Regional Science and Urban Economics 86 (2021) 103616

Contents lists available at ScienceDirect

Regional Science and Urban Economics

journal homepage: www.elsevier.com/locate/regec

The impact of fare-free public transport on travel behavior: Evidence from a randomized controlled trial☆

Owen Bull [a], Juan Carlos Muñoz [a], Hugo E. Silva [a,b,c,*]

[a] *Departamento de Ingeniería de Transporte y Logística, Pontificia Universidad Católica de Chile, Santiago, Chile*
[b] *Instituto de Economía, Pontificia Universidad Católica de Chile, Santiago, Chile*
[c] *Instituto Sistemas Complejos de Ingeniería (ISCI), Chile*

ARTICLE INFO

JEL classification:
R48
H23

Keywords:
Public transport pricing
Fare-free public transport

ABSTRACT

Fare-free public transportation has recently gained attention from policymakers and has been proposed as a measure to reduce pollution and road congestion in several cities around the world. We investigate the impact of fare-free public transport on travel behavior by randomly assigning a pass to workers in Santiago (Chile). The pass allowed them unlimited travel for two weeks, as opposed to paying the regular fare of approximately US$ 1 per trip. The main impact of fare-free public transport is an increase in overall travel of 12%. We also find a 23% increase in the total number of trips made during off-peak periods that is explained in equal shares by increases in public transport and non-motorized trips. Two-thirds of the aggregate effect on off-peak travel occurs during weekday off-peak periods and is mostly due to a 28% increase in trips made by public transport. We find no evidence of mode or period substitution and that the effect on public transport trips is entirely explained by trips that use the subway and by individuals who live within one km. from a station.

1. Introduction

Public transport is central to commuting in many cities around the world. In the main cities of the European Union, the share of trips made by public transport is 30%, which is almost as large as the share of trips made by all the other motorized modes (EMTA, 2018).[1] The analogous public transport shares are higher in most developing countries. For example, Hidalgo and Huizenga (2013) document that the average public transport share of trips in 16 leading cities in Latin America is 44%. Furthermore, government expenditures on public transportation are significant, as the majority of these public transport systems are heavily subsidized. In the same 26 main cities in the EU, the average share of the operational costs not covered by fares is 55% (EMTA, 2018). In the 20 largest cities in the US, on average, 70 percent of the operational costs are subsidized (Parry and Small, 2009).

As a response to increasing congestion and emissions from cars, fare-free public transportation has gained attention from researchers and policymakers. Parry and Small (2009) and Basso and Silva (2014) find that, absent first-best car congestion pricing, fare-free public transport may be efficient from a welfare standpoint.[2] The efficiency gains can come from reducing the unpriced negative externalities that car travel generates, from scale economies, and from the so-called Mohring

☆ We gratefully acknowledge financial support from the Center of Sustainable Urban Development CEDEUS (grant ANID/FONDAP 15110020), from the Bus Rapid Transit Centre of Excellence (BRT+) funded by Volvo Research and Educational Foundations (VREF), and from the ANID PIA AFB180003. We also acknowledge the valuable comments from Kenzo Asahi, Francisco Gallego, Felipe González, Pablo Guarda, Claudia A. Martínez, Juan de Dios Ortúzar, conference participants at the Urban Economic Association Meeting 2019 and from an anonymous referee and the Editor. We thank Pablo Valenzuela for excellent research assistance.

* Corresponding author. Departamento de Ingeniería de Transporte y Logística, Pontificia Universidad Católica de Chile, Santiago, Chile.
E-mail addresses: ombull@uc.cl (O. Bull), jcm@ing.puc.cl (J.C. Muñoz), husilva@uc.cl (H.E. Silva).

[1] These cities are Amsterdam, Barcelona, Berlin, Bilbao, Birmingham, Budapest, Cadiz, Copenhagen, Frankfurt, Helsinki, London, Lyon, Madrid, Mallorca, Manchester, Montreal, Oslo, Paris, Prague, Rotterdam/The Hague, Stockholm, Stuttgart, Torino, Vienna, Vilnius, and Warsaw.

[2] Parry and Small (2009) find that in some cases, it is welfare improving to reduce fares to zero, but they abstain from explicitly suggesting fare-free public transport as an efficient policy. They argue that the point elasticities available are not adequate for estimating the effects of setting fares close or equal to zero. Basso and Silva (2014) find a similar result in their application of the model to data from London. Prior contributions have also shown that subsidies are justified on efficiency grounds although the level varies; examples include Mohring (1972), Glaister and Lewis (1978), Proost and Van Dender (2008) and Börjesson et al. (2017).

https://doi.org/10.1016/j.regsciurbeco.2020.103616
Received 5 May 2020; Received in revised form 26 October 2020; Accepted 5 November 2020
Available online 20 November 2020

effect – which occurs when increased ridership induces an increase in frequency and service density, which diminishes waiting and walking times for all users.[3] Van Dender (2003) finds that the optimal public transport fare could be zero even in the presence of car congestion pricing, but because reducing commuting costs fosters labor supply, which is desirable when revenue-raising concerns are dealt with labor taxes. Another argument in favor of fare-free public transport is related to equity considerations, as transit is generally primarily used by low-income people. For example, Franklin (2018) shows that providing transport subsidies to unemployed youth in urban Ethiopia increases their job search intensity and probability of finding a permanent job.

Many policymakers have either studied, advanced, or implemented fare-free public transport. In 2009, Michael R. Bloomberg, the mayor of New York City (NYC), proposed a significant reform to NYC's transit system, which included making the crosstown buses fare-free (The New York Times, 2009). Although the proposal of making buses free in New York dates back to the 1960s, it regained attention and has been highlighted as a proposal worth considering after the proposal to implement congestion pricing was blocked by the New York State Legislature (The Economist, 2013). In 2013, Tallinn, the capital of Estonia, began offering fare-free public transport to all of its approximately 420,000 residents. More recently, in February 2018, through a letter to the European Environment Commissioner, the German government announced a plan to implement fare-free public transportation to decrease pollution, beginning with five cities by the end of 2018 (The Guardian, 2018). In March 2018, the Mayor of Paris, Anne Hidalgo, "announced plans for a study into the feasibility of fare-free city-wide public transport" (The Independent, 2018). Finally, Luxembourg announced that it would make public transportation in the entire country free by 2020 with the hope of reducing traffic congestion (Bloomberg, 2018). As is clear from the arguments made by these authorities, they hope that people will substitute car trips with trips using the fare-free public transport system.

This study investigates the causal effect of providing a fare-free public transport system on detailed travel behavior. Unlike previous studies, we do this experimentally, and we do not limit our attention to one particular transport mode or one specific type of day or trip purpose.[4] This consideration allows us to study the full impact on travel patterns and to understand the underlying mechanisms behind the change in travel behavior, or lack thereof, which is crucial for policy. To do so, we randomly allocate individuals to a treatment group ($N = 106$) that received a public transportation pass that allowed them unlimited fare-free travel for two weeks on the subway and buses and to a control group that did not receive a pass ($N = 101$). The randomization was conducted at the individual level among workers at 13 firms in Santiago, Chile. We focus on workers because commuting trips represent the majority of morning peak trips, particularly in Santiago, where the share is 74%.

Our first main result is that making public transport fare-free has a substantial effect on off-peak travel. We find that fare-free public transport increases the total number of off-peak trips by an average of three trips per individual during the two-week treatment period, which is a 23% increase relative to the control group. We also find that the pass did not change the number of trips made at peak periods. Therefore, the main impact of fare-free public transport is the generation of new trips rather than substitution from other modes or periods. We provide evidence that the mechanism behind the generation of trips is a change in activity patterns that lead to more leisure trips and errands. Fare-free public transport decreases the monetary cost of leisure activities and of errands that can be done traveling by public transport, such as visiting someone, eating out, or collecting something, and this leads to an increase in these types of trips.

Another main result of the analysis is that the increase in off-peak trips is due to a 23% increase in public transport trips and a 77% in non-motorized trips. The increase in public transport trips is mainly driven by new trips during weekday off-peak periods, where we find a 28% increase relative to the control group. The increase in off-peak non-motorized trips is explained by new trips both in weekday off-peak periods and in weekends. These causal estimations imply a 10% increase in aggregate (all day) public transport trips and a 44% in non-motorized trips.

The increase in trips by both modes may be because the lower cost of traveling by public transport induces the individual to do a set of leisure activities involving multiple trips, including non-motorized trips. An example could be visiting someone by subway, walking to a nearby place, and returning home by subway. We test this hypothesis and find that around one-third of the increase in non-motorized trips is explained by an increase in walking trips preceded or followed by a public transport trip within 3 h.

Finally, we find that having access to a fare-free public transport system did not have an impact on car trips. In particular, we did not find a significant effect on total car trips in the two-week treatment period, on car trips made during peak periods, or on car trips to travel to work or return home. Therefore, we find no evidence that fare-free public transport decreases negative externalities or that it increases public transport crowding during peak periods.

To examine the robustness of our results, we study the existence of heterogeneity in the impact of having a free pass. For this purpose, we develop a stylized short-run model of time allocation to activities with endogenous travel decisions using a discrete choice framework. The relevant tradeoff in traveling choices for a given activity (e.g., work or leisure) is between the value of travel time savings and the monetary and time costs of the (discrete) travel modes available. The model illustrates that the primary sources of heterogeneity in the effect of receiving a fare-free pass should be income, time available for leisure, and accessibility. We test the heterogeneity of the impact for these three variables, finding that the only source of statistically significant heterogeneity is accessibility, measured as the proximity of the household to the subway network, and only for off-peak trips. Therefore, our result that there is no effect on car trips is robust in the sense that it does not depend on the value of travel time savings or the accessibility of the subway network.

We find that the increase in off-peak trips is twice as large for individuals who live within 1 km of a subway station (which is the sample median proximity) and zero for the rest. To complement the analysis, we also study the impact on trips made by public transport differentiated by mode and find that the increase in weekday off-peak public transport trips is fully explained by an increase in trips with at least one subway stage.[5] In summary, we show that increased transit ridership by people who live within one km of a subway station explains the pass's effect on public transport trips.

To better understand the relevance of the analysis, we compare our results with previous findings and then discuss its implications. Cats et al. (2014) and Cats et al. (2017) analyze the outcomes of the implementation in 2013 of fare-free public transport in Tallinn, which is the largest city in the world so far to offer free public transport (420,000 inhabitants). Cats et al. (2014) estimate a 3% increase in public transport trips after three months, while Cats et al. (2017), comparing results from the municipal survey before and after, reports an overall increase of 14%. They also report an increase of 13% in the sub-sample of workers, which is the group most comparable to our sample. Our 10% in two weeks is large compared to the observed outcomes in Tallin. Part of the explanation is "[…] the good level of service provision, high public transport usage and low public transport fees that existed already prior to the fare-free public transport" (Cats et al., 2017). Another is that

[3] See Silva (2019) for a textbook discussion of the Mohring effect.

[4] We discuss the related literature in Section 2.1.

[5] A journey stage is a part of a trip made by a single mode of transport.

in congested cities, the metro system becomes a much more attractive alternative than buses, which may make the aggregate effect larger.

Cats et al. (2017) also reports a 40% decrease in trips for which walking was the primary mode. This is in stark contrast with our finding of a 40% increase in non-motorized trips. We believe that the results in Tallin may be due to a simultaneous change in service supply that includes “a greater priority lanes network and increased service frequency” (Cats et al., 2014), and to the smaller size of Tallin relative to Santiago.

Even though we estimate short-run impacts, we believe that they are relevant for several reasons. First, they contribute to the understanding of the effects of fare-free public transport, especially on travel patterns. Phillips (2014), Abebe et al. (2016), Franklin (2018), and Banerjee and Sequeira (2020) study the effects of fare-free public transport by conducting RCTs, but focus on labor market outcomes, and mostly on job intensity search.

Second, the fact that we can pin down the effect to an increase on weekday off-peak periods and to trips that use the subway is also relevant for policy, as the spare capacity and the marginal costs by mode are usually quite different. The result that the effect on public transportation trips is only present for those who have good accessibility to the subway is also relevant. It suggests that the valuation for accessibility that is typically reflected in higher housing prices could be enhanced importantly with a fare-free policy.

Third, in general, transport elasticities are larger in the long-run (see, e.g., Litman, 2017), so our causal trip generation effects most likely represent a lower bound of the true impact for the compliers. In other words, if a fare-free policy is implemented, the effect on workers who use transit often and live near a subway station could be higher in the long-run.

Finally, some qualifications are needed to interpret how our results would stand in the long-run. The zero impact on car travel, while very important for efficiency, has to be taken with caution, as changing travel habits, vehicle purchases or sales, and work and residential locations could play essential roles in this matter and are not captured by this experiment.

We also compare our sample with Santiago’s population in terms of income, household size, car ownership, commuting time, proximity to the subway network and other variables. The main difference between our sample and the city average is that we observe individuals who use transit more often. This is expected, as they are the ones who are more likely to benefit from fare-free public transport. Our results, therefore, are not representative of the Santiago population. However, if the policy is to be implemented at a city level, the individuals that will most likely lead the effects are precisely the ones that use transit intensively. In addition, we provide a comparison in terms of GDP per capita and population with other cities of middle-income countries and of public transport affordability with other Latin American cities. This is useful to get a sense of how Santiago and our results stands along with other comparable contexts.

The remainder of this paper is organized as follows. We begin by providing a general overview of the related literature and of Santiago and its public transport system together with the experimental design in Section 2. Then, in Section 3, we focus on the data used in the analysis. We present the empirical strategy and the results in Section 5, and the robustness tests in Section 6. Section 7 provides a discussion of the implications, external validity and concludes.

2. Background and experimental design

2.1. Related literature

There is a microeconomics and behavioral literature on how consumers respond to free goods. Shampanier et al. (2007) study the issue with an experiment that contrasts demand for products that have the same price difference, but the low-price good has either low or zero price. They find that dramatically more people choose the cheaper option when it is free as if they perceive higher benefits associated with zero-price products. They also provide evidence that the most likely explanation is that options that have no downside (no cost) trigger a more positive affective response. We do not expect to observe a strong zero-price effect in the case of public transport for several reasons. First, even when the price of traveling is zero the costs could be high because travel time costs (access, waiting and in-vehicle) can easily exceed the monetary costs. Second, transportation usually is not a good in itself as travel is a derived demand.

Fare-free public transport has been implemented in various places in recent decades. It has typically been introduced as a policy targeted to benefit a specific group such as the elderly or college students. There have also been small-scale implementations for a limited period of time or for a fraction of the network. Most of the studies that have investigated the impact of fare-free public transit on travel behavior have focused on reporting the outcomes before and after the implementation in these small-scale examples. For example, Fearnley (2013) reports that the implementation of a fare-free bus line in Stavanger, Norway, for five months did not induce reduced car usage and that half of the ridership would have otherwise walked. We do not linger on providing a detailed description of cases but instead refer the reader to Cats et al. (2017), who provide an overview of the main examples in recent decades.[6]

The largest city that has experimented with free public transport at a full scale is Tallinn (the capital city of Estonia), which has approximately 420,000 inhabitants. Cats et al. (2014) and Cats et al. (2017) compare outcomes before and after and report an increase in public transport ridership of 3% after three months and of 14% after a year. Cats et al. (2014) explains that 1.2% of the public transport ridership increase can be attributed to the fare-free policy as there was a simultaneous extension of the network of bus priority lanes and increased service frequency. Cats et al. (2017) compares the modal shares from the annual city transportation survey before and after the implementation. Public transport increased its modal share from 55% to 63% and the number of trips per person remained around 2 trips per day, making the increase 14%. This comparison of means does not control for any other factor that may be causing the change. The authors provide evidence that suggests that the increase in public transport usage comes mainly from substitution from car trips and walking, whose shares decreased by 10% and 40%, respectively.

In a study related to ours, Thøgersen (2009) examines the impact of giving a one-month pass for free public transport for commuting trips to car drivers in Copenhagen. Unfortunately, the authors do not report average treatment effects or adjust for the observed baseline imbalance (the control group makes 50% more trips than the treated in the baseline survey). Another closely related study is Brough et al. (2019) who study the effects of providing fare-free public transit to low-income individuals in King County, Washington. Their preliminary results show a significant impact on boardings and trips using card data.

To the best of our knowledge, ours is the first randomized controlled trial of fare-free public transport in the context of a large and congested city. It is also the first experimental study that we are aware of that investigates the effects of fare-free public transport on the complete travel patterns of individuals and thus sheds light on the underlying mechanisms behind these effects and the potential policy implications of the measure.

[6] Abou-Zeid and Ben-Akiva (2012) also summarizes some studies on fare-free public transport, focusing on the psychological variables that explain different responses.

2.2. Background

Santiago is the capital of Chile and the largest metropolitan region in the country, with approximately 7 million inhabitants. As of the end of 2017, its public transport system had a subway network of 119 km and 6 lines, a bus network of 377 lines covering 2834 km with a fleet of 6681 buses, and a light rail line of 20 km. (DTPM, 2017).[7] Car usage and congestion in Santiago have been increasing in recent decades. In 2012, the average share of trips made by car on a workday was 26%, while the percentage of trips made by public transportation only was 24% (SECTRA, 2014). In the same year, the average speed of a car trip during a workday was 16.2 km/h, and the average travel time for cars and buses in the morning peak was 42 and 66 min, respectively, which highlights the level of congestion in the city.

The city has an integrated fare payment system that works mainly with a contactless smartcard. The fares are flat in that they do not vary with distance, but they do vary slightly between modes and periods. The bus fare is fixed throughout the day, and in the period of our study was US$ 0.9. The subway fare was US$ 1.1 at peak periods, US$ 1.0 between the morning and the evening peak (called valley) and Saturdays, Sundays, and holidays, and US$ 0.9 before and after the peak periods.[8] Up to two transfers are allowed within 2 h without paying a full fare again; the transfer costs the fare difference, if any, thus it is, at most, US$ 0.2.

The contactless card is not personal, thus, multiple individuals can use the same card. The subway could be paid by cash at the moment of our experiment, but buses could only be paid with the contactless card. There are no travel passes nor quantity discounts, and only students have access to a discounted fare in the system. In contrast, the elderly can access a deduction only in the subway network.

A typical return trip to work costs around US$ 2; considering 22 working days per month, the expenditure on public transportation for commuting would be US$ 44. This figure represents 7.4% of the income per capita in Santiago (see Table F.1). However, for the poorest quintile, paying for 45 trips per month implies spending around 26% of the per-capita income (Rivas et al., 2018). While there are no estimations on the average monetary cost per trip for other modes, households in Santiago spend, on average, 49% more in gasoline than on public transport (INE, 2018).

The system has 5.3 million card validations on an average workday, 44% of which are on the subway network, and 55% of which are on the bus system (DTPM, 2017). In 2017, the system received approximately US$733 million in subsidies to cover students' discounted fares and to subsidize operating costs, among other factors (DTPM, 2017).

2.3. Experimental design

The focus of our study was on working adults, who were selected as our group of interest for many reasons. First, commuting trips are a large share of the trips in Santiago. Commuting represents 74% of the morning peak trips, and 42% of commuting trips are made by public transport (SECTRA, 2014). Commuting trips are also important within the public transport system, as they represent 44% of the total number of trips made by public transport in Santiago on a workday (SECTRA, 2014). Additionally, there are several experiences in which employees' public transport commuter costs are partly or wholly reimbursed by their employers or by government subsidies (see, e.g., De Witte et al., 2008, for the Belgian case).[9]

The evaluation was made using 13 firms. In selecting firms, we sought to obtain a distribution of workers across different industries that resembles the figures on employed persons by industrial classification derived from the National Employment Survey (INE, 2016). Within each industry we used as a criterion to contact those firms for which we could reach the human resources department through a referral (e.g., from acquaintances), and, within those, we chose the firms with the highest number of employees who work only at one location.[10] This criterion has practical advantages because it minimizes the number of firms that we need to involve and simplifies contacting workers because they can be reached at the same address. As 20% of workers in the Santiago region are self-employed, we also contacted one institution that provides financial training to entrepreneurs to offer the treatment to those being trained at the institution and who were self-employed. We assigned the firms into two periods to reduce the number of simultaneous individuals being contacted. The first period began in October 2016 with three employers, and the second period started in March 2017 with the remaining ten firms. The details of the number of individuals per firm and the share of treated and control at the firm level are in Table C.1.

People within each firm were offered the opportunity to participate in the experiment and those that initially accepted were asked to complete a survey about their basic information and socioeconomic characteristics. These included home address, household income, household size, gender, and age (see Appendix A for details). The selection of people for participation in the trial targeted individuals whose working schedules displayed regularity to ensure some degree of comparability between the work weeks covered by the study period. Therefore, we excluded workers who did not have the same work period every week.[11] We also excluded individuals who already enjoyed government-financed fare discounts, such as age discounts, to ensure that the treatment was homogeneous (full fare vs. fare free) and those who would be absent on more than 4 days in the following month, for example, because of holidays. There was no case of workers enjoying employer-subsidized passes.

Participants were asked to record every trip they took in a trip diary, documenting the trip's purpose, start time (departure time from place of activity), end time (arrival at destination), destination location (the district in Santiago) and mode of transport. The design and phrasing of the questions were based on the trip diary of the National Origin-Destination Survey SECTRA (2014) applied every decade. We implemented an online diary and also provided a written trip diary to those with no access to the internet or to a smartphone. It is important to use the trip diary instead of transit card validations for a number of reasons: card validations only provide information about public transport trips, and we are interested in the complete travel behavior pattern; because in Santiago validation is only required when boarding, the trip diary provides the opportunity to capture trip duration; if the measurement were based on validations, the control group would not be a reasonable counterfactual for the treatment because fare evasion on buses is approximately 30% in Santiago and almost non existent on the subway. In addition, the cards are not linked to a specific person so they may be borrowed and travelers may have multiple cards. Finally, the subway can be paid by cash or with a card, but buses can only be paid by card. Nevertheless, we obtained the card data and use it for a robustness test in Section 6. Appendix A describes the surveys used to define eligibility

[7] For differences in public transport accessibility within the city, see Tiznado-Aitken et al. (2018).

[8] The morning peak period starts at 7:00 and ends at 9:00, and the evening peak goes from 17:00 to 20:00. The valley period is between 9:00 and 17:00 and also includes a short period after the evening peak (from 20:00 and 20:45). The low fare is valid on weekdays from 6:00 to 7:00 and from 20:45 to 23:00.

[9] For an analysis of pricing of transport travel passes, see Jara-Díaz et al. (2016).

[10] In the case that our reference was a worker, we excluded her department from the potential sample to avoid conflicts of interest.

[11] For example, we excluded full-time workers who had work shifts in the morning in one week and night shifts in the next week.

Table 1
Timeline.

Firm	Year	Week 1 (baseline)	Weeks 2–3 (treatment)
1	2016	17 October −23 October	24 October - 6 November
2		19 October −25 October	26 October - 8 November
3		20 October −26 October	27 October - 9 November
4	2017	21 March - 27 March	28 March - 10 April
5–6		22 March - 28 March	29 March - 11 April
7		23 March - 29 March	30 March - 12 April
8–13		24 March - 30 March	31 March - 13 April

Table 2
Survey response rate.

	Baseline (week 1)	Treatment Period (weeks 2 and 3)	Response Rate
Control	101	76	0.75
Treatment	106	83	0.78
Total	208	160	0.77

to obtain the baseline data that are not related to travel patterns and the travel survey used in the three weeks of the experiment that allowed us to construct baseline values of travel patterns and the outcomes.

The randomization was carried out at the individual level in each of the 13 firms after the first week of recording trips. The first week allowed us to obtain baseline data on travel patterns. For firms where we had at least 12 participants,[12] we stratified the randomization using blocks. The first criterion was the participants' intensity of public transport use (measured using their Santiago fare card data for the 90 days immediately before the study period). Two blocks were defined based on whether the average public transport trips per week was below 10 or not. We used the number 10 to represent regular users, as a person working five days a week usually makes 10 commuting trips. The second criterion was accessibility to the subway network. Individuals were asked in the survey how would they access the subway network should they need to. Two blocks were defined based on whether they answer that they would walk to the subway or not.

Participants assigned to the treatment group were given a public transport card at the end of the baseline week that allowed them to travel on the entire public transport system (including buses and the subway) for two weeks without paying. Participants in the control group were given a lump-sum transfer at the end of the experiment of US$22.5. The transfer was only given to the control group and participants were aware what they would get in the two cases. The transfer was made only after the experiment ended to avoid having an income shock that would affect travel demand. The amount was set with the aim of offering similar benefits for individuals in the treatment and control group. The lump-sum transfer ended being US$4 higher on average than the fare subsidy to the treated group. To avoid under-reporting, we checked the diaries regularly. For those completing the online diary, we were able to check on a daily basis and send them an SMS when they were not reporting trips (there was an option to report no trips). For those completing the written diary, we visited their firm at least once per week to collect the diary and remind them to complete it.

Table 1 summarizes the timeline of the experimental study.

3. Data and summary statistics

We combined the application data and the data from the first week's trip diaries to construct the baseline information, and we use the subsequent two weeks to measure outcomes. Because individuals were aware that the randomization of the public transport pass was carried out independently of the first week's results, we do not expect any strategic response in the first week. The outcomes are computed directly from the diaries by aggregating individual trips. For example, for each individual, we sum the number of trips made by car in each of the three weeks; the first week serves as a predetermined control and the two other weeks as the outcome for the control and treatment groups. The same procedure is performed to obtain outcomes by time of the day, mode and purpose.

Table 2 summarizes the survey response rates. Randomization of the treatment was made over 207 workers, and the rate of (full) participation, meaning completion of the survey in the entire treatment period (weeks 2 and 3), is 77%. The participation rates do not differ between the control and treatment groups.

Panel (A) of Table 3 shows the (baseline) summary statistics for the individuals and the tests of balance using data from the baseline survey (week 1). The average monthly income of a household is US$1,843, and the average per capita monthly income is US$592. The average number of public transport trips per week is 8.5, with 57% of the individuals making at least ten trips per week. In total, 51% of the households own at least one car. Panel (B) of Table 3 present the summary statistics for the strata for which we study the heterogeneity of the effect: monthly household income and distance of the individual's home to work and to a subway station. We use the (sample) median of each variable to create two strata, and we choose these three variables based on the model in Section 4. Finally, Panel (C) of Table 3 shows the response rate by treatment arm.

Columns 4 and 5 present the average of the baseline descriptive statistics for the treatment and control groups. Column 6 shows the *p*-values of the tests of balance. The sample is balanced on all the variables (*p*-value > 0.10 for all variables), which suggests that the randomization was successful and that the comparison between the treatment and control after the intervention (weeks 2 and 3) represents an unbiased effect of having the public transport pass.

In Tables B.1 and B.2 in the Appendix, we describe the baseline travel times for each purpose and aggregate information about modal shares. In summary, the average travel time to work is 46 min, while returning home is 50 min. These are in line with the travel times at peak periods observed in Santiago (see Section 2.2). The average travel time for leisure trips is 31 min, which is consistent with off-peak travel.

The share of trips made by car in the baseline week is 22%, and those that combine car and public transportation represent a 0.5%. These figures are similar to the ones reported in the last Travel Survey in Santiago, where the share of trips made by car was 25% (SECTRA, 2014). On the other hand, the journeys made by public transport represent 51% of all trips, which is high compared to the 27% average observed in Santiago (SECTRA, 2014). This difference seems to be related to fewer trips made by walking, as in our study, they are 10% of all trips, while at the city level, they represent 31% (SECTRA, 2014). The shares for bicycle trips and other modes (mainly taxi and ride-hailing apps) are 3% and 6%, respectively. We discuss the difference in transit trips and walking in Section 7.1. Still, the main explanation is a combination of self-selection into the experiment and the fact that our sample is made up of workers. Finally, most of the public transport trips are made by combining bus and subway (43%), and the shares of trips made only by bus and only by subway are 28% and 29%, respectively.

As Table 2 shows, the attrition rate is 23%. The results in Panel (C) of Table 3 and in Table 4 show that attrition is balanced and that regardless of the baseline characteristics that we include as controls, the treatment dummy does not predict being observed in the two-week treatment period. This is also robust to including an interaction term with the variables that are significant as covariates. Therefore, attrition should not affect the internal validity of the results.

[12] As Table C.1 shows, only 3 firms had less than 12 participants.

Table 3
Summary statistics and balance between treatment and control groups observed in the treatment period (endline).

	Average (1)	SD (2)	N (3)	Treatment (4)	Control (5)	p-value T = C (6)
Panel A: Basic statistics						
Gender [1 = man]	0.60	0.49	159	0.58	0.62	0.609
Age	41.59	12.45	158	40.66	42.59	0.331
Commuting time in baseline week [min]	46.77	27.00	154	47.36	46.15	0.782
Size of household	3.88	1.99	154	3.86	3.91	0.894
Household monthly income [US]	1843	1581	143	1862	1824	0.889
Household per-capita monthly income [US]	592	578	139	561	622	0.541
Household car ownership [1 = one or more cars]	0.51	0.50	159	0.48	0.54	0.472
Household proximity to a subway station [km]	2.67	6.44	158	2.21	3.16	0.356
Public transport trips in baseline week (diary)	8.48	4.68	159	8.94	7.99	0.200
Public transport trips in baseline week (card data)	7.56	4.88	139	7.24	7.98	0.376
Panel B: Strata for heterogeneity of the effect						
Low income (N = 71)	828	264	143	826	829	0.958
High income (N = 72)	2844	1698	143	3198	2577	0.125
Low commuting time (N = 77)	27.53	8.95	154	26.96	28.15	0.565
High commuting time (N = 77)	66.01	25.25	154	68.28	63.68	0.427
Short home-subway distance (N = 79)	0.63	0.30	158	0.60	0.65	0.477
Long home-subway distance (N = 79)	4.72	8.65	158	3.75	5.81	0.293
Panel C: Response rate						
Response rate	0.76	0.43	208	0.78	0.75	0.605

Note: The baseline survey data were collected during October 2016 and March 2017 as Table 1 details. The sample size varies according to the amount of data without observations for each variable. Income is measured in US$, using the March 2017 exchange rate. Columns (1)–(3) show the variable mean for the total sample, the standard deviation and the number of observations, respectively. Columns (4) and (5) show the variable mean for the treatment and control group, respectively. Column (6) reports the p-value of the null hypothesis that Treatment = Control.

Table 4
Study of attrition and baseline characteristics.

	Found in the treatment period (1)	Found in the treatment period (2)	Found in the treatment period (3)	Found in the treatment period (4)
Treatment dummy	0.031	−0.021	0.008	−0.001
	(0.059)	(0.049)	(0.057)	(0.092)
Gender [1 = man]		0.044	0.049	0.046
		(0.054)	(0.055)	(0.055)
Age		−0.002	−0.002	−0.002
		(0.002)	(0.002)	(0.002)
Distance to work		0.010***	0.009***	0.011**
		(0.003)	(0.003)	(0.005)
Size of household		−0.022	−0.021	−0.022
		(0.017)	(0.017)	(0.018)
Monthly household income per capita		−0.000	−0.000	−0.000
		(0.000)	(0.000)	(0.000)
No. of cars in household		0.048	0.048	0.048
		(0.033)	(0.032)	(0.033)
Household proximity to a subway station		−0.013**	−0.011***	−0.014**
		(0.005)	(0.003)	(0.006)
Treatment x Proximity to subway			−0.012	
			(0.011)	
Treatment x Distance to work				−0.002
				(0.006)
Constant	0.752***	0.989***	0.988***	0.983***
	(0.043)	(0.146)	(0.147)	(0.148)
R-squared	0.001	0.085	0.095	0.086
N	207	153	153	153

Note: The dependent variable takes a value of 1 if the individual was not found in the treatment period. Column (1) shows the result of regressing the dependent variable on treatment for the entire sample. Column (2) presents the results of the same regression but with predetermined baseline controls. The sample includes all individuals who agreed to participate for whom we collected baseline information. The difference in the sample sizes in Column (1)–(4) is due to missing values of some predetermined baseline controls. Robust standard errors in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

4. A short-run model of time allocation and travel

We develop a stylized short-run model of time allocation to activities with endogenous travel decisions to illustrate how fare-free public transport should impact travel behavior and to guide the empirical analysis.[13] Consider an individual who derives utility from the consumption

[13] We generalize an extension of Train and McFadden (1978) by Jara-Díaz (2007). The exposition closely draws from Jara-Díaz (2007). Literal excerpts are not marked as such and are taken to be acknowledged by this footnote.

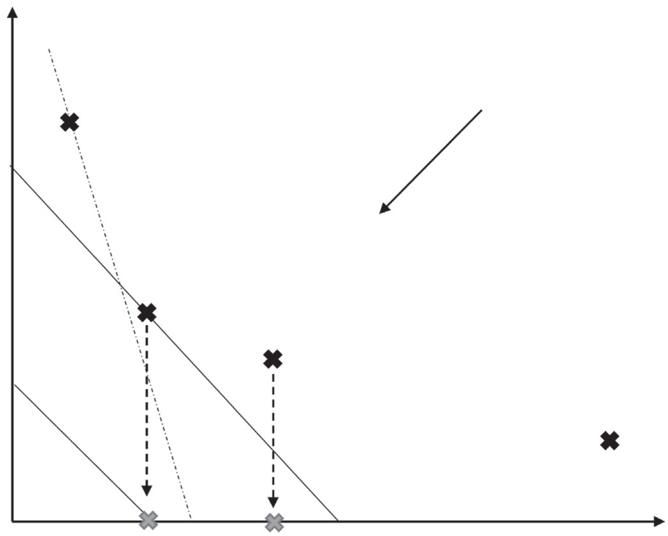

Fig. 1. A simple depiction of modal choice for commuting.

of goods (G) and from allocating time to leisure activities (L) and whose preferences are represented by a Cobb-Douglas utility function. Income is earned by allocating H hours to work at a wage rate of w. The individual must travel to work by any of the available modes represented by the set M_W. Each mode i is represented by travel time t_i^W and expenses c_i^W, such as fares or fuel.

There are two types of leisure: those that do not require travel (e.g., watching a movie at home), denoted by L_1, and those that do require travel (e.g., going to the movies), denoted by L_2. Traveling for leisure requires a discrete mode choice in M_L. Traveling to leisure by mode j implies traveling t_j^L hours and spending c_j^L on the trip. The individual's problem is:

$$\text{Max } U(G, L_1, L_2) = K \cdot G^{1-\beta_1-\beta_2} \cdot L_1^{\beta_1} \cdot L_2^{\beta_2} \tag{1}$$

$$\text{s.t. } I + w \cdot H = G + c_i^W + c_j^L \tag{2}$$

$$T = H + L_1 + L_2 + t_i^W + t_j^L \tag{3}$$

$$i \in M_W, \quad j \in M_L \tag{4}$$

where K is a constant, I is the income from other sources and T is the total time available for work and leisure. Solving the utility maximization conditional on the discrete travel choices $\{i, j\}$, we obtain the conditional indirect utility function and the rate of substitution between time and money at constant utility, i.e., the value of time. Formally:

$$\frac{\partial V_{i,j}/\partial T}{\partial V_{i,j}/\partial I} = \frac{\beta_1 + \beta_2}{1 - \beta_1 - \beta_2} \cdot \frac{I + w \cdot H - c_i^W - c_j^L}{T - H - t_i^W - t_j^L} \tag{5}$$

The modal choice is summarized by the trade-off between reduced travel times, which provide more time for leisure, at a higher cost and thus less money to spend on goods. This tradeoff is depicted in Fig. 1 for a given choice of j. The modes are represented by their monetary cost on the vertical axis and their travel time on the horizontal axis and are marked by an "X". The indifference curves are depicted by the solid lines, where utility is higher closer to the origin the curve (lower travel time and cost).

The slope of the indifference curve is the value of time derived above, which for ease of exposition is a straight line. The effect of facing fare-free public transport for the individual is represented in Fig. 1 by the downwards displacement shown by the dashed arrows. However, the individual chooses to commute using the subway in both cases. The dot-dashed line represents the indifference curve of an individual with a higher value of time who initially uses the car for commuting but after the fare reduction changes its choice to subway.

The model illustrates the relevant trade-offs and is informative for the empirical analysis in that the effect of fare-free public transport could be heterogeneous concerning income, available time for leisure, and the set of modes available to the individuals. A similar argument holds for the mode choice for traveling to a leisure activity.

5. Empirical strategy and results

5.1. Empirical strategy

Our empirical approach is based on the random assignment of a travel card that allows for unlimited travel in the public transport system among eligible applicants. Based on this allocation, we compare travel behavior patterns between the individuals who received the pass and those who did not. That is, for individual i, who works at firm f, the impact of receiving a fare-free public transport pass on outcome y is estimated using the following equation:

$$y_i = \alpha + \beta\, T_i + \gamma\, y_{i,0} + \mu_f + \epsilon_i \tag{6}$$

where y_i is the outcome variable of individual i in the entire treated period. We primarily consider the treatment effect on the outcomes measured in the two-week treatment period, but for robustness, we separately analyze the effects on the first and second weeks of treatment. T_i is a dummy for treatment status, and $y_{i,0}$ is the predetermined baseline value of the outcome, which is measured in week 1, prior to the treatment assignment. As we randomized within firms using stratification, we use strata fixed effects μ_f. Therefore, β measures the effect of possessing a public transport pass on travel outcomes, i.e., the treatment effect.

As discussed in the Introduction, determining the underlying mechanisms behind a potential increase in trips made by public transport is critical for studying the efficiency effects of a fare-free policy. A substitution from car trips to public transportation may lead to substantial gains due to decreased negative externalities, such as congestion and pollution. On the other hand, the generation of new trips could induce inefficiencies in the public transport system due to crowding externalities or increased operating costs, especially if the new trips are made in peak periods. However, the generation of new trips could also imply a social benefit if the additional trips benefit the individuals or induce gains from scale economies in off-peak periods.

By examining the effect on the total number of trips regardless of the mode, together with those made by the different modes, namely public transport, car, non-motorized modes such as walking and cycling and other modes (e.g., taxi), we can study the underlying changes in travel patterns. For example, an increase in the number of public transport trips, no effect on the total number of trips and a negative effect on the trips made in other modes are evidence of sheer mode substitution. On the other hand, an increase in the total number of trips with no negative effect on the trips made in any of the available modes is evidence of pure trip generation. To study period-specific effects or whether there is time-of-day substitution of trips, we also study outcomes for peak periods, weekday off-peak periods and weekends and public holidays.

As the model in Section 4 shows, the treatment effect could be heterogeneous with respect to the value of travel time savings, through income and time available for leisure, and the set of available modes. To study the heterogeneity of the impact of the treatment, we construct two strata defined as above and below the median value of the predetermined baseline variable. We use the distance to the nearest subway station as the measure of public transport accessibility because the bus network is dense and covers most of the city with 377 lines, while the subway network only has 7 lines and covers a limited fraction of the city. We do not have detailed information about time use for each individual, so we use travel time to work as the main source of variation of

Table 5
Treatment effect on all trips, peak-period trips and off-peak trips.

	Total (1)	Public Transport (2)	Car (3)	Non-motorized (4)	Other (5)
Panel A: All trips.					
Treatment	3.401***	1.372	0.499	1.442***	0.498
	(1.074)	(0.875)	(0.787)	(0.524)	(0.418)
R-squared	0.714	0.733	0.867	0.820	0.719
N	159	159	159	159	159
Control group mean	28.20	15.42	7.47	3.25	2.05
Panel B: Peak period trips.					
Treatment	−0.126	−0.109	−0.057	−0.109	0.124
	(0.496)	(0.472)	(0.340)	(0.264)	(0.142)
R-squared	0.775	0.829	0.896	0.841	0.784
N	159	159	159	159	159
Control group mean	12.92	8.57	2.58	1.26	0.51
Panel C: Off-Peak period trips.					
Treatment	3.486***	1.595**	0.373	1.545***	0.366
	(0.949)	(0.694)	(0.682)	(0.508)	(0.340)
R-squared	0.737	0.660	0.746	0.693	0.698
N	159	159	159	159	159
Control group mean	15.28	6.86	4.89	1.99	1.54

Note: The follow-up survey was collected during October–November 2016 and March–April 2017 as Table 1 details. The table indicates the treatment impact (being given a fare-free public transportation pass) on the total number of trips and on the number of trips by mode. All regressions include the predetermined baseline value of the outcome variable as a control. Strata fixed effects are included in all regressions. Panel A presents effects for all trips, while panel B shows the effects for trips made in peak periods, and panel C reports those in off-peak periods. The coefficients do not necessarily add up to the same amount when disaggregating trips by mode or period, as the total number of trips includes those without a stated mode or time of day. Robust standard errors in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

available time for leisure.

For the purpose of studying the heterogeneity of the impact, we estimate the following regression:

$$y_i = \alpha + \sum_k \beta_k S_{i,k} T_i + \gamma y_{i,0} + \mu_f + \epsilon_i \quad (7)$$

where $S_{i,k}$ is a dummy that takes the value of 1 if individual i belongs to group k for which we study heterogeneity. For example, to explore the heterogeneity concerning income, we define two groups: $k = 1$ for individuals below the median income of the sample and $k = 2$ for individuals above the median. Thus, β_1 measures the effect of the treatment on low-income users, and β_2 measures the effect on high-income users.

5.2. The average treatment effect by period

Table 5 summarizes the results of the estimation of the regression model without interactions (Eq. (6)) for the five outcomes of interest in the entire treatment period (aggregation of weeks two and three of the experiment). Column 1 shows the results for the total number of trips as the outcome, column 2 reports those for the total number of public transport trips, column 3 shows those for the trips made by car, column 4 presents those for non-motorized trips, and column 5 reports those for all the other modes. Note that the coefficients in Table 5 and in the following tables do not necessarily add up to the same amount when disaggregating trips by mode or period, as the total number of trips includes those without a stated mode or time of day.

Panel (A) of Table 5 focuses on the aggregation of all trips. Column 1 shows that the effect of having access to a fare-free public transport system is an increase of 3.4 trips, which is an 12% increase over the control group's average trips (coefficient of 3.401, significant at the 1% level). Columns 2 and 4 show that most of this effect is an increase in public transport and non-motorized trips (coefficients of 1.372 and 1.442) but that only the impact on non-motorized trips is significant at the 1% level.

Panels (B) and (C) show the effects of fare-free public transport on trips made during peak periods and off-peak periods, respectively. We use the definition of peak periods that the public transport authority (DTPM) uses to schedule buses.[14] All the coefficients for peak travel are close to zero and not significant, revealing that there are no behavioral changes during these periods. Moreover, this also implies that there is no substitution between the periods. Panel (C) shows that the effect on total trips is entirely explained by changes in off-peak periods. The coefficients for the total number of trips and trips in each mode during off-peak periods are very similar to those in panel (A), but the standard errors are lower. The effect on the total number of off-peak trips is a 23% increase relative to the control group average, which is explained in equal shares by new public transport and non-motorized trips. The impact on off-peak public transport trips is also a 23% increase (coefficient 1.595, panel (C), column (2), significant at the 5% level) and in non-motorized trips is a 77% increase (coefficient 1.545, panel (C), column (4), significant at the 1% level). Note that non-motorized trips are not stages of a trip by public transport (e.g. walking to the subway station), but trips entirely made by non-motorized modes.

To better understand the mechanisms behind these results, we first consider a disaggregation of the off-peak effect into weekday off-peak and weekend trips. The results are in Table 6, where panel (A) shows the impact on off-peak weekday trips, and panel (B) reports the effects on weekend trips.

The results in Table 6 reveal that two-thirds of the effect of fare-free public transport is explained by new trips made during weekday off-peak periods. The effect is an increase of 2.4 trips, which is 30% of the control group's average (panel (A), column 1, coefficient 2.434, significant at the 1% level). Panel (A) also reveals that the pass increases the number of public transport trips by 1.2 trips during off-peak weekdays

[14] Aggregating morning and evening peak periods, our definition of peak period is from 6:00 to 9:00 and from 17:30 to 20:00 on working days. Everything else is considered to be off-peak.

Table 6
Treatment effect on weekday off-peak trips and on weekend trips.

	Total (1)	Public Transport (2)	Car (3)	Non-motorized (4)	Other (5)
Panel A: Weekday off peak.					
Treatment	2.434***	1.220**	0.201	0.821**	0.163
	(0.595)	(0.475)	(0.370)	(0.361)	(0.213)
R-squared	0.811	0.752	0.678	0.759	0.732
N	159	159	159	159	159
Control group mean	8.13	4.33	1.71	1.32	0.78
Panel B: Weekend					
Treatment	0.865	0.479	−0.101	0.708***	0.061
	(0.635)	(0.401)	(0.486)	(0.262)	(0.255)
R-squared	0.547	0.435	0.691	0.522	0.312
N	159	159	159	159	159
Control group mean	7.14	2.59	3.18	0.67	0.76

Note: The follow-up survey was collected during October–November 2016 and March–April 2017 as Table 1 details. The table indicates the treatment impact (being given a fare-free public transportation pass) on the total number of trips and on the number of trips by mode during off-peak periods. All regressions include the predetermined baseline value of the outcome variable as a control. Strata fixed effects are included in all regressions. Panel A presents effects for trips made during weekday off-peak periods, while panel B shows the effects for trips made during weekends. The coefficients do not necessarily add up to the same amount when disaggregating trips by mode or period, as the total number of trips includes those without a stated mode or time of day. Robust standard errors in parentheses. *p < 0.1, **p < 0.05, ***p < 0.01.

(column 2, coefficient 1.220, significant at the 5% level). Unlike in the case of public transport trips, the effect of the pass on non-motorized trips is driven by increases in off-peak weekday and weekend trips, as shown in column (4) in both panels.

Summarizing the results in Tables 5 and 6, we find evidence that there is no trip substitution between modes and periods. The effect of the fare-free pass is trip generation during off-peak periods, driven mainly by a 28% increase in public transport trips made during weekday off-peak periods and a 77% increase in non-motorized off-peak trips, which occurs during both weekdays and weekends. We now turn to further explore the mechanisms behind these results and to test their robustness.

5.3. Effects by trip purpose

There are three types of mechanisms through which individuals could change their travel patterns when facing fare-free public transport. First, there could be a substitution effect. Because public transport is a substitute for other modes, individuals may choose to make the same trips as before but by public transport instead of, for example, by foot or car. As we discuss in Section 4, in the short run, this is the primary mechanism in action for commuting trips. We tested this mechanism in the previous section by examining the treatment effect on the number of trips by mode. We found a positive impact rather than a decrease in trips by some mode, and thus, we did not find any evidence of a mode substitution effect.

The second type of mechanism is related to changes in consumption and activity patterns. This mechanism is relevant because travel is a derived demand that is used mostly to facilitate a spatially varied set of activities such as work, recreation, shopping, and home life (Small and Verhoef, 2007). Fare-free public transport lowers the relative cost of activities that are intensive in or accessible by public transport, and this can change travel patterns. On the one hand, there could be substitution from an activity that was done traveling by another mode (e.g., driving to the cinema) to a different activity done by using public transport (e.g., visiting a downtown museum using the subway). This type of change would imply only mode substitution and no change in the number of trips. On the other hand, the move could be from an activity that did not require travel (e.g., having dinner delivered at home) to an activity that does require travel (e.g., eating out). It may even be a set of activities that involves multiple trips, some by public transport and others by a non-motorized mode (e.g. visiting someone by subway, walking to a park afterward, and returning home by subway).

To test the robustness of the lack of mode substitution and to explore the possible mechanisms, we estimate the treatment effect by trip purpose. As individuals were asked to report the purpose of every trip, we construct the number of trips by purpose and mode by grouping the individual trips into four categories: (i) to work, (ii) return home, (iii) leisure and errands, and (iv) other purposes. The leisure and errands category includes shopping, visiting someone, eating out, picking up or dropping off someone, and doing chores, among other activities. The details of the purpose definition and the summary statistics of trips per purpose in the baseline (pre-treatment week) are summarized in Appendix A.

Table 7 summarizes the treatment effect for our five outcome variables for the three main categories of trip purpose. The impact of the fare-free pass occurs mostly for trips to perform leisure activities or errands (panel (C)). Regarding the effects by mode, we find an increase in public transport trips for leisure and errands of 0.9 trips, which is a 40% increase (column 2, coefficient 0.871, significant at the 5% level). We also find a statistically significant increase in 0.7 non-motorized trips for leisure and errands and 0.6 for the purpose of returning home (column 4, panels (B) and (C)).

The results of the analysis by purpose reaffirm that there is no substitution from other modes to public transport and that the treatment effect is a generation of trips made by public transport and by non-motorized modes and mostly for leisure and errands. This is consistent with the mechanism described above for trip generation.

We also test the hypothesis that there is some degree of complementarity between walking trips and public transport trips. For every walking trip, we assessed whether the previous and subsequent trip were made by public transport and computed the time elapsed between trips. We then study the treatment effect on walking trips that occur within a certain amount of hours of a public transport trip. Table 8 summarizes the result using two, three and six hours between trips.

The fare-free pass increased the number of walking trips made preceded or followed by a transit trip within two, three, and six hours, by 0.36, 0.42, and 0.48 trips, respectively. This impact explains about one-third of the effect on non-motorized trips, and shows that indeed there is complementarity between transit and walking trips.

Table 7
Treatment effect by trip purpose.

	Total (1)	Public Transport (2)	Car (3)	Non-motorized (4)	Other (5)
Panel A: To work.					
Treatment	0.155	0.217	−0.271	0.046	0.137
	(0.349)	(0.369)	(0.205)	(0.168)	(0.174)
R-squared	0.576	0.784	0.893	0.870	0.747
N	159	159	159	159	159
Control group mean	9.16	6.01	1.68	0.54	0.54
Panel B: Return home.					
Treatment	0.548	−0.003	0.212	0.621**	0.021
	(0.444)	(0.422)	(0.381)	(0.289)	(0.230)
R-squared	0.544	0.691	0.818	0.703	0.584
N	159	159	159	159	159
Control group mean	12.24	6.88	3.09	1.01	1.01
Panel C: Leisure and errands.					
Treatment	2.052***	0.871**	0.281	0.712***	0.207
	(0.634)	(0.373)	(0.466)	(0.244)	(0.143)
R-squared	0.756	0.631	0.733	0.743	0.582
N	159	159	159	159	159
Control group mean	6.08	2.20	2.53	0.42	0.42

Note: The follow-up survey was collected during October–November 2016 and March–April 2017 as Table 1 details. The table indicates the treatment impact (being given a fare-free public transportation pass) on the total number of trips and on the number of trips by mode. All regressions include the predetermined baseline value of the outcome variable as a control. Strata fixed effects are included in all regressions. Panel A presents effects for trips made for the purpose of traveling to work, panel B shows the effects for trips made for the purpose of returning home, and panel C reports the effects for trips made for leisure and errands. The coefficients do not necessarily add up to the same amount when disaggregating trips by mode, as the total number of trips includes those without a stated mode. Robust standard errors in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table 8
Effect on walking trips preceded or followed by public transport trips within different amounts of time.

	Within 2 h (1)	Within 3 h (2)	Within 6 h (3)
Treatment	0.355**	0.417**	0.475**
	(0.161)	(0.188)	(0.211)
R-squared	0.206	0.255	0.296
N	159	159	159
Control group mean	0.13	0.21	0.29

Note: The follow-up survey was collected during October–November 2016 and March–April 2017 as Table 1 details. The table indicates the treatment impact (being given a fare-free public transportation pass) on the walking trips preceded or followed by public transport trips within certain amount of hours (two, three, or six). Strata fixed effects are included in all regressions. Robust standard errors in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

5.4. The heterogeneity of the effect

We now turn to study the heterogeneity of the treatment effect by considering two strata for the three main variables of heterogeneity presented in Section 4 and explained in Section 5.1: household income, travel time to work as a proxy for the available time for leisure and household proximity to the subway network. We only find statistically significant heterogeneity in the effect of household proximity to a subway station, which is summarized in Table 9. The results of the heterogeneity with respect to income and commuting time are in Tables D.1 and D.2 in the Appendix.

Panel (A) of Table 9 confirms that there is no effect on total and public transport trips in peak periods. Regarding off-peak travel, column 2 of panel (B) in Table 9 shows that the impact of the travel pass on public transport trips is observed only for individuals who live within 1 km of a subway station (which is the sample median). The effect for this group is an increase of 3 public transport trips, which is a 43% increase relative to the control group. The result is significant at the 1% level, and we can reject the null hypothesis of equal effects for both groups at the 10% level. The fact that the coefficient for the group with long distance to the subway station is 0.352 confirms that the effect on public transport trips discussed in Section 5.2 is entirely driven by individuals who live close to the subway network. Finally, the coefficients for the total number of trips and non-motorized trips are larger and statistically significant for those close to a subway station, but we cannot reject the null hypothesis of equal effects across groups (p-values of 0.17 in column 1 and 0.17 in column 4).

Therefore, our main results that there are no effects on car trips and peak travel and that the main impact is the generation of off-peak trips by public transport and non-motorized modes are robust in the sense that they do not depend on income, available time or accessibility of the subway network. Moreover, the analysis reveals that the increase in off-peak public transport trips is entirely explained by new trips by individuals who live close (within 1 km) to a subway station.

6. Robustness tests

6.1. Timing

As a first robustness check, we study if there is temporal substitution of trips by individuals. One possibility is that individuals, as a result of having a fare-free transit pass, moved forward planned travel (which would bias estimates upwards). If this is the case, we should observe a stronger effect in the final days of the treatment period. On the other hand, the results could be driven by an experimentation effect of having immediate access to a fare-free public transport system. If this is driving the results, it could be expected that there is a stronger effect at the beginning of the treatment period that disappears after a couple of days.

We first separately estimate the average treatment effect for the five outcomes for each of the two treatment weeks. Table E.1 shows that there are no significant differences between the first and second weeks. We then estimate the treatment effects by day for off-peak public trans-

Table 9
Heterogeneity of the effect by distance from the individual's home to a subway station.

	Total (1)	Public Transport (2)	Car (3)	Non-motorized (4)	Other (5)
Panel A: Peak period trips					
T × short distance to subway	−0.050	−0.236	0.055	−0.454	0.544**
	(0.809)	(0.789)	(0.442)	(0.411)	(0.220)
T × long distance to subway	−0.173	0.072	−0.180	0.210	−0.257
	(0.664)	(0.639)	(0.515)	(0.363)	(0.209)
R-squared	0.779	0.829	0.896	0.844	0.796
N	158	158	158	158	158
Test F (equal effects across distance to subway strata) - p-value	0.91	0.77	0.73	0.24	0.01
Control group mean					
Short distance to subway	12.10	8.54	1.90	1.49	0.18
Long distance to subway	13.78	8.59	3.30	1.03	0.86
Panel B: Offpeak trips					
T × short distance to subway	4.917***	2.971***	−0.608	2.344***	0.608
	(1.284)	(1.047)	(1.098)	(0.875)	(0.470)
T × long distance to subway	2.190	0.352	1.371	0.844	0.148
	(1.435)	(0.979)	(0.929)	(0.584)	(0.496)
R-squared	0.743	0.669	0.750	0.707	0.703
N	158	158	158	158	158
Test F (equal effects across distance to subway strata) - p-value	0.17	0.08	0.19	0.17	0.50
Control group mean					
Short distance to subway	17.00	6.90	5.00	3.15	1.95
Long distance to subway	13.46	6.81	4.78	0.76	1.11

Note: The follow-up survey was collected during October–November 2016 and March–April 2017 as Table 1 details. The table indicates the treatment impact (being given a fare-free public transportation pass) on the total number of trips and on the number of trips by mode. All regressions include the predetermined baseline value of the outcome variable as a control. Strata fixed effects are included in all regressions. Panel A presents effects for trips made during peak periods, while panel B shows the effects for trips made during off-peak periods. In both panels, we present the p-value for the test of equality of coefficients across strata. The coefficients do not necessarily add up to the same amount when disaggregating trips by mode, as the total number of trips includes those without a stated mode. Robust standard errors in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

port trips. Table E.2 reveals that the treatment effects on baseline days are small and not statistically different from zero. In contrast, for the two treatment weeks all of the coefficients are positive and of similar magnitude and some of them are statistically significant at the 5% level. The large standard errors reflect that our sample is not big enough to capture daily effects. However, we do not see trends in the treatment effects by day that suggest the presence of a novelty effect wearing off or a temporal substitution from future weeks.

6.2. Transit pass data

As we discussed in Section 2.3, using transit card validations as the outcome may be problematic for several reasons. As evasion in buses is around 30%, we may observe a positive effect of the fare-free pass even if the number of trips is the same because treated individuals have more incentives to use the card. Also, it is not easy to differentiate trip stages from trips. Finally, the cards can be used to pay for other individuals' trips, travelers may have multiple cards, and the subway can be paid by cash or with a card, but buses can only be paid by card.

Nevertheless, we test the effect of the fare-free pass on the number of card transactions for each of the main outcomes as a way to corroborate the diary data. The sample of individuals for which we have card data is 12.5% smaller ($N = 139$). The results are summarized in Table E.3. We estimate our main specification in Eq. (6) using two outcomes based on the card data. The first outcome, the number of trips, is constructed by removing all the transactions identified as a transfer. A full fare varies between CLP$ 610 and CLP$ 800 depending on the mode and time of day. The transfer fee (if any) is the difference between the second stage's full fare and the first if the transactions occur within two hours. By removing all transactions charged less than a full fare, we have the number of trips.

The second outcome improves on the previous one by eliminating card transactions that pay for someone else's trip. The system charges two (or more) consecutive full fares if the card is used to enter the subway twice or is used on the same bus. Therefore, by removing all but one of the full-fare transactions within 10 min of another, we control (imperfectly) for payments for other individuals.

The results for the number of trips with and without consecutive trips are in columns (1) and (2) of Table E.3, respectively. Column (3) displays the previous sections' results using trip diary data for ease of comparison. Each panel represents a different aggregation of public transport trips: all trips, peak period trips, off-peak period trips, and trips in weeks 2 and 3.

We find that the overall effect is significantly larger when we use card transactions instead of trip-dairy data. There is an increase of 3.9 and 3.6 transactions in the two-week treatment period, for the two measures, significant at the 1% level (columns 1 and 2). The effect is around three times the effect found using diary trips (column 3). The larger effect on card transactions is also observed in peak travel, off-peak travel, and trips in week one and two. Another essential difference between the two methods is that we observe a large and significant increase in public transport trips at peak periods using card data. In off-peak travel, the results are similar using card data or trip diary data.

The fact that the aggregate number of card transactions and diary trips are similar for the control group, and the result that there is a significant effect of the pass using card data that is larger than the effect on diary trips supports our main results. As we control for transfers and potential payment for other individuals, the three possible explanations for the more substantial effect when using validations are baseline fare evasion, shifting the means of payment (e.g., from cash or another card not registered in the experiment), and card lending.

6.3. Others

As proximity to subways and distance to work seems to predict attrition, we test whether treatment effects change when reweighting observations in the data. To do this, we estimate the treatment effect on all trips, peak-period trips and off-peak trips by mode (as in Table 5) using inverse probability weighting. We include the same covariates as in the main regressions and add proximity to a subway station and distance to work. The results, in Table E.4 of the Appendices, show that the size and significance of the effects are almost the same as those in Table 5 and thus that our results are robust in this sense.

Because the main dependent variables are non-negative integer counts of trips, we also estimate the treatment effects using a count data model. As the outcomes, except for the total number of trips (aggregated by period and mode), have a significant amount of zeros and are overdispersed we estimate the treatment effects using a zero-inflated negative binomial regression. The detailed results are in Table E.5. In summary, the incidence-rate ratios obtained with the count data model are very similar as the percentage increase implied by the OLS regression. The main impact of fare-free public transport is an increase in the total number of trips made during off-peak periods. With OLS the effect is a 27% increase while with the zero-inflated negative binomial regression is 16%. This is explained by a 28% increase in public transport trips and a 77% increase in non-motorized trips according to the OLS regression. With the zero-inflated negative binomial regression those percentages are 15% and 70%.

To obtain further insights and because it is relevant for efficiency, our fourth robustness test is to differentiate the effect on off-peak public transport trips between those that use the subway and those that are made only by bus. Table E.6 confirms that the effect of the fare-free pass on off-peak public transport trips is entirely explained by trips that use the subway, as the coefficient for weekday off-peak is 1.167, which is significant at the 1% level and practically the same as that in Table 6 (1.22), and the effect on bus trips is zero.

The final robustness test is related to the heterogeneity concerning commuting time. An alternative proxy for time available for leisure, but following the same logic, could be the distance of the individual's place of residence to work. Table E.7 shows that the conclusions are the same, as the coefficients are very similar to those in Table D.2, and we cannot reject the null of equal coefficients across strata at the 5% level for any outcome.

7. Discussion and conclusion

7.1. External validity

Even though our study estimates the causal effect of fare-free public transport on the travel behavior of the individuals, a possible concern is that we are identifying an effect for a specific group not representative of Santiago's workers or population. Table F.1 presents the basic statistics of our sample compared to those of an average household and worker in Santiago.[15]

Table F.1 reveals that the average household income in the Santiago region is only 1% higher than our sample's average. The difference in average age is also negligible, while for gender and commuting time it is around 10%. The largest differences between our sample and the average household are found in car ownership and proximity to the subway network, where differences are around 25%. In our sample, 51% of the households report to have at least one car while the average for the city is 41%; the average distance to a subway station in our sample is 2.7 km and in Santiago is estimated at 3.4 km. We believe that these differences are not significant enough to raise strong concerns. Closer proximity and higher car ownership work in opposite directions as one favors transit usage and the other car travel. In addition, our main results are explained by individuals who live within 1 km of a subway station. We do not expect substantial changes when generalizing the results to a population that includes more individuals living further than one km. from the subway network.

As we discussed in Section 3, the modal shares in the baseline week for our sample are higher for public transport and lower for walking than the average observed in the 2012 Santiago Travel Survey.[16] This is a concern for the external validity of our results because, most likely, the difference is partially explained by self-selection into the experiment by people that use transit often. A second explanation is that our sample consists of workers, and travel patterns are different. Regardless of the reason, we are indeed obtaining the effect of fare-free public transport on individuals that use transit relatively more. However, as we explain above, the fact that the effect of the free transit card on public transport trips is positive only for individuals living within one km. of a subway station softens the concerns for external validity because these individuals are precisely those who use transit intensively.

To get a sense of how Santiago stands along with other middle-income cities, Table F.2 shows the 2014 GDP per capita and population for 20 other cities. In terms of GDP per capita, in 2014, Santiago is comparable with George Town, Saint Petersburg, Beijing, Buenos Aires, Shanghai, Hangzhou, Dubai, and Istambul. Among these, only Saint Petersburg and Hangzhou are similar in terms of population. Other main cities in Latin America, such as Lima, Bogota, Mexico City, and Sao Paulo, have a GDP per capita that is between 14% and 30% lower but have a population between 30% and 200% larger.

In terms of public transport affordability, measured as the ratio of expenditure in 45 public transport trips and the average per capita monthly income, Santiago is very similar to Lima and Mexico City. However, when using the average per capita income of the bottom income quintile, Santiago is considerably less affordable than Lima and Mexico City (Rivas et al., 2018). In other words, on average, it is not an expensive system, but for low-income households, it is.

7.2. Other considerations

Our main results are that access to fare-free public transport leads to an increase in the total number of trips that is entirely explained by an increase in off-peak travel. We find strong evidence that the impact of the fare-free pass is the generation of trips, and we see no evidence of transport mode or period of day substitution. We provide evidence that the mechanism behind this result is a change in activity patterns due to the change in the relative costs of the combination of activities and modes of transport. The effect of having access to fare-free public transportation is driven by an increase in the number of public transport trips in weekday off-peak periods by individuals that live within walking distance of a subway station.

In the short run, if fare-free public transport is applied to a group of workers, our results imply that the benefits come from increased mobility from those who live close to a subway station at the cost of fully subsidizing all public transport trips of the group that receives the pass. In this case, it seems that if fare-free transit is to be provided partially, it should target specific groups according to equity concerns such as those without the ability to pay for the trip or to foster the efficacy of job search for the unemployed (as in Franklin (2018)).

There are two potential sources of bias in our estimates. First, it is possible that individuals, as a result of having a fare-free transit pass, moved forward planned travel, which would bias estimates upwards. We do not have any data from the post-treatment period that could be used to test this, but the timing of effects within the two weeks are not

[15] Most of the data comes from the 2017 National Socioeconomic Survey and the 2012 Santiago Travel Survey. The details are explained in Table F.1.

[16] We use the shares in Table 30 of SECTRA (2014)'s "*Informe Ejecutivo*", which is the summary report.

consistent with this behavior. Second, as the randomization took place within employers, there could be spillover effects. If a set of individuals commute together by a mode other than transit (e.g., car) and only some are treated, our estimates may be downward biased if they continue to travel together. A similar bias can happen when planning the return trip. To get a sense of the size of the potential bias, we computed the number of individuals in a firm that live within one km from each other and are not in the same group (treated vs control). We found five sets satisfying these conditions (three trios and two pairs). We believe that the number of individuals living close, working at the same place and in different treatment arms is not large enough to bias our results significantly.

Extending our findings to obtain broader conclusions would require making assumptions. Since the experiment tested the effects of a fare-free public transport system for two weeks, the individuals had a somewhat limited opportunity to change their behavior over a medium- or long-term horizon and, for example, to reorganize their regular activities and routines. The changes in work routines or residential and work locations could imply reduced car travel. These effects are not captured in the experiment; however, most of them cannot be studied experimentally because people will not pay the fixed costs needed for large, discrete changes in transportation modes (e.g., buying a car or changing jobs). Nevertheless, the limited empirical evidence suggests that car travel is not sensitive to transit fare changes. For example, De Borger et al. (1996) report elasticities of car peak travel with respect to transit fares of 0.03, Storchmann (2003) reports a cross-elasticity of 0.017, and Börjesson et al. (2017) reports an elasticity of 0.13 for Stockholm.

Our findings of the impact of fare-free public transport on travel behavior contribute to understanding such policies' broader effect. While the causal effects on job search are well documented, there are fewer causal estimations on commuting and travel behavior in general. An important avenue for future research is to study the effects of fare-free transit in the long-run, primarily to assess the substitution between car and public transportation.

Appendix A. Survey questions and variable construction

In this section, we first present the questions used to define eligibility and the baseline data that are not related to travel patterns (e.g., income, household size). We then present the travel survey used in the three weeks of the experiment that allowed us to construct the baseline values of travel patterns and their outcomes. We end with a description of firms and the share of treated and control workers by firm.

The initial survey asked about basic information, socioeconomic characteristics and work schedules. The questions included name, date of birth, gender, address, household size, income, number of cars and motorcycles available in the household, transport modes used in the previous week and contact information. We also asked the following questions to define eligibility.

- Number of working hours per week that you work at this firm.
- Do you work or study somewhere else?
- Do you have a public transport smart card?
- If you have one, write your smart card number:

With this information, we define eligibility by excluding people with irregular work shifts (such as those who work every other week) and those in possession of a smart card with discounts (such as students and the elderly).

To obtain the travel patterns and outcomes, we used a survey to record daily trips based on the Santiago Travel Survey (SECTRA, 2014). For three weeks, participants were asked to report their trips every day. For each day, participants were given a travel diary in which they had to fill in the date and had 12 entries (one for each trip). Each entry asked 5 questions about the trip: trip purpose, time of departure, destination municipality, time of arrival and mode of transport used.

For trip purpose, the participants had to select one of the following 12 options:

Table A.1
Travel dairy: purpose selection.

To work	To study	Return home
Work trip	Shopping	Pick up/drop off someone
Errands	Visiting someone	Pick up/drop off something
Drink or eat out	Health-related trip	Other

From these options, we defined the purposes studied in Section 5. The purposes "to work" and "return home" are directly declared. Leisure and errands are the aggregation of shopping, visiting someone, drinking or eating out, errands and picking up/dropping off something. The rest of the purposes, categorized as "others", are those in Table A.1.

Table A.2
Summary statistics by trip purpose.

Variables	Average (1)	SD (2)	N (3)	Treatment (4)	Control (5)	P-value T = C (6)
To work	5.08	1.33	159	5.04	5.12	0.699
Return home	6.45	1.83	159	6.25	6.66	0.164
Leisure and errands	3.11	3.28	159	3.00	3.22	0.668
Others	0.52	1.09	159	0.46	0.58	0.486

Note: The baseline survey data were collected during October 2016 and March 2017 as Table 1 details. Columns (1)–(3) show the variable mean for the full sample, the standard deviation and the number of observations, respectively. Columns (4) and (5) show the variable mean for the treatment and control groups, respectively. Column (6) reports the p-value of the null hypothesis that Treatment = Control.

Table A.2 shows that individuals in the baseline week make 5.1 trips to work, which is consistent with a typical workweek, 3.1 trips for leisure and errands, 6.5 return trips to home, and 0.5 trips for other purposes. While all individuals reported trip purposes, some trips do not have a purpose stated, which means that the total number of trips may differ from those in the tables in previous sections. Nevertheless, the sample of trips with a stated purpose is also balanced, as column (6) of Table A.2 displays, and the number of trips without a purpose is only 0.2% of the total (14 out of 7045, not displayed in the table).

The participants had to write their mode of transport, and the travel diary mentioned several possible modes of transport:

- Car (driver or share)
- Bus
- Subway
- Bus and subway
- Walk
- Bicycle
- Taxi, Uber or similar
- Motorcycle

Appendix B. Travel patterns in the baseline week

Table B.1
Travel times in baseline by purpose.

Purpose	Average [min]	SD	Observations
To work	46.46	38.03	807
Return home	49.53	45.75	1014
Leisure	31.06	30.14	489
Other	38.43	48.83	82

Table B.2
Modal share in baseline. All trips.

Mode	Trips	Share
Car	572	22.1%
Car and other mode	14	0.5%
Bus	361	14.0%
Subway	382	14.8%
Bus and Subway	569	22.0%
Public transport and other	23	0.9%
Bicycle	76	2.9%
Walking	257	9.9%
Other	152	5.9%
N/A	180	7.0%
Total	2586	100.0%

Appendix C. Treatment arms by firm.

Table C.1
Number of treated and control workers by firm.

Firm	Total individuals	Treated (share)	Control (share)
1	43	0.51	0.49
2	18	0.56	0.44
3	13	0.46	0.54
4	31	0.48	0.52
5	10	0.5	0.5
6	8	0.5	0.5
7	20	0.5	0.5
8	12	0.5	0.5
9	15	0.53	0.47
10	8	0.5	0.5
11	5	0.6	0.4
12	13	0.54	0.46
13	11	0.55	0.45
Total	207	0.51	0.49

Appendix D. Heterogeneity with respect to income and commuting time

Table D.1
Heterogeneity of the effect by household income.

	Total (1)	Public Transport (2)	Car (3)	Non-motorized (4)	Other (5)
Panel A: Peak period trips					
T × low income	−0.311	−0.109	−0.355	−0.132	0.251
	(0.583)	(0.683)	(0.342)	(0.385)	(0.239)
T × high income	−0.179	−0.303	0.300	−0.270	0.032
	(0.916)	(0.839)	(0.607)	(0.383)	(0.244)
R-squared	0.780	0.825	0.911	0.872	0.801
N	143	143	143	143	143
Test F (equal effects across income strata) - p-value	0.91	0.86	0.34	0.80	0.55
Control group mean					
Low household income	12.35	8.39	1.97	1.23	0.77
High household income	13.46	8.83	3.29	0.98	0.37
Panel B: Offpeak trips					
T × low income	2.408	0.005	0.248	2.334***	0.251
	(1.540)	(1.164)	(0.820)	(0.798)	(0.500)
T × high income	4.553***	2.214**	1.266	1.152	0.234
	(1.440)	(0.895)	(1.341)	(0.821)	(0.571)
R-squared	0.722	0.643	0.768	0.688	0.683
N	143	143	143	143	143
Test F (equal effects across income strata) - p-value	0.33	0.14	0.52	0.31	0.98
Control group mean					
Low household income	14.97	8.26	4.03	1.32	1.35
High household income	16.15	6.02	5.78	2.63	1.71

Note: The follow-up survey was collected during October–November 2016 and March–April 2017 as Table 1 details. The table indicates the treatment impact (being given a fare-free public transportation pass) on the total number of trips and on the number of trips by mode. All regressions include the predetermined baseline value of the outcome variable as a control. Strata fixed effects are included in all regressions. Panel A presents effects for trips made during peak periods, while panel B shows the effects for trips made during off-peak periods. In both panels, we present the p-value for the test of equality of coefficients across strata. The coefficients do not necessarily add up to the same amount when disaggregating trips by mode, as the total number of trips includes those without a stated mode. Robust standard errors in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table D.2
Heterogeneity of the effect by commuting travel time.

	Total (1)	Public Transport (2)	Car (3)	Non-motorized (4)	Other (5)
Panel A: Peak period trips					
T × low commuting time	−1.255*	−0.602	−0.448	−0.277	0.093
	(0.721)	(0.702)	(0.576)	(0.472)	(0.232)
T × high commuting time	1.025	0.300	0.404	0.150	0.086
	(0.770)	(0.730)	(0.356)	(0.283)	(0.194)
R-squared	0.761	0.826	0.897	0.837	0.798
N	154	154	154	154	154
Test F (equal effects across commuting time strata) - p-value	0.04	0.39	0.19	0.45	0.98
Control group mean					
Low commuting time	14.30	7.38	4.35	1.81	0.76
High commuting time	11.87	9.95	0.89	0.76	0.26
Panel B: Offpeak trips					
T × low commuting time	4.725***	1.728*	0.536	2.171***	0.878*
	(1.290)	(1.022)	(1.143)	(0.813)	(0.529)
T × high commuting time	2.285	1.532	0.249	0.616	0.081
	(1.516)	(1.108)	(0.918)	(0.532)	(0.370)
R-squared	0.744	0.671	0.746	0.695	0.704
N	154	154	154	154	154
Test F (equal effects across commuting time strata) - p-value	0.24	0.90	0.85	0.11	0.21
Control group mean					
Low commuting time	16.08	5.51	6.32	2.41	1.84
High commuting time	14.16	8.29	3.63	1.21	1.03

Note: The follow-up survey was collected during October–November 2016 and March–April 2017 as Table 1 details. The table indicates the treatment impact (being given a fare-free public transportation pass) on the total number of trips and on the number of trips by mode. All regressions include the predetermined baseline value of the outcome variable as a control. Strata fixed effects are included in all regressions. Panel A presents effects for trips made during peak periods, while panel B shows the effects for trips made during off-peak periods. In both panels, we present the p-value for the test of equality of coefficients across strata. The coefficients do not necessarily add up to the same amount when disaggregating trips by mode, as the total number of trips includes those without a stated mode. Robust standard errors in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Appendix E. Robustness tests

Table E.1
Robustness: treatment effect differentiated by week.

	Total trips (1)	PT trips (2)	Car trips (3)	Non-motorized trips (4)	Other (5)
Panel A: Main effects (week 2 + week 3)					
Treatment	3.401***	1.372	0.499	1.442***	0.498
	(1.074)	(0.875)	(0.787)	(0.524)	(0.418)
R-squared	0.714	0.733	0.867	0.820	0.719
N	159	159	159	159	159
Control group mean	28.20	15.42	7.47	3.25	2.05
Panel B: Week 2					
Treatment	1.695***	0.659	0.337	0.431	0.396
	(0.529)	(0.472)	(0.399)	(0.312)	(0.243)
R-squared	0.722	0.732	0.851	0.799	0.728
N	159	159	159	159	159
Control group mean	14.71	8.01	3.87	1.78	1.05
Panel C: Week 3					
Treatment	1.706**	0.713	0.162	1.011***	0.102
	(0.736)	(0.532)	(0.496)	(0.341)	(0.245)
R-squared	0.592	0.641	0.821	0.700	0.598
N	159	159	159	159	159
Control group mean	13.49	7.41	3.61	1.47	1.00

Note: The follow-up survey was collected during October–November 2016 and March–April 2017 as Table 1 details. The table indicates the treatment impact (being given a fare-free public transportation pass) on the total number of trips and on the number of trips by mode. All regressions include the predetermined baseline value of the outcome variable as a control. Strata fixed effects are included in all regressions. Panel A presents effects for all trips, panel B shows the effects for trips made during the first week of treatment, and panel C reports those for the second week. The coefficients do not necessarily add up to the same amount when disaggregating trips by mode, as the total number of trips includes those without a stated mode. Robust standard errors in parentheses. *p < 0.1, **p < 0.05, ***p < 0.01.

Table E.2
Robustness: treatment effect differentiated by day.

	Public Transport (1)
Baseline day 1	0.092
	(0.097)
Baseline day 2	0.113
	(0.138)
Baseline day 3	−0.079
	(0.123)
Baseline day 4	0.206*
	(0.114)
Baseline day 5	0.133
	(0.103)
Baseline day 6	0.061
	(0.118)
Baseline day 7	0.081
	(0.106)
Treatment Day 1	0.196*
	(0.106)
Treatment Day 2	0.282**
	(0.141)
Treatment Day 3	0.113
	(0.113)
Treatment Day 4	0.043
	(0.115)
Treatment Day 5	0.133
	(0.119)
Treatment Day 6	0.194
	(0.124)
Treatment Day 7	0.142
	(0.116)
Treatment Day 8	0.107
	(0.101)
Treatment Day 9	0.295**
	(0.126)
Treatment Day 10	0.137
	(0.123)
Treatment Day 11	0.167
	(0.109)
Treatment Day 12	0.022
	(0.131)
Treatment Day 13	0.081
	(0.126)
Treatment Day 14	0.108
	(0.119)
R-squared	0.162
N	3311

Note: The follow-up survey was collected during October–November 2016 and March–April 2017 as Table 1 details. The table indicates the treatment impact (being given a fare-free public transportation pass) on the total number of trips per day by public transport. The regression includes day of the week and strata fixed effects and a dummy that takes the value of one for working days. Robust standard errors in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table E.3
Robustness: treatment effect using card transaction data differentiated by week.

	Card transactions	Card transactions without consecutive trips	Trips (diary)
	(1)	(2)	(3)
Panel A: All trips.			
Treatment	3.893***	3.582***	1.372
	(1.110)	(1.095)	(0.875)
R-squared	0.648	0.640	0.733
N	139	139	159
Control group mean	15.38	15.12	15.42
Panel B: Peak period			
Treatment	1.923***	1.883***	−0.109
	(0.589)	(0.585)	(0.472)
R-squared	0.749	0.734	0.829
N	139	139	159
Control group mean	7.03	6.97	8.57
Panel C: Off-Peak period			
Treatment	1.978**	1.723**	1.595**
	(0.867)	(0.855)	(0.694)
R-squared	0.529	0.511	0.660
N	139	139	159
Control group mean	8.35	8.15	6.86
Panel D: Week 2			
Treatment	2.582***	2.489***	0.659
	(0.612)	(0.601)	(0.472)
R-squared	0.686	0.682	0.732
N	139	139	159
Control group mean	7.82	7.63	8.01
Panel E: Week 3			
Treatment	1.341**	1.093*	0.713
	(0.654)	(0.650)	(0.532)
R-squared	0.538	(0.527)	0.641
N	139	139	159
Control group mean	7.57	7.48	7.41

Note: The follow-up survey was collected during October–November 2016 and March–April 2017 as Table 1 details. The table indicates the treatment impact (being given a fare-free public transportation pass) on the total number of transit pass validations and on the total number of public transport trips declared in the dairy. All regressions include the predetermined baseline value of the outcome variable as a control and strata fixed effects. Panel A presents effects for all trips, panel B shows the effects for trips made during the first week of treatment, and panel C reports those for the second week. Robust standard errors in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table E.4
Treatment effect on all trips, peak-period trips and off-peak trips using inverse probability weighting.

	Total (1)	Public Transport (2)	Car (3)	Non-motorized (4)	Other (5)
Panel A: All trips.					
Treatment	3.263***	1.367	0.638	1.290***	0.452
	(0.978)	(0.841)	(0.816)	(0.486)	(0.390)
N	158	158	158	158	158
Control group mean	28.20	15.42	7.47	3.25	2.05
Panel B: Peak period trips.					
Treatment	−0.128	−0.067	−0.081	−0.049	0.089
	(0.454)	(0.463)	(0.310)	(0.230)	(0.145)
R-squared	0.732	0.788	0.872	0.817	0.742
N	158	158	158	158	158
Control group mean	12.92	8.57	2.58	1.26	0.51
Panel C: Off-Peak period trips.					
Treatment	3.179***	1.490**	0.488	1.357***	0.313
	(0.914)	(0.658)	(0.673)	(0.281)	(0.313)
R-squared	0.658	0.584	0.687	0.636	0.655
N	158	158	158	158	158
Control group mean	15.28	6.86	4.89	1.99	1.54

Note: The follow-up survey was collected during October–November 2016 and March–April 2017 as Table 1 details. The table indicates the treatment impact (being given a fare-free public transportation pass) on the total number of trips and on the number of trips by mode. All regressions use the predetermined baseline value of the outcome variable, fixed effects at the firm level, distance to work and proximity to a subway station as the vector of covariates. Panel A presents effects for all trips, while panel B shows the effects for trips made in peak periods, and panel C reports those in off-peak periods. The coefficients do not necessarily add up to the same amount when disaggregating trips by mode or period, as the total number of trips includes those without a stated mode or time of day. Robust standard errors in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table E.5
Treatment effect on all trips, peak-period trips and off-peak trips. Zero-inflated negative binomial regression.

	Total (1)	Public Transport (2)	Car (3)	Non-motorized (4)	Other (5)
Panel A: All trips.					
Treatment	0.093***	0.053	−0.091	0.462***	−0.338
	(0.032)	(0.050)	(0.184)	(0.151)	(0.230)
R-squared	.	.	.	.	.
N	159	159	159	159	159
Control group mean	28.20	15.42	7.47	3.25	2.05
Panel B: Peak period trips.					
Treatment	0.005	−0.022	0.000	0.685***	−0.445
	(0.034)	(0.048)	(0.151)	(0.244)	(0.476)
R-squared	.	.	.	.	.
N	159	159	159	159	159
Control group mean	12.92	8.57	2.58	1.26	0.51
Panel C: Off-Peak period trips.					
Treatment	0.157***	0.153*	−0.133	0.695***	−0.176
	(0.054)	(0.079)	(0.194)	(0.201)	(0.160)
R-squared	.	.	.	.	.
N	159	159	159	159	159
Control group mean	15.28	6.86	4.89	1.99	1.54

Note: The follow-up survey was collected during October–November 2016 and March–April 2017 as Table 1 details. The table indicates the coefficient of the treatment dummy (being given a fare-free public transportation pass) in the binomial regression, for the total number of trips and the number of trips by mode. All regressions use the predetermined baseline value of the outcome variable, and fixed effects at the firm level. Panel A presents effects for all trips, while panel B shows the effects for trips made in peak periods, and panel C reports those in off-peak periods. The coefficients do not necessarily add up to the same amount when disaggregating trips by mode or period, as the total number of trips includes those without a stated mode or time of day. Robust standard errors in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table E.6
Treatment effect on weekday off-peak trips that use the subway and that are made by bus.

	Trips that use the subway (1)	Trips made by bus (2)
Panel A: Weekday off peak.		
Treatment	1.167***	0.033
	(0.410)	(0.275)
R-squared	0.782	0.696
N	159	159
Control group mean	2.93	1.39
Panel B: Weekend		
Treatment	0.119	0.285
	(0.332)	(0.265)
R-squared	0.509	0.350
N	159	159
Control group mean	1.59	0.93

Note: The follow-up survey was collected during October–November 2016 and March–April 2017 as Table 1 details. The table indicates the treatment impact (being given a fare-free public transportation pass) on the number of trips that use the subway and those made by bus only. All regressions include the predetermined baseline value of the outcome variable as a control. Strata fixed effects are included in all regressions. Panel A presents effects for trips made during weekday off-peak periods, while panel B shows the effects for trips made during weekends. Robust standard errors in parentheses. *p < 0.1, **p < 0.05, ***p < 0.01.

Table E.7
Heterogeneity of the effect by distance to work.

	Total (1)	Public Transport (2)	Car (3)	Non-motorized (4)	Other (5)
Panel A: Peak period trips					
T × short commuting distance	−0.875	−0.754	0.303	−0.319	0.065
	(0.837)	(0.791)	(0.427)	(0.478)	(0.234)
T × long commuting distance	0.771	0.742	−0.285	0.088	0.141
	(0.672)	(0.707)	(0.482)	(0.301)	(0.155)
R-squared	0.782	0.833	0.898	0.842	0.786
N	158	158	158	158	158
Test F (equal effects across commuting distance strata) - p-value	0.15	0.19	0.32	0.50	0.79
Control group mean					
Short commuting distance	13.82	7.94	2.94	2.00	0.94
Long commuting distance	12.23	9.05	2.30	0.70	0.19
Panel B: Offpeak trips					
T × short commuting distance	3.862***	1.324	0.389	2.158**	0.485
	(1.240)	(1.026)	(1.115)	(0.854)	(0.592)
T × long commuting distance	2.235	1.775	−0.018	0.743	0.259
	(1.408)	(1.124)	(0.795)	(0.475)	(0.363)
R-squared	0.758	0.662	0.754	0.704	0.699
N	158	158	158	158	158
Test F (equal effects across commuting distance strata) - p-value	0.41	0.78	0.77	0.15	0.74
Control group mean					
Short commuting distance	17.06	6.21	5.48	3.18	2.18
Long commuting distance	13.91	7.35	4.44	1.07	1.05

Note: The follow-up survey was collected during October–November 2016 and March–April 2017 as Table 1 details. The table indicates the treatment impact (being given a fare-free public transportation pass) on the total number of trips and on the number of trips by mode. All regressions include the predetermined baseline value of the outcome variable as a control. Strata fixed effects are included in all regressions. Panel A presents effects for trips made during peak periods, while panel B shows the effects for trips made during off-peak periods. In both panels, we present the p-value for the test of equality of coefficients across strata. The coefficients do not necessarily add up to the same amount when disaggregating trips by mode, as the total number of trips includes those without a stated mode. Robust standard errors in parentheses. *p < 0.1, **p < 0.05, ***p < 0.01.

Table E.8
Heterogeneity of the effect by workplace-subway proximity.

	Total (1)	Public Transport (2)	Car (3)	Non-motorized (4)	Other (5)
Panel A: Peak period trips					
T × short workplace-subway distance	−0.208	−0.086	0.230	−0.621	0.255
	(0.909)	(0.741)	(0.550)	(0.401)	(0.282)
T × long workplace-subway distance	−0.025	−0.016	−0.319	0.288	0.003
	(0.497)	(0.639)	(0.400)	(0.328)	(0.155)
R-squared	0.775	0.835	0.896	0.853	0.785
N	159	159	159	159	159
Test F (equal effects across workplace-subway distance strata) - p-value	0.86	0.94	0.41	0.08	0.47
Control group mean					
Short workplace-subway distance	11.83	9.44	0.72	1.25	0.42
Long workplace-subway distance	13.90	7.78	4.25	1.27	0.60
Panel B: Offpeak trips					
T × short workplace-subway distance	5.095***	1.949*	0.858	1.798**	0.842
	(1.393)	(1.067)	(1.081)	(0.743)	(0.559)
T × long workplace-subway distance	1.784	1.115	−0.050	1.311*	−0.090
	(1.290)	(0.909)	(0.967)	(0.711)	(0.416)
R-squared	0.748	0.671	0.747	0.693	0.704
N	159	159	159	159	159
Test F (equal effects across workplace-subway distance strata) - p-value	0.08	0.55	0.55	0.63	0.19
Control group mean					
Short workplace-subway distance	15.56	7.64	3.28	2.78	1.86
Long workplace-subway distance	15.03	6.15	6.35	1.27	1.25

Note: The follow-up survey was collected during October–November 2016 and March–April 2017 as Table 1 details. The table indicates the treatment impact (being given a fare-free public transportation pass) on the total number of trips and on the number of trips by mode. All regressions include the predetermined baseline value of the outcome variable as a control. Strata fixed effects are included in all regressions. Panel A presents effects for trips made during peak periods, while panel B shows the effects for trips made during off-peak periods. In both panels, we present the p-value for the test of equality of coefficients across strata. The coefficients do not necessarily add up to the same amount when disaggregating trips by mode, as the total number of trips includes those without a stated mode. Robust standard errors in parentheses. *p < 0.1, **p < 0.05, ***p < 0.01.

Appendix F. External validity

Table F.1
Comparison of our sample with Santiago's population.

Variable (Mean and standard error)	Our Sample	Socio-economic National Survey
Gender [1 = man]	0.60	0.54
	(0.49)	(0.50)
Age	41.59	41.86
	(12.45)	(14.18)
Commuting time [min]	46.77	42.50
	(27.00)	(33.86)
Size of household	3.88	3.13
	(1.99)	(1.62)
Household monthly income [US]	1843	1864
	(1581)	(2632)
Household car ownership [1 = one or more cars]	0.51	0.41
	(0.50)	(0.49)
Household proximity to a subway station [km]	2.67	3.42
	(4.68)	(4.14)

Note: The data for gender, age, commuting time, household size, and household income are computed directly from MDS (2017). Car ownership is computed from SECTRA (2014). The proximity to a subway station is not available in any survey; to obtain an estimation, we calculate the minimum distance from every block in the city to the nearest subway station using the shapefile from the SII and geo-referenced information on subways Observatory of cities of the Pontificia Universidad Católica de Chile (Observatorio de Ciudades UC), and the pre-census street shapefile.

Table F.2
Comparison of Santiago's population and GDP with other cities.

Metro area	Country	GDP per capita - 2014 (PPP, US$)	Population - 2014
Porto Alegre	Brazil	15,078	4,120,900
Belo Horizonte	Brazil	15,134	5,595,800
Lima	Peru	16,530	10,674,100
Guadalajara	Mexico	17,206	4,687,700
Bogota	Colombia	17,497	9,135,800
Mexico City	Mexico	19,239	20,976,700
Naples	Italy	19,451	4,394,400
Sao Paulo	Brazil	20,650	20,847,500
Porto	Portugal	21,674	1,983,200
George Town	Malaysia	23,079	1,646,200
Saint Petersburg	Russia	23,361	5,120,200
Beijing	China	23,390	21,639,100
Buenos Aires	Argentina	23,606	13,381,800
Santiago	Chile	23,929	7,164,400
Shanghai	China	24,065	24,683,400
Hangzhou	China	24,637	8,909,700
Dubai	UAE	24,866	3,332,500
Istanbul	Turkey	24,867	14,023,500
Monterrey	Mexico	28,290	4,344,200
Guangzhou	China	29,014	13,106,300
Nanjing	China	31,434	6,448,200

Source: Parilla et al. (2015).

References

Abebe, G., Caria, S., Fafchamps, M., Falco, P., Franklin, S., Quinn, S., 2016. Curse of Anonymity or Tyranny of Distance? the Impacts of Job-Search Support in Urban ethiopia. National Bureau of Economic Research. Technical report.

Abou-Zeid, M., Ben-Akiva, M., 2012. Travel mode switching: comparison of findings from two public transportation experiments. Transport Pol. 24, 48–59.

Banerjee, A.V., Sequeira, S., 2020. Spatial Mismatches and Imperfect Information in the Job Search.

Basso, L.J., Silva, H.E., 2014. Efficiency and substitutability of transit subsidies and other urban transport policies. Am. Econ. J. Econ. Pol. 6 (4), 1–33.

Bloomberg, 2018. Free Public Transportation Isn't for Everyone. December 14. Bloomberg Opinion, https://www.bloomberg.com/opinion/articles/2018-12-14/luxembourg-s-free-public-transportation-isn-t-for-everyone. (Accessed 19 December 2018).

Börjesson, M., Fung, C.M., Proost, S., 2017. Optimal prices and frequencies for buses in stockholm. Econ. Transport. 9, 20–36.

Brough, R., Freedman, M., Phillips, D., 2019. A (Free) Ticket to Ride: Evidence on the Effects of Subsidized Public Transportation.

Cats, O., Reimal, T., Susilo, Y., 2014. Public transport pricing policy: empirical evidence from a fare-free scheme in tallinn, Estonia. Transport. Res. Rec. 2415 (1), 89–96.

Cats, O., Susilo, Y.O., Reimal, T., 2017. The prospects of fare-free public transport: evidence from tallinn. Transportation 44 (5), 1083–1104.

De Borger, B., Mayeres, I., Proost, S., Wouters, S., 1996. Optimal pricing of urban passenger transport: a simulation exercise for Belgium. J. Transport Econ. Pol. 31–54.

De Witte, A., Macharis, C., Mairesse, O., 2008. How persuasive is free public transport?: a survey among commuters in the brussels capital region. Transport Pol. 15 (4), 216–224.

DTPM, 2017. Informe de Gestión 2017. Directorio de Transporte Público Metropolitano.

EMTA, 2018. Barometer 2016 of Public Transport in the European Metropolitan Areas.

Fearnley, N., 2013. Free fares policies: impact on public transport mode share and other transport policy goals. Int. J. Transport. 1 (1).

Franklin, S., 2018. Location, search costs and youth unemployment: experimental evidence from transport subsidies. Econ. J. 128 (614), 2353–2379.

Glaister, S., Lewis, D., 1978. An integrated fares policy for transport in london. J. Publ. Econ. 9 (3), 341–355.

Hidalgo, D., Huizenga, C., 2013. Implementation of sustainable urban transport in Latin america. Res. Transport. Econ. 40 (1), 66–77.

INE, 2016. Encuesta Nacional de Empleo. Trimestre móvil Octubre-Diciembre 2015. Instituto Nacional de Estadísticas, Chile.

INE, 2018. Síntesis de Resultados, VIII EPF. Instituto Nacional de Estadísticas.

Jara-Díaz, S., Cruz, D., Casanova, C., 2016. Optimal pricing for travelcards under income and car ownership inequities. Transport. Res. Pol. Pract. 94, 470–482.

Jara-Díaz, S.R., 2007. Transport Economic Theory. Elsevier.

Litman, T., 2017. *Transportation Elasticities: How Prices and Other Factors Affect Travel Behavior*. Technical Report. Victoria Transport Policy Institute, Victoria, BC, Canada, http://www.vtpi.org/elasticities.pdf. (Accessed 20 March 2017).

MDS, 2017. Encuesta de Caracterización Socioeconómica Nacional: ingreso de los hogares. Ministerio de Desarrollo Social, Chile.

Mohring, H., 1972. Optimization and scale economies in urban bus transportation. Am. Econ. Rev. 62 (4), 591–604.

Parilla, J., Trujillo, J.L., Berube, A., Ran, T., 2015. Global Metro Monitor 2014: an Uncertain Recovery. The Brookings institution, Metropolitan policy program, USA.

Parry, I.W., Small, K.A., 2009. Should urban transit subsidies be reduced? Am. Econ. Rev. 99 (3), 700–724.

Phillips, D.C., 2014. Getting to work: experimental evidence on job search and transportation costs. Lab. Econ. 29, 72–82.

Proost, S., Van Dender, K., 2008. Optimal urban transport pricing in the presence of congestion, economies of density and costly public funds. Transport. Res. Pol. Pract. 42 (9), 1220–1230.

Rivas, M., Serebrisky, T., Suárez-Alemán, A., 2018. How Affordable is Transportation in Latin America and the Caribbean?, vol. 1588. Inter-American Development Bank Technical Note.

SECTRA, 2014. Actualización y Recolección de Información del Sistema de Transporte Urbano, Etapa IX. Secretaría Interministerial de Planificación de Transporte, Chile.

Shampanier, K., Mazar, N., Ariely, D., 2007. Zero as a special price: the true value of free products. Market. Sci. 26 (6), 742–757.

Silva, H.E., 2019. The Mohring Effect. Documento de Trabajo IE-PUC. No. 529.

Small, K.A., Verhoef, E.T., 2007. The Economics of Urban Transportation. Routledge, New York.

Storchmann, K., 2003. Externalities by automobiles and fare-free transit in Germany - a paradigm shift? J. Publ. Transport. 6 (4), 5.

The Economist, 2013. Maybe Buses Should Be Free. June 19. Gulliver, https://www.economist.com/gulliver/2013/06/19/maybe-buses-should-be-free. (Accessed 30 August 2018).

The Guardian, 2018. German Cities to Trial Free Public Transport to Cut Pollution. International Edition. February 14 https://www.theguardian.com/world/2018/feb/14/german-cities-to-trial-free-public-transport-to-cut-pollution. (Accessed 31 August 2018).

The Independent, 2018. Paris Considers Making Public Transport Free to Reduce Pollution. March 23 https://www.independent.co.uk/news/world/europe/paris-public-transport-free-pollution-anne-hidalgo-cars-a8269581.html. (Accessed 31 August 2018).

The New York Times, 2009. Bloomberg Calls for Free Crosstown Buses. August 3, City Room Blog. https://cityroom.blogs.nytimes.com/2009/08/03/bloomberg-calls-for-free-crosstown-buses/. (Accessed 30 August 2018).

Thøgersen, J., 2009. Promoting public transport as a subscription service: effects of a free month travel card. Transport Pol. 16 (6), 335–343.

Tiznado-Aitken, I., Muñoz, J.C., Hurtubia, R., 2018. The role of accessibility to public transport and quality of walking environment on urban equity: The case of Santiago de Chile. Transportation Research Record.

Train, K., McFadden, D., 1978. The goods-leisure trade-off and disaggregate work trip mode choice models. Transport. Res. 12, 349–353.

Van Dender, K., 2003. Transport taxes with multiple trip purposes. Scand. J. Econ. 105 (2), 295–310.