11,169
	65	0.0073 (0.0105)	0.5779	0.0127	10	10	47,125	30,914
	Weighted	0.0110 (0.0089)	0.5708	0.0192	9	9	60,348	42,083
	Pooled	0.0071 (0.0080)	0.5779	0.0123	10	10	67,682	46,526
Income per capita								
	60	−117.98 (82.16)	1242.2404	−0.0950	9	9	20,557	15,612
	65	−180.93 (75.92)	1116.4565	−0.1621	5	5	24,789	19,328
	Weighted	−152.57 (55.77)	1242.2404	−0.1228	7	7	45,346	34,940
	Pooled	−125.78 (50.33)	1116.4565	−0.1127	7	7	51,178	38,173
Retired								
	60	0.0699 (0.0185)	0.3663	0.1907	6	6	10,863	9652
	65	0.0195 (0.0171)	0.4115	0.0473	5	5	24,792	19,332
	Weighted	0.0355 (0.0131)	0.3663	0.0968	5	5	35,655	28,984
	Pooled	0.0452 (0.0127)	0.4115	0.1098	6	6	35,655	28,984

Notes: Fig. 3, Panel B, reports the weighted relative effects from this table. For each variable and cutoff, we conducted robust and bias-corrected RD estimations (Calonico et al., 2014). The rows labeled "Weighted" report the aggregation of cutoff-specific results following Cattaneo et al. (2020), while the rows labeled "Pooled" report the mean RD estimates without any weighting of cutoff-specific results. For all specifications, a common MSE-optimal bandwidth was selected on both sides of the cutoff. The size of each bandwidth, in years, is reported in the columns under the "Bandwidth" header, and the sample sizes within the each side of the selected cutoff-specific bandwidths are reported in the rightmost columns of the table.

Table E.3
Regression discontinuity results: travel behavior discontinuities at age 60.

Dependent variable	Free-fare eligibility	Policy effect [1] (s.e. in parenthesis)	Outcome mean at cutoff [2]	Relative effect [1]/[2]	Bandwidth		Obs	
					Left	Right	Left	Right
Number of trips								
	60 years old	0.0087 (0.0169)	0.6688	0.0130	9	9	20,187	15,341
	65 years old	0.0006 (0.0107)	0.5716	0.0011	8	8	39,536	30,337
Number of trips by private vehicle								
	60 years old	0.0165 (0.0145)	0.2990	0.0550	8	8	18,011	14,098
	65 years old	0.0176 (0.0082)	0.2357	0.0746	9	9	46,542	34,141
Number of trips by public transit								
	60 years old	0.0337 (0.0105)	0.2049	0.1643	10	10	20,187	15,341
	65 years old	−0.0145 (0.0068)	0.1531	−0.0948	8	8	39,536	30,337
Number of trips by walking								
	60 years old	−0.0424 (0.0108)	0.1693	−0.2504	9	9	20,187	15,341
	65 years old	−0.0063 (0.0081)	0.1696	−0.0369	7	7	39,536	30,337
Number of vehicles								
	60 years old	−0.0020 (0.0040)	0.6700	−0.0031	13	13	28,303	19,264
	65 years old	0.0032 (0.0034)	0.5622	0.0057	11	11	60,932	41,124
Travel time								
	60 years old	−0.5440 (0.9249)	36.0411	−0.0151	12	12	15,876	8,876
	65 years old	−1.2391 (0.9195)	38.3576	−0.0323	8	8	26,658	15,613
Travel time by private vehicle								
	60 years old	0.8720 (1.2363)	26.7417	0.0326	8	8	3944	2726
	65 years old	−0.4103 (1.0694)	30.8997	−0.0133	10	10	14,285	7,361
Travel time by public transit								
	60 years old	−7.1814 (1.8364)	60.4040	−0.1189	11	11	5338	3,402
	65 years old	0.1104 (1.9737)	58.0874	0.0019	8	8	7295	4465
Travel time by Walking								
	60 years old	0.2417 (1.0409)	16.0109	0.0151	10	10	2802	1532
	65 years old	−2.1648 (1.2552)	28.7362	−0.0753	11	11	9927	5,337

Notes: Fig. 3, Panel C, reports the relative effects from this table. For each variable and cutoff, we conducted robust and bias-corrected RD estimations (Calonico et al., 2014). The rows labeled "Weighted" report the aggregation of cutoff-specific results following Cattaneo et al. (2020), while the rows labeled "Pooled" report the mean RD estimates without any weighting of cutoff-specific results. For all specifications, a common MSE-optimal bandwidth was selected on both sides of the cutoff. The size of each bandwidth, in years, is reported in the columns under the "Bandwidth" header, and the sample sizes within the each side of the selected cutoff-specific bandwidths are reported in the rightmost columns of the table.

Data availability

Data will be available in the Repository containing the codes used to produce the analysis in the following link: https://github.com/PedroJorge7/Fare-Free-elderly.

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