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# 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)*

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**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) that allowed them unlimited travel for two weeks. The main impact of fare-free public transport is a 21% increase in the total number of trips made during off-peak periods. Two-thirds of the effect occurs during weekday off-peak periods and is mostly explained by a 24% 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.

*Keywords:* Public transport pricing, Fare-free public transport
JEL Codes: R48, H23

## 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

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*Email addresses:* `ombull@uc.cl` (Owen Bull), `jcm@ing.puc.cl` (Juan Carlos Muñoz), `husilva@uc.cl` (Hugo 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.

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 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,

[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).

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

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.

In this study, we investigate the causal effect of providing a fare-free public transport system on 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 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. We also find that the pass did not change the number of trips made by public transport at peak periods. Therefore, we find no evidence that fare-free public transport decreases negative externalities or increases public transport crowding during peak periods.

Another main result of the analysis 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 21% increase relative to the control group. Thus, 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. The analysis also reveals that two-thirds of the effect of fare-free public transport occurs during weekday off-peak periods, where we find a 24% increase in public transport trips.

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.

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

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 one kilometer 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]

To interpret our results and their implications, we need to distinguish the short-run effects from the long-run effects that would exist if the policy were implemented at a system-wide scale. First, 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)).

To interpret the long-term implications of implementing fare-free public transport in the entire system, we need to make several assumptions. Before any demand and supply-side adaptation, the direct cost of the policy can be approximated by the marginal cost of the public funds required to make the system fare-free. Using the 2018 revenues from fares in the Santiago system published by DTPM (2018), US$ 941 million, and a marginal cost of public funds of 15%, the direct cost would be US$ 141 million per year.[6] On the other hand, one source of direct savings is the cost of the fare collection and the network of card sale and top-up points. For Santiago, in 2018, this cost was US$ 124 million, which is approximately 7% of the total operational cost (DTPM, 2018). This shows that direct benefits and costs are similar, at least for the current situation in Santiago.

Next, assuming that the effects that we observe stand in the long run, there would be a 24% increase in public transport ridership on weekday off-peak periods. We use estimates of

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

[6] This is obtained using the exchange rate as of March 2017 and assuming that the only cost of the transfer is 15%. A more realistic calculation would consider other factors, such as the operational costs of raising and distributing the funds. Our figure is not meant to be precise.

the marginal costs and scale economies from Batarce and Galilea (2018) for Santiago and the weekday off-peak travel pattern from SECTRA (2014) to approximate the additional cost if supply is adjusted accordingly. We estimate that our results imply a 13% overall increase in ridership and a 6% decrease in average operating costs, which together lead to an increase of US$ 90.7 million per year in operating costs. However, the supply adjustment should also imply a reduction in waiting times for off-peak trips on weekdays. We estimate that every minute reduction in waiting time for weekday off-peak transit users yields a benefit of US$ 41 million per year. Therefore, the supply adjustment has to induce an average reduction of 3 minutes to generate benefits that equal the increased operating costs and the net result of the direct effects discussed above. This simple back-of-the-envelope calculation reveals that it is feasible that a fare-free policy in Santiago would require an investment of 1 US$ billion per year and generate benefits from decreased waiting times and fare-collection cost savings that are offset by the increased operational costs and the marginal cost of the public funds.[7]

Some qualifications need to be considered for the large scale and long-run implications. First, there are benefits from increased access to opportunities during off-peak periods that we ignore in the calculations. Second, when buses are fare-free, there is no need to place the travel card on the card reader, and thus there could be substantial gains from faster boarding that would increase service quality and reduce operational costs.[8] Third, in the long run, fare-free public transport may induce people to change their work routines or residential and work locations, which 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, our results are consistent with the limited evidence on transit price elasticities of car usage. 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. Nevertheless, the benefits from increased service quality can be achieved by investing in road infrastructure for buses, stops and payment technology and those from reduced car travel through car congestion pricing. Basso and Silva (2014) show, using data from London and Santiago, that dedicating road capacity exclusively to buses while optimally adjusting the supply can yield benefits that are comparable to those of car congestion pricing. Moreover, both dedicated bus lanes and congestion pricing yield larger benefits than the optimal subsidization.

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

[7] The details of the calculations are in Appendix A.

[8] Jara-Díaz and Tirachini (2013) find that off-vehicle payment can imply a boarding time reduction of between 0.1 and 0.3 seconds per passenger relative to a contactless card.

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 a discussion and conclusions in Section 6.

## 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, but a derived demand. Finally, assigning time to travel, and especially in the case of commuting, harms utility as people would rather be doing something else.

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.[9]

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. They argue that the effect is low because of the particular conditions that existed before the elimination of the fare, namely, a good level of service, high usage, and low public transport fares.

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

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. He finds that the share of public transport commuting trips increased from 5% to 10%. However, the results are difficult to interpret because the allocation to treatment was complex. First, participants were randomly assigned to treatment and control, leading to 70% of participants in the treatment group. Those in the treatment group that expressed an intention to commute by mass transit in the near future were randomly assigned to two possible treatments: a planning exercise or a planning exercise together with a free monthly travel pass. Those in the treatment group who declared no intention to commute by public transport were also assigned to either one of the two treatments above or a third group in which information on timetables was given. After analyzing the results, the author excluded all treated individuals who did not receive the monthly pass. The result was a treatment group 66% larger than the control group, and the author does not report whether the sample and attrition are balanced.

To the best of our knowledge, this 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.

### *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 2,834 km with a fleet of 6,681 buses, and a light rail line of 20 km. (DTPM, 2017).[10] The city has an integrated fare payment system that works with a contactless smartcard. The fares on the subway and buses are similar and approximately equal to US$1.1, and multiple transfers are allowed at no additional cost.[11] 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).

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

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

[11] The maximum amount that is paid for the various transfers is the most expensive fare between the two modes. Because subway fares vary with the time of day, the maximum fare paid for a trip with multiple transfers varies over the day.

average speed of a car trip during a workday was 16.2 km/hr, and the average travel time for cars and buses in the morning peak was 42 and 66 minutes, respectively, which highlights the level of congestion in the city.

### 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).

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). We also used as a criterion to contact those firms with the highest number of employees who work only at one location. 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 the largest three employers, and the second period started in March 2017 with the remaining ten firms.

People within each firm were offered the opportunity to participate in the experiment and 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.1 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.[12] We also excluded individuals who already enjoyed government-financed fare discounts, such as age discounts, to ensure that the treatment was homogenous (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.

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

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. Appendix A.1 describes the surveys used to define eligibility 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. Participants assigned to the treatment group were given a public transport card 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 (approximately equivalent to paying twenty public transport trips). To avoid under-reporting by the control group, we checked their 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.

Stratified randomization was performed within each firm when the sample size was large enough to allow for it, according to the participants' intensity of public transport use (measured using their Santiago fare card data for the 90 days immediately before the study period). Table 1 summarizes the timeline of the experimental study.

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 |

## 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.

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 | 207 | 159 | 0.77 |

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. One possible concern with our sample is that we are obtaining effects for the wealthy part of the distribution, as we are focusing only on workers. However, the National Socio-economic Survey reveals that the average household income in the Santiago region is US$1,849 (MDS, 2017), ruling out this concern. 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. The last rows 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.

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.

Table 3: Summary statistics and balance between treatment and control groups at baseline

| Variables | Average (1) | SD (2) | N (3) | Treat. (4) | Control (5) | p-value T=C (6) |
|---|---|---|---|---|---|---|
| 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 [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] | 1,843 | 1,581 | 143 | 1,862 | 1,824 | 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 |
| No. of public transport trips in baseline week | 8.48 | 4.68 | 159 | 8.94 | 7.99 | 0.200 |
| Household proximity to a subway station [km] | 2.67 | 6.44 | 158 | 2.21 | 3.16 | 0.356 |
| Low income (N= 71) | 828 | 264 | 143 | 826 | 829 | 0.958 |
| High income (N= 72) | 2,844 | 1,698 | 143 | 3,198 | 2,577 | 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 |

*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.

As Table 2 shows, the attrition rate is 23%. The results in Table 4 show that attrition is balanced because, regardless of the baseline characteristics that we include as controls, the treatment dummy does not predict being observed in the two-week treatment period. Therefore, attrition should not affect the internal validity of the results.

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

In this section, we develop a stylized short-run model of time allocation to activities with endogenous travel decisions. The objective is to illustrate how fare-free public transport should impact travel behavior and to guide the empirical analysis. The short-run nature is represented by the assumption that the time allocated to work is fixed; that is, the working hours are constant. We believe that this is an accurate description in the context of the experiment because the treatment lasts two weeks. We also use a discrete choice framework for travel decisions, which is a generalization of the extension of Train and McFadden (1978) by Jara-Díaz (2007).[13]

Consider an individual who derives utility from the consumption 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 $W$ hours to work at a wage rate of

[13]The exposition of the model closely draws from Jara-Díaz (2007) Section 2.2.3 on page 57. Literal excerpts are not marked as such and are taken to be acknowledged by this footnote.

Table 4: Study of attrition and baseline characteristics

| | Found in the treatment period (1) | Found in the treatment period (2) |
|---|---|---|
| Treatment dummy | 0.031 | -0.021 |
| | ( 0.059) | ( 0.049) |
| Gender [1 = man] | | 0.044 |
| | | ( 0.054) |
| Age | | -0.002 |
| | | ( 0.002) |
| Distance to work | | 0.010*** |
| | | ( 0.003) |
| Size of household | | -0.022 |
| | | ( 0.017) |
| Monthly household income per capita | | -0.000 |
| | | ( 0.000) |
| No. of cars in household | | 0.048 |
| | | ( 0.033) |
| Household proximity to a subway station | | -0.013** |
| | | ( 0.005) |
| Constant | 0.752*** | 0.989*** |
| | ( 0.043) | ( 0.146) |
| R-squared | 0.001 | 0.085 |
| N | 207 | 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. Column (2) present 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. Robust standard errors in parentheses. *p <0.1, **p<0.05, ***p <0.01.

$w$. A long-run model would include an endogenous decision of $W$, but we assume that it is fixed to represent the short run. The individual must travel to work by any of the available modes represented by the set $M_W$. Going to work by mode $i$ implies traveling $t_i^W$ hours and spending $c_i^W$ on the return trip. For example, for public transport trips, the travel time includes waiting, access, and in-vehicle time, and $c_i^W$ is the fare.

We disaggregate leisure time into two types: leisure time allocated to activities that do not require travel (e.g., watching a movie at home), denoted by $L_1$, and to those that do require travel (e.g., going to the movies), denoted by $L_2$. Allocating time to leisure that requires travel includes a mode choice decision that we also model with a discrete choice of modes 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 as follows:

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

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

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

$$i \in M_W \tag{4}$$

$$j \in M_L \tag{5}$$

where $K$ is a constant, $I$ is the income from other sources and $T$ is the total time available for work and leisure.

The problem can be studied as a two-stage problem where, conditional on discrete travel choices $\{i, j\}$, the individual maximizes utility over time assigned to leisure and the budget assigned to consumption. It is clear that the solution is simply to dedicate all the time net of travel time to leisure $L_1 + L_2 = T - W - t_i^W - t_j^L$ and all the income net of transportation costs to goods consumption $G = I + w \cdot W - c_i^W - c_j^L$. Solving for $L_1$ and $L_2$, we obtain the traditional Cobb-Douglas result that a fraction $\beta_1/(\beta_1 + \beta_2)$ of the time is allocated to leisure without travel ($L_1$) and a fraction $\beta_2/(\beta_1 + \beta_2)$ to leisure that requires travel. Substituting, we obtain the conditional indirect utility function:

$$V_{i,j} = K \cdot (I + w \cdot W - c_i^W - c_j^L)^{1-\beta_1-\beta_2} \cdot (T - W - t_i^W - t_j^L)^{\beta_1} \cdot (T - W - t_i^W - t_j^L)^{\beta_2} \cdot \hat{\beta} \quad (6)$$

where $\hat{\beta}$ is a constant that depends on $\beta_1$ and $\beta_2$.

The mode choices are determined by a comparison of $V_{i,j}$ for all discrete alternatives. From this conditional indirect utility function, we can obtain the value of time, which is the rate of substitution between time and money at constant utility and represents the willingness to pay to increase available time by one unit. Formally:

$$\frac{\partial V_{i,j}/\partial T}{\partial V_{i,j}/\partial I} = \frac{\beta_1 + \beta_2}{1 - \beta_1 - \beta_2} \cdot \frac{I + w \cdot W - c_i^W - c_j^L}{T - W - t_i^W - t_j^L} \quad (7)$$

The trade-off between goods and leisure, which is the relevant one for utility, depends on choosing faster and more expensive modes or slower and cheaper ones. Therefore, the value of travel time savings is simply the value of time derived above and depends on the ratio between money to spend and time to allocate to leisure (the expenditure rate). This tradeoff is depicted in Figure 1 for a given choice of $j$.

Figure 1 shows the modes 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). In this simple example, the slope of the indifference curve is the value of time derived above, which for ease of exposition is a straight line. In the case depicted in Figure 1, the individual chooses to travel to work using the subway, as his value of time is lower than the ratio of monetary and time savings of the car $(c_{\text{Car}}^W - c_{\text{Subway}}^W)/(t_{\text{Car}}^W - t_{\text{Subway}}^W)$ but higher than the analogous values for the bus $(c_{\text{Subway}}^W - c_{\text{Bus}}^W)/(t_{\text{Subway}}^W - t_{\text{Bus}}^W)$.

The effect of facing fare-free public transport for the individual is also represented in Figure 1. Now, the public transport modes have a monetary cost equal to zero, so the "new" modes are displaced downwards as the dashed arrows show. However, the individual does not change her choice, as the subway is faster than the bus. Figure 2 shows two different examples for individuals with a higher value of time.

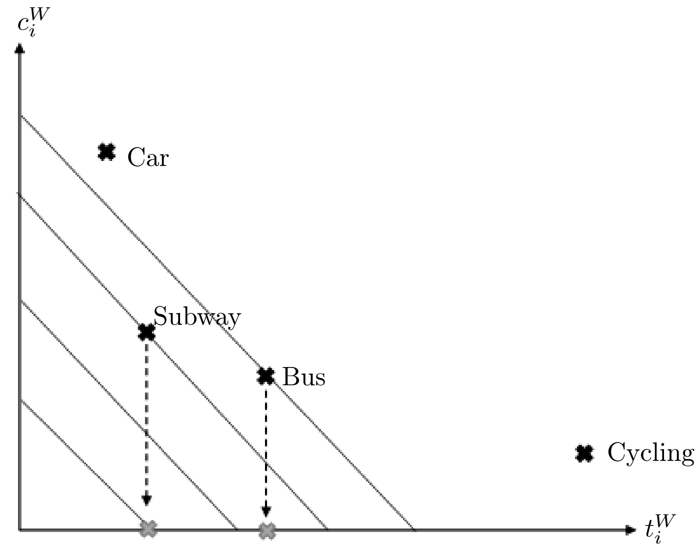


Figure 1: A simple depiction of modal choice for commuting.

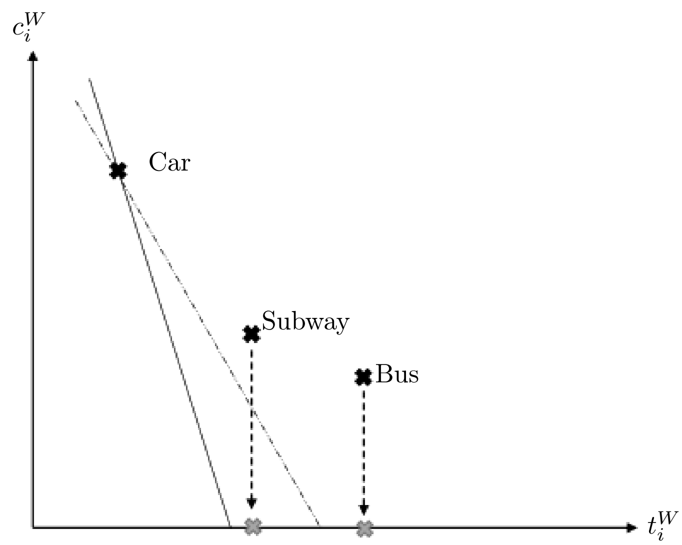


Figure 2: A simple depiction of modal choice.

The individual with the highest value of time, represented by the straight-line indifference curve, chooses to travel by car even when public transport is fare-free. The other individual, with a lower value of time and whose indifference curve is depicted by a dot-dashed line, switches from traveling by car to traveling by (fare-free) subway.

The model illustrates the relevant trade-offs between monetary cost and time. Moreover, as Eq. (7) shows, the model is informative for the empirical analysis in that the effect of fare-free pubic 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.

Before turning to the empirical strategy and results, we want to stress that a more general model would allow for the time assigned to work and to travel to directly affect utility and for the time allocated to activities and to expenditure to be linked, but the focus of this section is on modeling the main tradeoffs. Jara-Díaz et al. (2008) develops such a model and shows that the value of time, in that case, is closely related to the expenditure rate within the framework of this paper. Therefore, in a more complex and detailed framework, the heterogeneity concerning income, available time for leisure, and accessibility are relevant.[14]

## 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:

$$y_i = \alpha + \beta\, T_i + \gamma\, y_{i,0} + \mu_f + \epsilon_i \tag{8}$$

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, we use firm fixed effects $\mu_f$. Therefore, $\beta$ 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

[14] For a framework that explicitly treats the timing of activities, see (Fosgerau and Small, 2017).

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 available time for leisure.

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

$$y_i = \alpha + \sum_k \beta_k \, S_{i,k} \, T_i + \gamma \, y_{i,0} + \mu_f + \epsilon_i \tag{9}$$

where $S_{i,k}$ is a dummy that takes the value of 1 if individual $i$ belongs to strata $k$ for which we study heterogeneity. For example, to explore the heterogeneity concerning income, we define two strata: $k = 1$ for individuals below the median income of the sample and $k = 2$ for individuals above the median. Thus, $\beta_1$ measures the effect of the treatment on low-income users, and $\beta_2$ 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. 1) 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 in the total number of trips by 3.1, which is an 11% increase over the control group's average trips

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

| | Total<br>(1) | Public Transport<br>(2) | Car<br>(3) | Non-motorized<br>(4) | Other<br>(5) |
|---|---|---|---|---|---|
| ***Panel A: All trips.*** | | | | | |
| Treatment | 3.131*** | 1.272 | 0.310 | 1.279** | 0.493 |
| | ( 1.049) | ( 0.875) | ( 0.771) | ( 0.503) | ( 0.400) |
| R-squared | 0.650 | 0.667 | 0.836 | 0.787 | 0.678 |
| 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 | -0.114 | -0.048 | -0.140 | -0.058 | 0.115 |
| | ( 0.468) | ( 0.470) | ( 0.310) | ( 0.237) | ( 0.142) |
| R-squared | 0.732 | 0.788 | 0.872 | 0.817 | 0.742 |
| 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 | 3.225*** | 1.363** | 0.333 | 1.336*** | 0.364 |
| | ( 0.963) | ( 0.688) | ( 0.687) | ( 0.478) | ( 0.321) |
| R-squared | 0.658 | 0.584 | 0.687 | 0.636 | 0.655 |
| 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. Fixed effects at the firm level 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.

(coefficient of 3.131, significant at the 1% level). Columns 3 and 4 show that most of this effect is an increase in public transport and non-motorized trips (coefficients of 1.272 and 1.279) but that only the impact on non-motorized trips is significant at the 5% 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.[15] 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

[15] 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.

errors are lower. The effect on the total number of off-peak trips is a 21% increase relative to the control group average, which is explained in equal shares by public transport trips and non-motorized trips. Importantly, the impact on off-peak public transport trips is a 20% increase (coefficient 1.363, panel (C), column (2), significant at the 5% level).

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.

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

| | Total | Public Transport | Car | Non-motorized | Other |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| ***Panel A: Weekday off peak.*** | | | | | |
| Treatment | 2.219*** | 1.050** | 0.298 | 0.662* | 0.150 |
| | ( 0.622) | ( 0.469) | ( 0.380) | ( 0.344) | ( 0.197) |
| R-squared | 0.739 | 0.700 | 0.606 | 0.702 | 0.699 |
| N | 159 | 159 | 159 | 159 | 159 |
| Control group mean | 8.13 | 4.33 | 1.71 | 1.32 | 0.78 |
| ***Panel B: Weekend*** | | | | | |
| Treatment | 0.824 | 0.404 | -0.152 | 0.647** | 0.084 |
| | ( 0.629) | ( 0.406) | ( 0.487) | ( 0.251) | ( 0.240) |
| R-squared | 0.434 | 0.258 | 0.606 | 0.418 | 0.203 |
| 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. Fixed effects at the firm level 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.

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 2.2 trips, which is 27% of the control group's average (panel (A), column 1, coefficient 2.219, significant at the 1% level). Panel (A) also reveals that the pass increases the number of public transport trips by 1 trip during off-peak weekdays (column 2, coefficient 1.05, 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 both 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 24% increase in public transport trips made during weekday off-peak periods and a 67% 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 two 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).

To test the robustness of the lack of mode substitution and to explore the second type of mechanism, 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 are in Appendix A.1, and the summary statistics of trips per purpose in the baseline (pre-treatment week) are summarized in Table 7.

Table 7 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 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 7 displays, and the number of trips without a purpose is 0.2% (14 out of 7045, not displayed in the table).

Table 7: 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 8 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 0.8 trips, which is a 39% increase (column 2, coefficient 0.847, significant at the 5% level) and a statistically significant increase in non-motorized trips for leisure and errands and 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.

### *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 B.1 and B.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 one kilometer of a subway station (which is the sample median). The effect for this group is an increase of 2.8 public transport trips, which is a 41% 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 5% level. The fact that the coefficient for the group with long distance to the subway station is -0.05 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

Table 8: Treatment effect by trip purpose

| | Total | Public Transport | Car | Non-motorized | Other |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| ***Panel A: To work.*** | | | | | |
| Treatment | 0.070 | 0.152 | -0.274 | 0.015 | 0.171 |
| | ( 0.358) | ( 0.363) | ( 0.192) | ( 0.162) | ( 0.172) |
| R-squared | 0.473 | 0.741 | 0.870 | 0.848 | 0.697 |
| N | 159 | 159 | 159 | 159 | 159 |
| Control group mean | 9.16 | 6.01 | 1.68 | 0.54 | 0.54 |
| ***Panel B: Return home.*** | | | | | |
| Treatment | 0.468 | -0.003 | 0.029 | 0.549** | 0.031 |
| | ( 0.424) | ( 0.413) | ( 0.370) | ( 0.273) | ( 0.224) |
| R-squared | 0.458 | 0.622 | 0.768 | 0.638 | 0.525 |
| 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 | 1.963*** | 0.847** | 0.301 | 0.649** | 0.187 |
| | ( 0.652) | ( 0.365) | ( 0.465) | ( 0.257) | ( 0.129) |
| R-squared | 0.681 | 0.554 | 0.685 | 0.654 | 0.536 |
| 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. Fixed effects at the firm level 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 $< 0.01$.

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 0.1 in column 1 and 0.22 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.

### *5.5. Robustness tests*

As a first robustness check, we separately estimate the average treatment effect for the five outcomes for each of the two treatment weeks. We do this to study whether the results are 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

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

| | Total | Public Transport | Car | Non-motorized | Other |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| ***Panel A: Peak period trips*** | | | | | |
| T $\times$ short distance to subway | -0.022 | -0.076 | -0.031 | -0.418 | 0.465** |
| | ( 0.692) | ( 0.705) | ( 0.371) | ( 0.387) | ( 0.204) |
| T $\times$ long distance to subway | -0.173 | 0.033 | -0.259 | 0.285 | -0.218 |
| | ( 0.646) | ( 0.658) | ( 0.492) | ( 0.315) | ( 0.210) |
| R-squared | 0.733 | 0.788 | 0.872 | 0.821 | 0.752 |
| N | 158 | 158 | 158 | 158 | 158 |
| Test F (equal effects across distance to subway strata) - p-value | 0.87 | 0.91 | 0.71 | 0.17 | 0.02 |
| 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 $\times$ short distance to subway | 4.887*** | 2.851*** | -0.303 | 2.010** | 0.471 |
| | ( 1.402) | ( 1.079) | ( 0.955) | ( 0.830) | ( 0.426) |
| T $\times$ long distance to subway | 1.696 | -0.054 | 1.028 | 0.748 | 0.283 |
| | ( 1.310) | ( 0.865) | ( 0.941) | ( 0.557) | ( 0.499) |
| R-squared | 0.671 | 0.596 | 0.689 | 0.652 | 0.662 |
| N | 158 | 158 | 158 | 158 | 158 |
| Test F (equal effects across distance to subway strata) - p-value | 0.10 | 0.04 | 0.30 | 0.22 | 0.78 |
| 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. Fixed effects at the firm level 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.

effect in the first week. Table C.1 shows the main conclusion: there are no significant differences between the first and second weeks.

To obtain further insights and because it is relevant for efficiency, our second 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 C.2 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 1.081, which is significant at the 1% level and practically the same as that in Table 6 (1.05), and the effect on bus trips is almost zero.

The third 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 C.3 shows that the conclusions are the same, as the coefficients are very similar to those in Table B.2, and we cannot reject the null of equal coefficients across strata at the 5% level for any outcome.

## 6. Conclusions

We conducted a randomized controlled trial to determine the causal effect of fare-free public transport on the number of public transport trips and travel behavior. We focus on a sample of workers in Santiago, Chile, who were provided a free travel pass for a two-week treatment period following a one-week baseline. The results of the experiment approximate the short-term effect of having access to fare-free public transport. Making public transport fare-free has been highlighted as an efficient policy in the literature, and policy-makers have proposed it as a measure to reduce car usage and urban pollution.

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 also find that the main result is robust when allowing for heterogeneity in the treatment effect for the relevant variables that determine travel choices (value of travel time savings and accessibility); we also find evidence of generation.

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. A simple back-of-the-envelope calculation shows that it is highly feasible that benefits from scale economies and reduced fare-collecting costs are offset by increased operating costs and the cost of the required public funds. Thus, benefits could come from other indirect effects, such as decreased travel times due to faster boarding, increased equity, and reduced job-search costs.

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. Nevertheless, our results are consistent with the estimates available for the elasticity of car trips with respect to transit fares that range between 0.017 and 0.13.

## Appendix A. Calculations for costs and benefits

DTPM (2018) reports that the total revenues in 2018 were CLP$ 630,377 million and that 98.6% are revenues from fares. Using the exchange rate as of March 2017, which we use throughout the paper, US$ 1 = CLP$ 659.93 and a 15% marginal cost of public funds, we obtain the direct cost of US$ 141 million per year. The total costs of the system in 2018 were CLP$ 1,209,523 million. The network of card sale and top-up points represents 3.4% of the costs, the entity that manages the funds 0.3% and the provider of validators 3.1%. This leads to a cost of US$ 124 million.

To obtain a measure of the increased ridership, we simply assume that the 24% increase that we observe holds for all workdays. The latest information on the number of trips in the system that we have comes from the Santiago origin-destination survey (SECTRA, 2014). The survey reports a total of 2,096,429 public transport trips during the weekday off-peak period. Our results imply that there would be 503,143 additional trips, which represent 13% of the daily demand. There are no detailed estimations of the degree of scale economies for the subway and bus system. To obtain an approximation, we use the results in Batarce and Galilea (2018) for buses as representative of the system. Therefore, the 13% increase in ridership leads to a 6.3% reduction in the average cost, which together imply a 5.8% increase in total costs. Using the total costs above, we estimate that operating costs would increase by US$ 90.7 million per year.

To compute the benefits from reduced waiting times, we use the value of travel time savings estimated for Santiago by Rizzi and De La Maza (2017), US$ 2.46, and use US$ 4.9 as the value of waiting time savings to reflect that it is usually valued twice as much (Small, 2012). Therefore, one minute of reduced waiting times for the 2,096,429 off-peak public transport passengers gives a savings of US$ 171,208 per day. Using 240 working days per year, we obtain a benefit of US$ 41 million per year per minute of waiting time that is reduced.

Finally, an average reduction of three minutes plus the direct savings yields a benefit of US$ 247.9 million. The increased operating costs plus the cost of public funds needed yields a total cost of US$ 245.6 million.

### *Appendix A.1. 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.

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 National 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

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. Heterogeneity with respect to income and commuting time

## Appendix C. Robustness tests

Table B.1: Heterogeneity of the effect by household income

| | Total | Public Transport | Car | Non-motorized | Other |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| ***Panel A: Peak period trips*** | | | | | |
| T × low income | -0.153 | 0.062 | -0.319 | -0.060 | 0.174 |
| | ( 0.549) | ( 0.673) | ( 0.283) | ( 0.352) | ( 0.250) |
| T × high income | -0.512 | -0.538 | 0.101 | -0.199 | -0.009 |
| | ( 0.899) | ( 0.805) | ( 0.539) | ( 0.337) | ( 0.218) |
| R-squared | 0.731 | 0.776 | 0.882 | 0.845 | 0.758 |
| N | 143 | 143 | 143 | 143 | 143 |
| Test F (equal effects across income strata) - p-value | 0.75 | 0.58 | 0.49 | 0.79 | 0.60 |
| 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 | 1.930 | -0.368 | 0.316 | $2.000^{***}$ | 0.215 |
| | ( 1.409) | ( 1.077) | ( 0.749) | ( 0.693) | ( 0.467) |
| T × high income | $3.515^{**}$ | $1.956^{**}$ | 0.653 | 0.784 | 0.286 |
| | ( 1.385) | ( 0.910) | ( 1.305) | ( 0.729) | ( 0.507) |
| R-squared | 0.633 | 0.578 | 0.693 | 0.631 | 0.630 |
| N | 143 | 143 | 143 | 143 | 143 |
| Test F (equal effects across income strata) - p-value | 0.43 | 0.10 | 0.82 | 0.22 | 0.92 |
| 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. Fixed effects at the firm level 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 B.2: Heterogeneity of the effect by commuting travel time

| | Total | Public Transport | Car | Non-motorized | Other |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| ***Panel A: Peak period trips*** | | | | | |
| T × low commuting time | -1.228* | -0.618 | -0.414 | -0.202 | 0.112 |
| | ( 0.714) | ( 0.686) | ( 0.533) | ( 0.418) | ( 0.241) |
| T × high commuting time | 1.047 | 0.490 | 0.181 | 0.162 | 0.040 |
| | ( 0.698) | ( 0.729) | ( 0.319) | ( 0.266) | ( 0.151) |
| R-squared | 0.715 | 0.780 | 0.872 | 0.812 | 0.756 |
| N | 154 | 154 | 154 | 154 | 154 |
| Test F (equal effects across commuting time strata) - p-value | 0.03 | 0.28 | 0.32 | 0.47 | 0.80 |
| 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 | 4.928*** | 2.036** | 0.163 | 2.151*** | 0.939* |
| | ( 1.424) | ( 1.006) | ( 1.124) | ( 0.763) | ( 0.534) |
| T × high commuting time | 1.592 | 0.852 | 0.573 | 0.281 | -0.031 |
| | ( 1.322) | ( 1.017) | ( 0.811) | ( 0.526) | ( 0.317) |
| R-squared | 0.668 | 0.601 | 0.688 | 0.644 | 0.662 |
| N | 154 | 154 | 154 | 154 | 154 |
| Test F (equal effects across commuting time strata) - p-value | 0.09 | 0.41 | 0.76 | 0.05 | 0.12 |
| 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. Fixed effects at the firm level 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 C.1: Robustness: treatment effect differentiated by week

| | Total trips | PT trips | Car trips | Non-motorized trips | Other |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| ***Panel A: Main effects (week 2 + week 3)*** | | | | | |
| Treatment | $3.131^{***}$ | 1.272 | 0.310 | $1.279^{**}$ | 0.493 |
| | ( 1.049) | ( 0.875) | ( 0.771) | ( 0.503) | ( 0.400) |
| R-squared | 0.650 | 0.667 | 0.836 | 0.787 | 0.678 |
| N | 159 | 159 | 159 | 159 | 159 |
| Control group mean | 28.20 | 15.42 | 7.47 | 3.25 | 2.05 |
| ***Panel B: Week 2*** | | | | | |
| Treatment | $1.517^{***}$ | 0.540 | 0.256 | 0.389 | $0.434^{*}$ |
| | ( 0.542) | ( 0.478) | ( 0.386) | ( 0.302) | ( 0.232) |
| R-squared | 0.626 | 0.657 | 0.818 | 0.764 | 0.679 |
| N | 159 | 159 | 159 | 159 | 159 |
| Control group mean | 14.71 | 8.01 | 3.87 | 1.78 | 1.05 |
| ***Panel C: Week 3*** | | | | | |
| Treatment | $1.614^{**}$ | 0.732 | 0.054 | $0.889^{***}$ | 0.059 |
| | ( 0.694) | ( 0.519) | ( 0.489) | ( 0.322) | ( 0.238) |
| R-squared | 0.540 | 0.569 | 0.781 | 0.657 | 0.518 |
| 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. Fixed effects at the firm level 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 C.2: Treatment effect on weekday off-peak trips that use the subway and that are made by bus

| | Trips that use the subway<br>(1) | Trips made by bus<br>(2) |
|---|---|---|
| ***Panel A: Weekday off peak.*** | | |
| Treatment | 1.081*** | -0.054 |
| | ( 0.404) | ( 0.273) |
| R-squared | 0.738 | 0.629 |
| N | 159 | 159 |
| Control group mean | 2.93 | 1.39 |
| ***Panel B: Weekend*** | | |
| Treatment | 0.151 | 0.179 |
| | ( 0.343) | ( 0.243) |
| R-squared | 0.289 | 0.221 |
| 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. Fixed effects at the firm level 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 C.3: Heterogeneity of the effect by distance to work

| | Total | Public Transport | Car | Non-motorized | Other |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| ***Panel A: Peak period trips*** | | | | | |
| T × short commuting distance | -0.747 | -0.731 | 0.313 | -0.291 | 0.090 |
| | ( 0.746) | ( 0.715) | ( 0.378) | ( 0.412) | ( 0.247) |
| T × long commuting distance | 0.616 | 0.799 | -0.490 | 0.163 | 0.111 |
| | ( 0.643) | ( 0.692) | ( 0.472) | ( 0.252) | ( 0.137) |
| R-squared | 0.736 | 0.792 | 0.875 | 0.818 | 0.743 |
| N | 158 | 158 | 158 | 158 | 158 |
| Test F (equal effects across commuting distance strata) - p-value | 0.19 | 0.14 | 0.16 | 0.36 | 0.94 |
| 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 | $4.151^{***}$ | 1.338 | 0.370 | $2.072^{**}$ | 0.575 |
| | ( 1.409) | ( 1.043) | ( 1.085) | ( 0.794) | ( 0.576) |
| T × long commuting distance | 1.943 | 1.500 | 0.096 | 0.480 | 0.129 |
| | ( 1.321) | ( 1.017) | ( 0.745) | ( 0.463) | ( 0.315) |
| R-squared | 0.663 | 0.584 | 0.689 | 0.645 | 0.656 |
| N | 158 | 158 | 158 | 158 | 158 |
| Test F (equal effects across commuting distance strata) - p-value | 0.26 | 0.91 | 0.84 | 0.09 | 0.49 |
| 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. Fixed effects at the firm level 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. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

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