The effect of transport policies on car use: Theory and evidence from Latin American cities

Francisco Gallego, Juan-Pablo Montero and Christian Salas*

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**** PRELIMINARY DRAFT — DO NOT QUOTE OR CITE *****

Abstract

Latin American cities have tried different policies to get people out of their cars. In 1989, authorities in Mexico City introduced a driving restriction program, Hoy-No-Circula, that prevents most drivers from using their vehicles one weekday per week. More recently, in 2007, authorities in Santiago embarked in a city-wide transportation reform, Transantiago, to improve and increase the use of public transportation. This paper presents both a theoretical framework and an empirical analysis on the short and long-run effect of these policies on vehicle use during both peak and off-peak hours. Based on the fact that vehicles are responsible for above 90% of the carbon monoxide, we look at hourly records of this pollutant for years before and after policy implementation. We are able to distinguish short and long run effects particularly well for peak hours (and consistent with the theoretical model). In addition, we find households to rapidly adjust their stock of vehicles, within 12 months, in response to these policies. We check the validity (or not) of these results for the case of Transantiago using monthly observations from alternative sources including fuel consumption, car registrations and prices of taxi licences. Hourly records of vehicle traffic from traffic-control stations are also examined.

1 Introduction

Air pollution and congestion remain a serious problem in many cities around the world, particularly in emerging economies because of the steady increase in car use. Latin

*Department of Economics, Pontificia Universidad Católica de Chile (PUC-Chile). We thank Lucas Davis, Tomas Rau, Stephen Ryan, Rainer Schmitz and seminar participants at PUC-Chile and PUC-Rio for comments. Montero also thanks Instituto Milenio SCI (P05-004F) for financial support.

America have tried with different policies in an effort to contain such trend. In 1989, for example, authorities in Mexico City introduced a program, Hoy-No-Circula (HNC), that restricts drivers from using their vehicles one weekday per week. More recently, in 2007, authorities in the city of Santiago-Chile embarked in a city-wide transportation reform, Transantiago, to improve and increase the use of the public transportation system. As shown in Table 1, other major efforts in Latin America fall in one of the above type of policies: driving restrictions (DR) or investments/reforms in public transportation (PT).[1]

Table 1: Transport policies in Latin America

Program	City	Start date	Type	Scope	In force?
Restricción Vehicular	Santiago	April 1986	DR	gradual	yes
Hoy No Circula	Mexico D.F.	November 1989	DR	drastic	yes
Operação Rodizio	Sao Paulo	August 1996	DR	gradual	yes
Pico y Placa	Bogotá	August 1998	DR	gradual	yes
Transmilenio	Bogotá	December 2000	PT	gradual	yes
Pico y Placa	Medellín	February 2005	DR	drastic	yes
Metrobus	México D.F.	August 2005	PT	gradual	yes
TranSantiago	Santiago	February 2007	PT	drastic	yes
Pico y Placa Quito	Quito	May 2010	DR	drastic	yes

DR: driving restriction; PT: public transportation reform. Source: Lizana (2011).[2]

There is quite a bit of controversy on the effectiveness of these type of policies in moving people away from the car and towards cleaner forms of transportation (e.g., subway, low-emission buses, etc). In fact, EIU (2010) finds that many Latin American cities have successfully set up extensive public transportation networks but they have not performed nearly as well on getting people out of their cars. The problem with evaluating these policies is that it is hard to construct a counterfactual against which the performance of the policy can be contrasted to. Transportation systems are remarkably complex and dynamic which makes any evaluation even more difficult because we are often not much interested in the short-run effect of the policy but in its long-run effect, i.e., whether and how fast people adjust their stock of vehicles.[3]

[1] It is interesting that we do not observe more market oriented policies such as road pricing (London's congestion charging scheme is the best example on that), car fees or tradeable quotas (see Singapur's Certificate of Entitlement) or fuel taxes aimed at correcting pollution and/or pollution externalities. The political economy of why this is so is beyond the scope of the paper but it's nevertheless interesting.

[2] Lizana (2011) provides a more detailed description of these programs.

[3] See Duranton and Turner (2011) for a discussion on how investment in infraestructure and public transportation affect vehicle travel.

The objective of this paper is two evaluate the effectiveness of these kind of policies. In so doing, we first develop a simple theoretical model with the basic elements that capture how households adapt to these policies in the short and long-run. Using the insights of the model, we then go to test the performance of two programs in particular: HNC and Transantiago. We focus on these two programs not only because they represent a different policy each, but more importantly, because they amount to a one-time drastic interventions like any other program. The driving restriction in Mexico-City, as implemented in 1989, affected almost all drivers and permanently; other driving restriction implemented in Latin America affects only a fraction of drivers (e.g., those using older cars) and under special circumstances (e.g., days of unusually high pollution). Transantiago, on other hand, intervened the public transportation system of an entire city; among other things, it involved a significant and sudden reduction in the number of buses from 7500 to 5500.[4] Other public transportation reforms like Transmilenio in Bogotá have been more limited in scope and introduced gradually.

To tackle the identification problem we use hourly observations of concentration of carbon monoxide (CO), which are recorded by a network of monitoring stations distributed around the cities, for years before and after policy implementation (stations also keep record of other pollutants such as sulfur dioxide, ozone, nitrogen oxides, particulates). According to emissions inventories, vehicles are responsible for 97% of the carbon monoxide in Mexico-City (Molina and Molina, 2002) and for 92% in Santiago (DICTUC, 2009), so we should expect any change in vehicle use be picked up by changes in CO concentrations. These pollution observations are relatively easy to access and in many cases available for several years in cities where pollution is more acute, which makes its use attractive for policy evaluation. Davis (2008) and Chen and Whalley (2010) are two good recent examples on the use of this high-frequency data.[5]

Given the complexity of transport dynamics in large cities like Mexico City and Santiago, the use of hourly CO observations for policy evaluation appears encouraging for several reasons. In addition to the fact that vehicles are responsible for most of it, CO is the only pollutant that can be regarded as non-reactive on a time scale of 1 day (Schmitz, 2005), which is what we use in our empirical estimations. Thus, under stable meteorological conditions, changes in vehicle use (i.e., in CO emissions) should be rapidly reflected in changes in CO concentrations. The second reason is that CO measures, unlike hourly records of vehicle traffic, for example, are better at capturing effects of a policy

[4] In fact, DICTUC (2008) predicted a 30% reduction of CO emissions after the 5th year of implementation of Transantiago.

[5] Davis (2009) explores the effect of HNC on various pollutants and so do Chen and Whalley (2010) for an investment in public transportation in Taipei, Taiwan. Their focus and methods are different than ours. They use a regression discountinuity design that looks at the effect of the policy right after implementation.

at the scale of the city rather than at a particular location. As we explain latter, we find the use of traffic data a bit problematic not only because they contain a partial count of the total vehicle traffic in the city at any hour but also because of local interventions that can greatly affect the counting and are hard to spot (some of these interventions can be part of the same public transportation reform). And it is not yet obvious to us how to aggregate this partial traffic data in a way that can correct for those "local biases".

A third reason, which comes from results of the theoretical model, is that CO data allows, in principle, to separate the effect of the policy on peak hours and off-peak hours (and weekends as well). Accounting for these potential differences is crucial for the estimation as the theoretical model shows that the effect in peak hours can be quite different than that in off-peak hours, particularly in the long-run. Households must decide how to allocate their limited car capacity to both uses: peak and off-peak travel. In addition, they must decide whether or not adjust their stock of vehicles, and if so, how to reallocate that new capacity among both uses. In some cases households may even want reduce their stock of vehicles as a result of the policy, as explained by Eskeland and Feyzioglu (1997) for the case of HNC. A quick look at the data confirm some of these annotations. Figures 1 and 2 show, respectively, for HNC and Transantiago, 24 hrs CO average profiles for weekdays of the same period before and after the policy intervention. For the case of HNC we see off-peak effects to be larger than peak effects; for Transantiago we observe the opposite: an important effect in peak hours but almost no effect during off-peak hours.

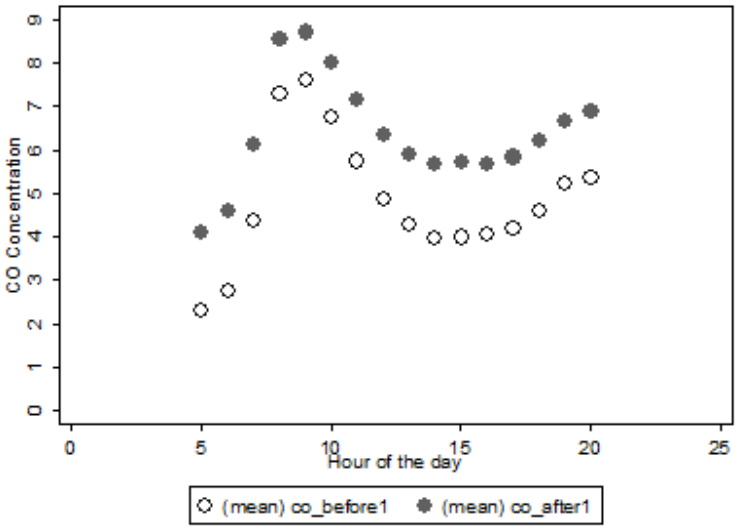

Figure 1: Peak and off-peak CO concentrations for HNC

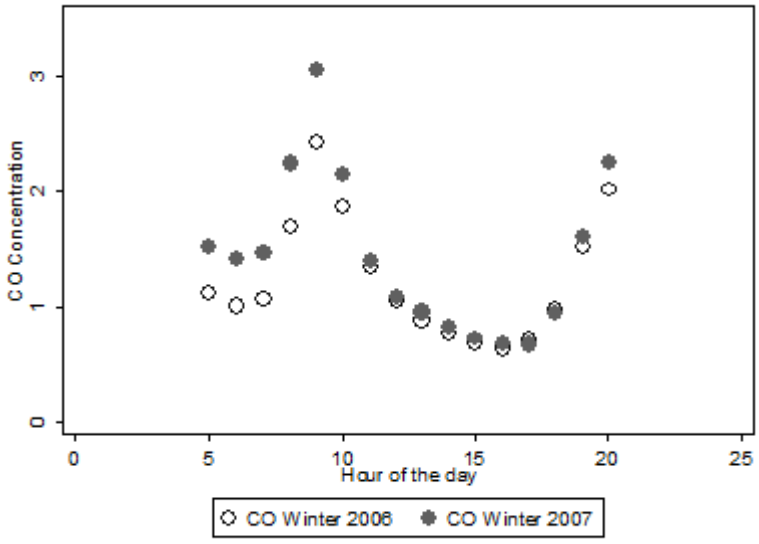

Figure 2: Peak vs off-peak CO concentrations for TS

The use of CO data for policy evaluation is not free of hurdles, however. As explained by Jorquera (2002) for the case of Santiago, there is never a perfect mapping between CO emissions and CO concentrations even after controlling for all the available meteorological variables collected by the monitoring stations such as temperature, humidity, wind speed and wind direction. This imperfect correlation can be readily seen in Figure 3, where we show for the month of January 2002 both concentrations and the emission profile reported by Schmitz (2005). This imperfect correlation would not be much of a problem if we believe the policy to have a uniform effect on emissions across the day. But that is rarely the case, as both the theory and empirical estimations show. One way to get around this problem is to keep the focus on concentrations at peak-hours (8-9 AM) and control for the background pollution that remains right before the peak starts. This is because the concentration build-up at peak is quite rapid and during a relatively short period of time of very stable atmospheric conditions (which translates in low dispersion). The increase in concentration at peak should then closely reflect vehicle activity at that time.[6] We adopt these views in our empirical estimations but also look at concentrations during off-peak and weekends.

Empirical results for HNC show a (statistically significant) reduction 11.4% of CO during peak hours in the short run (say, first month). For off-peak hours (during week-days) the short-run reduction is a bit lower 10.6% but still significant. This short-run

[6] We thanks Rainer Schmitz (Geophisycs Department, University of Chile) for all these explanations.

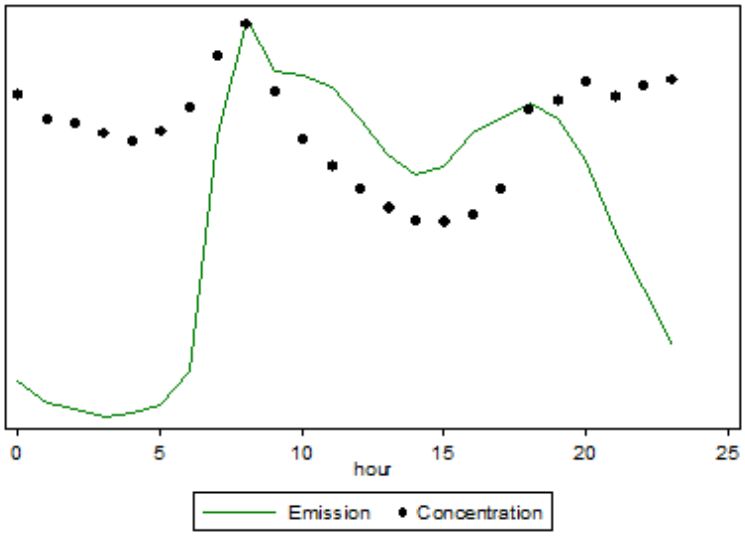

Figure 3: Correlation between CO emissions and concentrations (Santiago, January 2002)

results is entirely consistent with the perception that compliance with the program has been always high. It is also consistent with Eskeland and Feyzioglu's (1997) drop in gasoline consumption for the first quarter after implementation. Estimates show that CO concentrations gradually increase, relative to the no-program scenario, over time to reach a long-run increase of 13.2% during peak hours (significant at 12%) and of 12.3% during of peak hours. These levels are reached before the end of the year. Estimates for weekends show no reduction in the short-run, as expected, and a significant increase in the long run of 19.2%. It is important that in all three estimations we find the long-run level is reached about the same time 9-11 months.

Empirical results for Transantiago for peak hours show no impact on CO in the short run but a rapid increase until reaching an increase of 31%. This long-run level is estimated to be reached by the 9th month. Surprisingly, we find no effect for both off-peak hours and weekends. This confirms, at least for Santiago, our concerns of estimating policy effects outside peak hours. Motivated by some of these results, we check their validity (or not) using monthly observations from alternative sources including fuel consumption, car registrations and prices of taxi licences. Hourly records of vehicle traffic from traffic-control stations are also examined. Results from all these additional sources are consist with our CO results for peak hours, that is, that the policy had the exact opposite effect it was designed for.

Several lessons can be drawn from this paper. Both the theory and empirical results show the importance of estimating separately the effects of the policy at different

times of the day and of properly capturing the stock-adjustment process. In fact, results for both Mexico-City and Santiago are consistent in showing how rapid households adjust their vehicle stocks to policy changes leaving little room for policy makers to make ex-post adjustments.[7] The paper also provides lessons on the importance of complementing/replacing this type of policies with by/other measures. There is a large literature now looking at policy instruments to affect vehicle use and pollution (e.g., Feng et al., 2005; Fullerton and Gan, 2005).

2 A model of car ownership and use

The effect of almost any transport policy on air quality depends to a large extent on its effect on auto demand and use. We develop a (linear-city) model that captures in a simple way an essential element of the problem that is the allocation of vehicle capacity to different uses (peak and off-peak) overtime. The model will help us visualize the kind of paths pollution might follow for peak and off-peak hours after the introduction of a particular policy.

2.1 Notation

There is continuum of agents (households) of mass 1 that decide between two modes of transportation –polluting cars and pollution-free buses– to satisfy its demand for travel during both peak and off-peak hours (we will often refer to peak demand as high (h) demand and off-peak demand as low (l) demand). We normalize car pollution to one unit per km driven (unless indicated otherwise). Households differ in two ways: in their preferences for one mode of transportation over the other (horizontal differentiation) and in the quantity of transportation (i.e., kms traveled) they wish to consume (vertical differentiation).[8] Horizontal preferences are captured with a two-dimensional Hotelling model. A household's horizontal preferences are denoted by $(x^h, x^l) \in [0,1] \times [0,1]$, where x^h is the household's distance to the car option for peak hours and x^l is the distance to the car option for off-peak hours. This same household's distance to the bus option is $(1 - x^h, 1 - x^l)$. The density of (x^h, x^l) is $f(x^h, x^l)$. Furthermore, the product differentiation (or transport cost) parameter is t^h for the peak product and t^l for the off-peak product. A household's vertical preferences are captured with inelastic travel demands which are denoted by $(q^h, q^l) \in [0,1] \times [0,1]$, where q^h and q^l are the household's

[7] Eberly (1994) explains how transaction costs and liquidity constraint lead to gradual rather than instant stock adjustments.

[8] As we will see below, all else equal, cars become more attractive with the level of travel demand.

travel quantities during peak and off-peak hours, respectively.[9] The density of (q^h, q^l) is denoted by $g(q^h, q^l)$.[10]

A household is assumed to have a choice of owning zero, one or two vehicles. Unlike public transportation (i.e., buses), private transportation comes with a capacity restriction that depends on the stock $s \in \{0, 1, 2\}$ of vehicles owned by the household. A household that owns a single vehicle ($s = 1$) has $k < 1$ trips available to be shared between peak and off-peak travel. A household that owns two vehicles ($s = 2$) faces no capacity constraints. The unit cost of using a car during peak hours is p_c^h and during off-peak hours is p_c^l. The unit cost of taking a bus is p_b^i for $i = h, l$. In principle these costs should also depend on congestion (i.e., aggregate consumption of car travel), but to keep the analysis simple we take them as exogenously given. Let $\Delta p^i \equiv p_b^i - p_c^i$ for $i = h, l$.

A type-(q^h, q^l, x^h, x^l) household enjoys a gross utility of $\upsilon(q^h, q^l)$ from consuming q^h and q^l trips, which we assume large enough that all types complete all their trips either by bus or car. If the household owns two vehicles, so it faces no capacity constraints, its (net) utility is

$$u(\cdot|s=2) = \begin{cases} \upsilon - p_c^h q^h - p_c^l q^l - t^h x^h - t^l x^l & \text{if car for } h \text{ and } l \\ \upsilon - p_c^h q^h - p_b^l q^l - t^h x^h - t^l(1-x^l) & \text{if car for } h \text{ and bus for } l \\ \upsilon - p_b^h q^h - p_c^l q^l - t^h(1-x^h) - t^l x^l & \text{if bus for } h \text{ and car for } l \\ \upsilon - p_b^h q^h - p_b^l q^l - t^h(1-x^h) - t^l(1-x^l) & \text{if bus for } h \text{ and } l \end{cases} \tag{1}$$

If instead the household owns a single vehicle its utility, $u(\cdot|s = 1)$, is still given by (1) provided that $q^h + q^l \leq k$. If, however, $q^h + q^l > k$, the household may need to rely on buses to complete one or both of its travel demands. There are two cases to consider. The first case is when the household allocates the entire car capacity $k < q^i$ to satisfy $i = h, l$ and the bus to satisfy $j \neq i$. If so, its utility is

$$u(\cdot|s=1) = \upsilon - p_c^i k - p_b^i(q^i - k) - p_b^j q^j - t^i x^i - t^j(1 - x^j) \tag{2}$$

This household completes its demand for i trips with buses despite it was not its preferred option. Note that under this formulation two households, say 1 and 2, that only differ in their demand for i travel ($q_2^i > q_1^i \geq k$) are equally likely to use and buy a single vehicle. In other words, if household 1 was just indifferent between using (or buying) the one car or taking the bus for i, household 2 is also just indifferent (having a larger demand does

[9] The model can be easily extended, at the cost of additional notation, to elastic demands, e.g., $q^i(p^i) = \theta^i D(p^i)$ for $i = h, l$ and with $\theta^i \in [0, 1]$.

[10] Note that to illustrate many of our results we do not need specify the four-dimension density function.

not make the single-car option more attractive; it may eventually move the household buy two vehicles).

The second case is when the household splits the car capacity between h and l (right below we discuss what is the optimal allocation). Letting $k^i \leq k$ be the fraction of capacity going to i and $k^j = k - k^i$ to j, the household's utility in this case is

$$u(\cdot|s=1) = \upsilon - p_c^i k^i - p_b^i(q^i - k^i) - p_c^j k^j - p_b^j(q^j - k^j) - t^i x^i - t^j x^j \tag{3}$$

where $k^i \leq q^i$ and $k^j \leq q^j$. Note that if $\Delta p^i > \Delta p^j$, the household would like to allocate as much as possible of the car capacity towards i. But an allocation such as $k^i = k$ and $k^j = 0$ would invalidate (3) almost by construction since none of j demand would be satisfied with car trips. A simple way to solve this is to impose a minimum-use restriction upon the car option to be viable for either demand h or l. Let then $k^i \geq \min\{\gamma, q^i\}$ for $i = h, l$, where γ is some small value. Again, under this formulation a household that is indifferent between relying on buses and splitting a single car between high and low demands will remain equally indifferent if we increase both or one of its demands (not too much that it may start considering two vehicles).

Finally, if the household owns no vehicles its utility $u(\cdot|s=0)$ is given by the fourth row in (1). In deciding whether to own zero, one or two vehicles the household solves

$$\max_s \{\max u(\cdot|s) - rs\} \tag{4}$$

where $\max u(\cdot|s)$ is the utility from the best (short-run) transportation mix for a given vehicle stock $s \in \{0, 1, 2\}$ and $r < \min\{t^h, t^l\}$ is the cost of buying a car.[11] Implicit in (4) is the assumption that households constantly adjust their stock of durables to their optimal level while in reality liquidity constraints and/or transaction costs may create a range of inaction where agents do not adjust their stocks at all either upwards or downwards (e.g., Eberly, 1994).[12] We will come back to this issue below, particularly that of downward adjustment, as we look at the effect of some policy interventions.

2.2 Short and long-run choices

We now compute a household's optimal use and ownership choices. We introduce two additional assumptions. To accommodate for the facts that most agents would rather take the car before the bus, provided they have one available, and that (aggregate) car

[11] The latter ensures that households with strong preferences for cars, say $x^h = 0$ or $x^l = 0$, would buy a car even if $q^h = q^l \approx 0$.

[12] Transaction costs may come from sales fees, sales taxes, search costs or a lemons problem affecting used vehicles.

travel at peak is much higher than at off-peak, we assume that $\Delta p^h > \Delta p^l > 0$.[13] Thus, households with a single vehicle that have strong preferences for car-travel during both peak and off-peak hours will allocate most of the car capacity to peak.

The structure of the model allows us to conveniently sequence the analysis from vertical preferences to horizontal preferences. We can first segment households on their likelihood of buying one or two vehicles from looking at their demands q^h and q^l; then we can tell which of these households will indeed buy and use the vehicle(s) from looking at their horizontal preferences x^h and x^l.

Consider first households with $q^h + q^l \leq k$. These households, those in group A in Figure 1, will at best consider buying and using a single vehicle; the ones that do are shown in Figure 2 (for now, ignore the dotted lines in both figures 1 and 2 and the α's in figure 2). As in any (multi-product) bundling problem, some consumers will choose to consume both products (h and l travel) from the same supplier (car or bus), i.e., "consume the bundle", while others will choose to consume from both suppliers. Figure 2 consolidates in one place both household's long- and short-run choices. All households with $x^i \leq \hat{x}^i(q^i) \equiv 1/2 + \Delta p^i q^i / 2t^i$ would rather use the car than the bus for i-travel (provided they have one available). And all households with $x^i \leq \hat{x}^i - r/2t^i$, buy a vehicle despite it will only be used for i-travel, i.e., despite $x^j > \hat{x}^j(q^j) \equiv 1/2 + \Delta p^j q^j / 2t^j$. There is fraction of households with weaker preferences for cars, i.e., $\hat{x}^i - r/2t^i < x^i < \hat{x}^i$ for $i = h, l$, that also buy the car because of the "bundle discount" associated to it. The car-bundle discount is exactly equal to r.[14]

We can now use Figure 2 to illustrate the short and long run effects of a policy intervention like TS. Suppose the policy (e.g., bigger buses but lower frequency) results in a slight deterioration of the quality of public transportation during peak hours, which can be captured with an increase of $\Delta p^h / t^h$ by some small amount ε, as illustrated by the dotted line in the figure.[15] Unlike households that buy (and use) the car-bundle, households that only use the car for l-travel (the "two-stop shoppers" of the bottom-right corner) have spare car-capacity that is ready to be used for h-travel. Hence, there is an immediate (i.e., short-run) increase in car trips and pollution P during peak hours

[13] Note that if $\Delta p^h = \Delta p^l = 0$, $r = 0$ and $f(x^h, x^l) \equiv 1$, only 50% of trips will be made on cars.

[14] The (long-run) purchasing cost of consuming car for i-travel only is $r - \Delta p^i q^i$ while for both h and l travel is $r - \Delta p^h q^h - \Delta p^l q^l$. The "bus-bundle" does not come with any discount.

[15] Since $\Delta p > 0$, reducing product differentiation (i.e., making a bus ride as (un)comfortable as a car ride) will move many people from the bus to the car. Then the two reasons that keep people riding buses are strong preferences towards the bus ($t > 0$ and large x) and the cost of buying a car ($r > 0$).

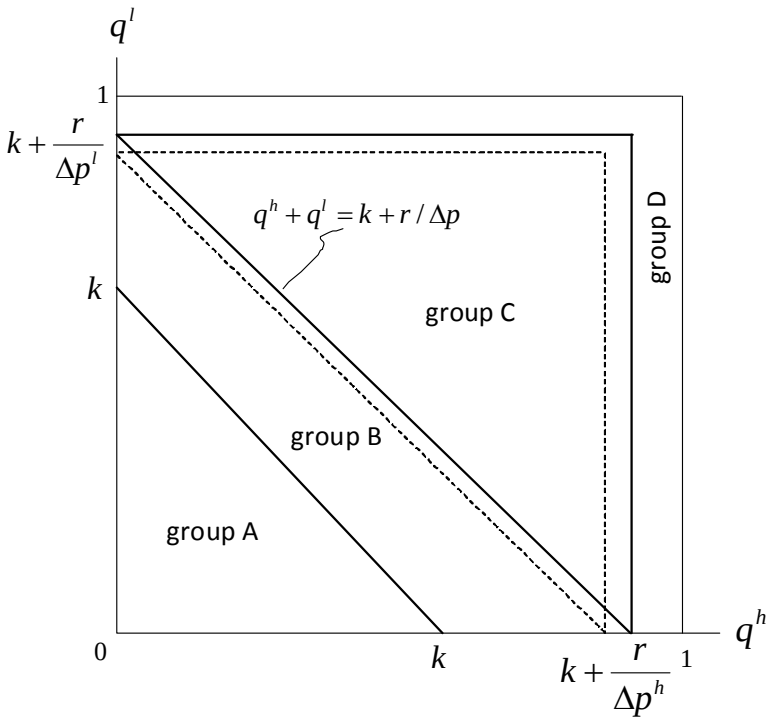

Figure 4: Decision to own a vehicle based on vertical preferences

from households in group A equal to

$$\Delta P^h_{SR}(A) = \iint\limits_A \varepsilon q^h \alpha^h_1(q^h, q^l) g(q^h, q^l) dq^l dq^h = \int\limits_0^k \int\limits_0^{k-q^h} \varepsilon q^h \alpha^h_1(\cdot) g(\cdot) dq^l dq^h$$

where α^h_1 (see the figure) is given by

$$\alpha^h_1(q^h, q^l) = \int_0^{\hat{x}^l(q^l)-r/2t^l} f(\hat{x}^h(q^h), x^l) dx^l \tag{5}$$

If the increase ε is expected to be permanent, there will be an extra increase in car trips and pollution from additional car purchases, so the long-run effect of the policy upon group A is

$$\Delta P^h_{LR}(A) = \iint\limits_A \varepsilon q^h (\alpha^h_1 + \alpha^h_2 + \alpha^h_3) g(\cdot) dq^l dq^h$$

where $\alpha^h_2(q^h, q^l)$ and $\alpha^h_3(q^h, q^l)$ are given by expressions similar to (5).

Consider now households with $q^h + q^l > k$. There are three cases to study: groups B, C and D in figure 1. Like those in group A, households in group B buy at most one

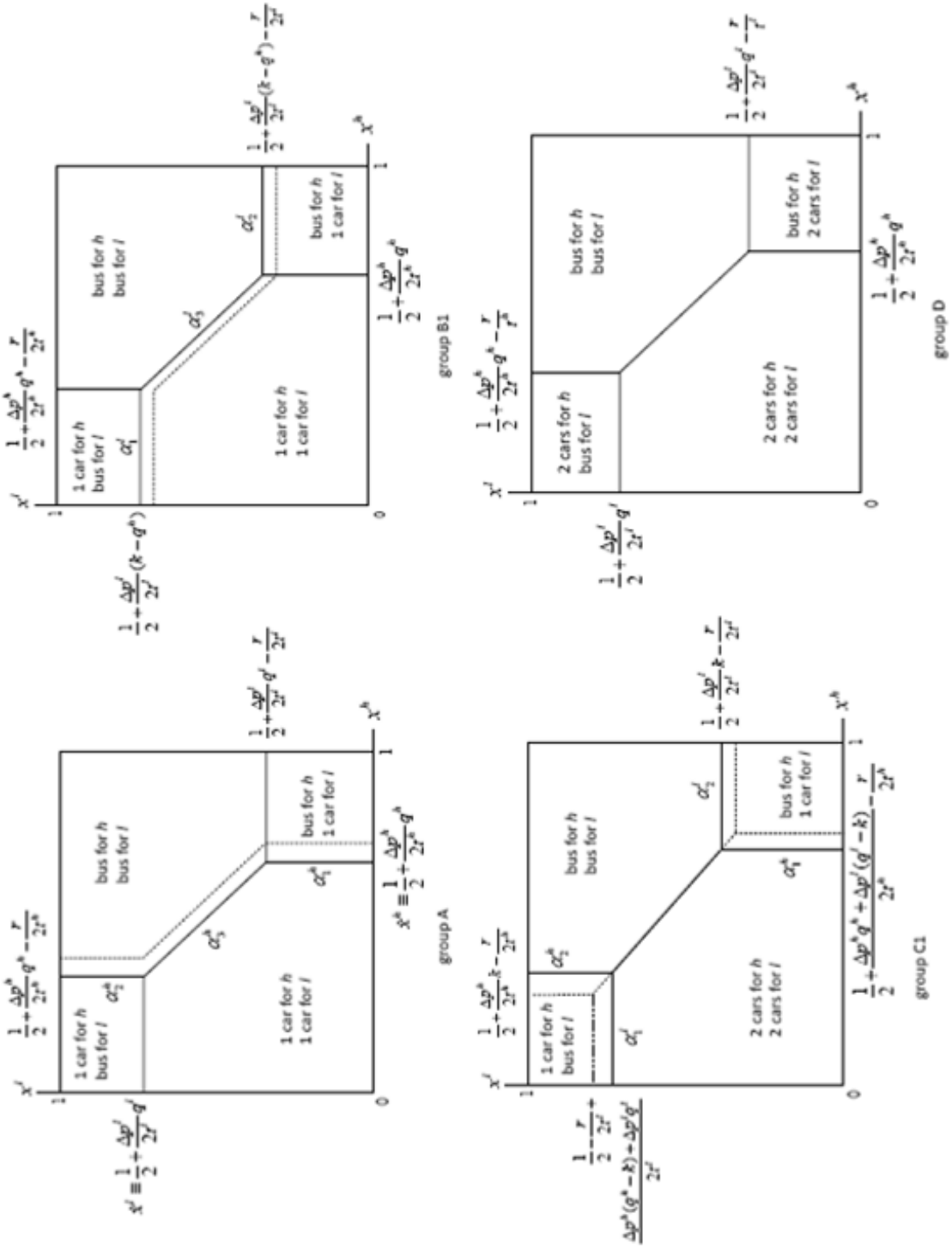

Figure 5: Decision to own and use a car based on horizontal preferences

vehicle, if at all, because q^h and q^l are, either individually or together, not large enough to justify the purchase (and use) of two vehicles. It does not pay to buy two vehicles for multiple use if $u(\cdot|s=2) \leq u(\cdot|s=1)$, or more precisely, if

$$2r - \Delta p^h q^h - \Delta p^l q^l \geq r - \Delta p^h k^h - \Delta p^l k^l \tag{6}$$

where $k^h = \min\{k-\gamma, q^h\}$ and $k^l = k - k^h$. Note that if $\Delta p^h \approx \Delta p^l = \Delta p$ then (6) reduces to $q^h + q^l \leq k + r/\Delta p$: It only pays to buy a second (multi-purpose) car if the saving $\Delta p(q^h + q^l - k)$ more than offset the cost r. The equivalent of (6) for a (single-purpose) vehicle is $q^i \leq k + r/\Delta p^i$ (see figure 1). The fraction of households in group B that effectively end up buying and using the car is shown in figure 3 (to simplify the exposition, the figure focus on the case in which $q^h, q^l < k - \gamma$, say subgroup B1; it is straightforward to extend the figure to other vertical preferences within group B).[16] Note that the car-bundle discount continues to be r despite the capacity constraint.

More interestingly, we can now use figure 3 to illustrate the short- and long-run effect of a second type of policy intervention: driving restrictions like HNC. Suppose the policy reduces car capacity k by a small amount ε. There are two short-run effects. The first is the ε drop in car trips from households that use (and continue using) the car at full capacity, i.e., those that consume the car-bundle. Since $\Delta p^h > \Delta p^l$, this drop is entirely felt over peak hours. The second short-run effect, which is captured by the dotted line in the upper-left corner in the figure, is the reduction of car trips during off-peak from households that no longer consume the car-bundle. This drop in off-peak pollution amounts to $\iint_{B1} \varepsilon(\Delta p^l/2t^l)\alpha_1^l g(\cdot)dq^l dq^h$.

Potentially, the driving restriction can also have a positive effect on air quality in the long-run. For some households owning a car is not that attractive any more (although using it is). In fact, if the resale price of cars is r, a fraction of households in B1 would sell their cars reducing car trips, in both peak and off-peak, by a total of $\iint_{B1} \varepsilon(\Delta p^l/2t^l)(\alpha_2^l + \alpha_3^l)g(\cdot)dq^l dq^h$. However, if these households face a transaction or lemon cost (see Eberly, 1994) equal to

$$\lambda \geq \varepsilon \frac{\Delta p^l}{r},$$

the resale price lowers to $(1-\lambda)r$ and with that the households' incentives to get rid of their cars.[17]

That the driving restriction reduces pollution (in the short-run and potentially in the long-run) extends to all other households in group B except to those close to the

[16] In fact, there are xx subgroups: {B1: qh>k, ql<k}, {B2: qh>k, ql etc.

[17] Some numbers here for λ (eberly uses 5%)

border $q^h + q^h = k - r/\Delta p$.[18] As captured by the (downward) sloping dotted line in figure 1, these households now belong to group C, so some of them will find it attractive to increase the size of their car-bundle and buy a second car; not only buy-passing the driving restriction altogether but what is worse, increasing car trips during both peak and off-peak.[19] Figure 4 distinguishes precisely those households in group C that buy two vehicles from those that buy one and from those that buy none (again, to simplify the exposition the figure focus on the case in which $q^h, q^l > k$, say subgroup C1).[20] In this case the bundle discount is not longer r but $\Delta p^l(q^l - k) + \Delta p^h(q^h - k)$. This is because households that want the car only for i-travel do not buy two vehicles but just one.

The dotted line in figure 4 depicts the effect of the driving restriction on group C1.[21] The short-run effect is simply the drop by the amount ε of car trips from the two-stop shoppers. The long-run effect can be divided in two parts. The first corresponds to the two-stop shoppers that would like to sell their cars if the resale price were r; if so, this would reduce car trips by $\iint_{C1} \varepsilon[(\Delta p^h/2t^h)\alpha_2^h + (\Delta p^l/2t^l)\alpha_2^l]g(\cdot)dq^l dq^h$. And the second part corresponds to two-stop shoppers that buy a second car; not only buy-passing the driving restriction for their i trips but now also using the car for all of their j trips. This increase in cars trips amounts to $\iint_{C1} \varepsilon(\Delta p^h/2t^h)\alpha_1^h g(\cdot)dq^l dq^h$ during peak and $\iint_{C1} \varepsilon(\Delta p^l/2t^l)\alpha_1^l g(\cdot)dq^l dq^h$ during off-peak. This is by far the most adverse effect of a driving restriction.

As shown by the horizontal and vertical dotted lines in figure 1, this adverse effect extends to households in group C that now belong group D; a group in which households own either two vehicles or none. The fraction of households within group D that own two vehicles is depicted in figure 5. Note that the bundle discount is $2r$ since these are households that would buy two cars even if they are only used for i-travel.

2.3 Numerical examples of policy interventions

With this theoretical framework we now generate plausible travel (and pollution) paths after a policy intervention for peak and off-peak hours. Suppose households' preferences are drawn from uniform distributions, i.e., $f(x^h, x^l) = g(q^h, q^l) \equiv 1$, and that $\Delta p^h = \Delta p^l = t^h = t^l = 1$. Car capacity before the policy is $k_0 = 1/2$. The ex-ante levels of peak travel (normalized to 1) and off peak travel are shown under the column q_{car} in Table

[18] There is another case worth noticing, that of subgroup B2: $q^h > k - \gamma$ and $q^l > \gamma$. The driving restriction results in some two-stop shoppers in the bottom-right corner abandoning the car for h-travel; this releases $k - \gamma$ of car capacity, some of which is moved to l-travel.

[19] Note The same inward shift of the border qh+ql=k+r/Dp would happen with a policy intervention that increases Dpl and Dph by ε.

[20] The other subgroup, C2, corresponds to $q^h, q^l < k$ (and $q^h + q^l > k + r/\Delta p$).

[21] Note also that we do not insist further with illustrations of the effect of a TS-type policy since it follows directly from the analysis in figure 2.

2. We work with parameter values such that ratio of car travel during peak to travel during off peak is close enough for all four cases. Travel figures can also be thought as CO emissions.

Table 2. Numerical results for a driving restriction policy

Case	variable	q_{car}	q_{car}/q	SR	LR	LR(1)	LR(2)
1	peak	1	72.3%	-11.7%	1.4%	2.0%	8.9%
	off-peak	0.45	65.6%	-7.1%	2.6%	3.4%	8.6%
	Δ stock	-	-	0%	11.8%	13.6%	13.6%
2	peak	1	39.0%	-21.2%	-15.6%	-10.3%	-4.8%
	off-peak	0.42	32.8%	-7.2%	8.1%	11.8%	21.3%
	Δ stock	-	-	0%	-0.3%	7.8%	7.8%
3	peak	1	32.5%	-25.0%	-26.9%	-18.0%	-14.6%
	off-peak	0.45	14.8%	-18.6%	-4.9%	5.5%	17.6%
	Δ stock	-	-	0%	-9.3%	5.8%	5.8%
4	peak	1	46.9%	-18.1%	0.3%	3.4%	14.2%
	off-peak	0.42	52.1%	-4.0%	0.3%	1.9%	4.9%
	Δ stock	-	-	0%	9.2%	13.4%	13.4%

Consider now a driving restriction that takes the form of a reduction in car capacity from $k_0 = 1/2$ to $k_1 < 1/2$. Case 1 consider the case in which $k_1 = 1/5$. The other parameter values are $r = 1/4$, $\gamma = 0$, and $q_l \leq q_h$. Because the cost of buying a car is relatively low, column q_{car}/q indicates that 72% of peak travel is done by car (and 66% of the off-peak travel). Note that these figures are larger than what we observe for Mexico-City (in early 90s) and for Santiago (in 2007). As shown in columns SR and LR, the policy has similar effects for peak and off-peak hours. An important reduction of 12 and 7%, respectively, in the short-run and a mild increase in the LR. Despite the mild long-run increase in car use, there is nevertheless an important (net) increase in the stock of cars of 12%.[22]. Numbers in LR can be interpreted as long-run CO levels under a "standard" policy implementation, that is, when there are no lemon costs ($\lambda = 0$) and the additional cars are equally dirty (or clean) than the existing stock. However, there are two reasons why this "standard" implementation is unlikely to hold in practice. As shown in LR(1), in the presence of lemon costs, such that no household sales their cars,[23] we should find long-run increases in both peak and off-peak hours. And if in addition to introducing transaction costs we allow additional cars to be 50% dirtier than existing

[22] If we beleive that car ownership induces additional trips (i.e., increases q^h and/or q^l) we should expect even higher increases in LR.

[23] See Eskeland and Feyzioglu (1997) for a discussion applied to HNC.

ones, we obtain further long-run increases. The next three cases increase the cost of the car to make it comparable with numbers we observe in Mexico-City and in Santiago, and unlike case 1, serve to illustrate that peak and off-peak car travel can evolve quite differently.[24]

3 Data and empirical strategy

Below the description of the policies, the data and the empirical strategy, followed by some preliminary results.

3.1 Transport policies in Mexico-City and Santiago-Chile

Record levels of airborne pollutants led Mexico-City's government to implement the HNC on November 20, 1989. This program consisted in banning every vehicle, except taxis, buses, ambulances, fire trucks and police cars, from driving one day of the week, from 5am to 10pm, based on the last digit of its license plate. The program was implemented all at once on the start date and, according to Eskeland and Feyzioglu (1997), Davis (2008) and many journalist sources, the driving restriction program's heavy fines and high police control provoked a near universal compliance. The program did not experience any relevant changes at least up until 4 years after its start.

Nearly 15 years later, Chile's government was preparing a major public transportation reform, with similar air pollution and traffic objectives as HNC, to be implemented in February 10, 2007. The TranSantiago, as the authorities named it, was to modernize, integrate and consequently improve Santiago's public transportation. Due to delays in the necessary infrastructure, low number of buses, poorly designed contracts and badly planned routes the new system failed to provide a good quality service, drastically increasing waiting times of buses and persons per square meter in the subway, thereby creating great public discontent. In the following four years, TranSantiago has relatively solved some of its pitfalls, yet public opinion and several service quality indicators are still a heavy burden on the system.

Because of their drastic implementation and effective enforcement, HNC and TranSantiago are unique transport policies, both similar in purpose but different in nature, that can allow us to study household's response to changes in their mobilization decisions. Since cars, in the case of Mexico-City, and alternatives to public transportation such as cars and taxis, in the case of Santiago, are the (almost) sole emitters of carbon monoxide, this pollutant is a natural choice to study household's transport decisions.

[24] Case 2 uses $k_1 = 1/3$, $r = 3/4$, $\gamma = 0$, and $q_l \leq q_h$; case 3 uses $k_1 = 1/3$, $r = 1$ and $\gamma = 0$; and cases 4 uses $k_1 = 1/3$, $r = 1/2$, $\gamma = 1/4$, and $q_l \leq 3q_h/4$.

3.2 The Data

Concentration of pollutants in the air at Mexico-City is measured by the atmospheric monitoring network of the city, belonging to the Department of Environment and Natural Resources of the Government of Mexico. This network consists of four subsystems, one of which reports hourly measures of ozone (ground-level), nitrogen dioxide, nitrogen oxides, sulfur dioxide, carbon monoxide and total suspended particulate matter smaller than 10 and 2.5 micrometers; another subsystem reports hourly measures of temperature, real humidity, wind speed and wind direction. During the time the HNC was implemented, this network reported all weather variables but only the first five pollutants.

On the other hand, concentration of pollutants in Santiago is measured by atmospheric monitoring network belonging to the National Environmental Commission. The system reports hourly measures of ozone (ground-level), nitrogen dioxide, nitrogen oxides, sulfur dioxide, carbon monoxide and total suspended particulate matter smaller than 10 and 2.5 micrometers as well as hourly measures of temperature, real humidity, precipitation, atmospheric pressure,wind speed and wind direction. Additional economic variables such as monthly production, unemployment rate, real exchange rate and gasoline prices were extracted from several official sources.

3.3 Empirical framework

Main empirical strategy consists in using hourly average of all stations in both cities and focus on a narrow window around policy change. Main estimations point to identifying the immediate impact of the policy by also allowing the estimation to capture the future process of adaptation to the policy. We use two similar approaches: (i) a flexible polynomial fit with a treatment dummy for the whole period under the policy and monthly dummies to capture adaptation; and (ii) a similar approach but instead of dummies we include a first or second degree polynomial to capture adaptation in a more structured way.

$$y_t = \alpha + \phi y_t^b + \beta T_t + \sum \delta_t d_t + \theta P(t) + \gamma x_t + \varepsilon_t \tag{7}$$

$$y_t = \alpha + \phi y_t^b + \beta T_t + f(t, \delta_1) + g(t, \delta_2) + ... + \theta P(t) + \gamma x_t + \varepsilon_t \tag{8}$$

Equations (7) and (8) represent the two empirical approaches. As we explained in the introduction, we control for background pollution, y_t^b, which we assumed equal to the average between 2 and 5 AM. x_t includes fixed effects (hour, day of the week, month),

climate characteristics, and economic covariates when necessary.[25]

4 Results

This section discusses preliminary results of the paper. Tables and figures are located in the appendix at the end of the document.

4.1 Results for HNC

Using an approach such as equations (8) to give some structure to the results, appendix A shows the impact of HNC on CO concentration. Results show a significant 11% decrease in pollution in the short-run during peak hours followed by a 13% increase in the long-run (significant at 12%), which happens after 12 months of adaptation. On the other side, weekend hours do not show a decrease in the short-run yet followed by a significant 19% increase in the long-run. These results are consistent with the fact that HNC effectively constrained only week days hence a strong immediate effect should be seen in peak hours and none effect during weekends. Additionally, the results are consistent with the hypothesis that households in the margin will tend to buy cars to try to return to their pre-policy use in peak, behavior that will leave households with additional cars during weekends, and eventually off-peak hours, to use hence increasing pollution during such hours. Off-peak results mix both peak and weekend behaviors since the policy did constrain the car use during these hours yet the needs of mobilization are more similar to the weekend hours, hence the decrease in the short-run and the increase in the long-run.

4.2 Results for TranSantiago

Using an approach such as equations (8) to give some structure to the results, appendix A shows the impact of TranSantiago on CO concentration. Results show that TranSantiago increased pollution by a significant 31% in peak hours in the long-run, that is after 9 months of adaptation, yet showing no relevant effect immediately after policy implementation. In off-peak hours and weekends TranSantiago does not seem to have any significant effect. These peak results are consistent with the fact that households waited before moving away from the public transportation system, perhaps evaluating how permanent the problems of the new public transportation system were going to be or perhaps because of credit constraints. This is consistent with the survey analysis conducted by Yanez et al. (2010). Despite this effect, off-peak hours and weekends did not show much

[25] In all estimations standard errors are clustered at the 5-week level.

change because of the policy. This supports the hypothesis that additional cars and taxis were only used as a substitute for public transportation during the peak hours in order to bypass the highly crowded and awfully unpredictable public transportation.

Auxiliary data is analyzed in order to corroborate the results just seen. If concentration (and therefore emission) of CO increases after implementation of the program, more car sales, car use, gasoline sales and other forms of public transportation substitution should be observed. Appendix C presents results that suggest higher gasoline sales, higher taxi permit prices, higher registration of cars and higher car traffic in Santiago. Table 4 of the appendix uses monthly gasoline sales in Chile to show a 5% increase in gasoline sales in Santiago after the program's implementation. Figure 3 and Table 5 of the appendix present results of the impact of the program on taxi permit prices using a novel data base recently compiled. The hypothesis is that a different way of substituting public transportation is using taxis and the deterioration caused by TranSantiago should have driven people to the taxis, increasing their future profits and pushing the permit price up. Important evidence of a 50 to 100% increase in the permit price is shown. Next, evidence is presented that shows a short-run and long-run increase in car registration due to the TranSantiago, evidencing a greater stock of cars being used by households, and only a short-run increase in car transfers. Finally, preliminary evidence of the impact of TranSantiago on street traffic suggest a change in the behavior due to the policy most likely increasing car circulation.

5 Conclusions

To be written.

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Appendix

Below are the results of the empirical part of the paper. Standard significance levels for estimates apply.

A Results for HNC

Results below correspond to equation (8) in the empirical framework. The idea is to jointly estimate the short-run and long-run impact of the policy while modelling the adaptation process in a very simple way. This is done by forcing the interception of two lines: the first one with intercept given by the "Short-run" coefficient and slope given by the "Adaptation trend" coefficient, line which starts when the policy is implemented and ends when it reaches the level of the second line; the second line is forced not to have slope (only an intercept) that starts where the first line ends and that ends when the sample does. The idea behing the second line if to partially average (after controlling for everything else) whatever happens after the adaptation period (long-run effect), and the idea behind the first line is to capture the short-run effect as well as the adaptation slope condditional on reaching the long-run effect.

Table 1 presents and figure 1 plots the results for three different day times: peak (8 and 9hrs), off-peak (12 to 14hrs) and weekend (sundays). The point where both lines intercept (end of adaptation) is endogenuous in the three times.

Table 2, on the other hand, fits a second-order time trend polynomial for the sample from the start of the policy to show the adaptation process in an even more flexible way.

Table 1: Effect of HNC on CO

	Peak	Off-Peak	Weekend
Short-run	-0.114**	-0.106***	0.025
	(0.053)	(0.033)	(0.036)
Adaptation trend	3.03e-05***	3.53e-05***	2.69e-05***
	(1.04e-05)	(6.56e-06)	(9.41e-06)
Long-run	0.132	0.123**	0.192***
	(0.083)	(0.055)	(0.041)

Figure 1: Impact of HNC on CO

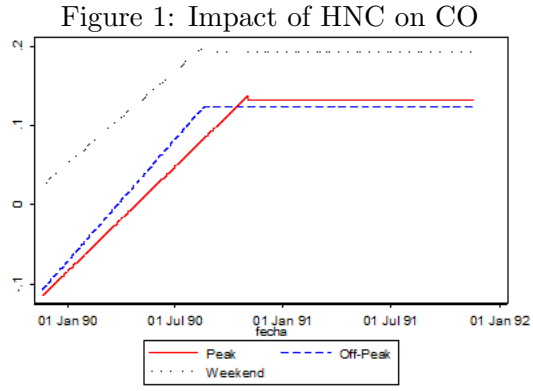

Table 2: Effect of HNC on CO

	Peak	Off-Peak	Weekend
Short-run	-0.165***	-0.170***	-0.019
	(0.052)	(0.029)	(0.034)
Policy trend	4.88e-05***	5.82e-05***	3.98e-05***
	(1.14e-05)	(7.39e-06)	(7.26e-06)
(Policy trend)^2	-2.39e-09***	-3.19e-09***	-2.21e-09***
	(6.01e-10)	(4.27e-10)	(3.85e-10)

B Results for TranSantiago

Results below correspond to equation (8) in the empirical framework. The idea is to jointly estimate the short-run and long-run impact of the policy while modelling the adaptation process in a very simple way. This is done by forcing the interception of two lines: the first one with intercept given by the "Short-run" coefficient and slope given by the "Adaptation trend" coefficient, line which starts when the policy is implemented and ends when it reaches the level of the second line; the second line is forced not to have slope (only an intercept) that starts where the first line ends and that ends when the sample does. The idea behing the second line if to partially average (after controlling for everything else) whatever happens after the adaptation period (long-run effect), and the idea behind the first line is to capture the short-run effect as well as the adaptation slope condditional on reaching the long-run effect.

Table 3 presents and figure 2 plots the results for three different day times: peak (8 and 9hrs), off-peak (12 to 14hrs) and weekend (sundays). The point where both lines intercept (end of adaptation) is endogenuous in the three times.

Table 4, on the other hand, fits a second-order time trend polynomial for the sample from the start of the policy to show the adaptation process in an even more flexible way.

Table 3: Effect of TS on CO

	Peak	Off-Peak	Weekend
Short-run	0.045	0.011	0.128
	(0.084)	(0.105)	(0.126)
Adaptation trend	3.87e-05*	6.77e-07	-4.98e-06
	(2.08e-05)	(2.51e-05)	(2.40e-05)
Long-run	0.310***	-0.020	0.062
	(0.067)	(0.095)	(0.124)

Figure 2: Impact of TS on CO

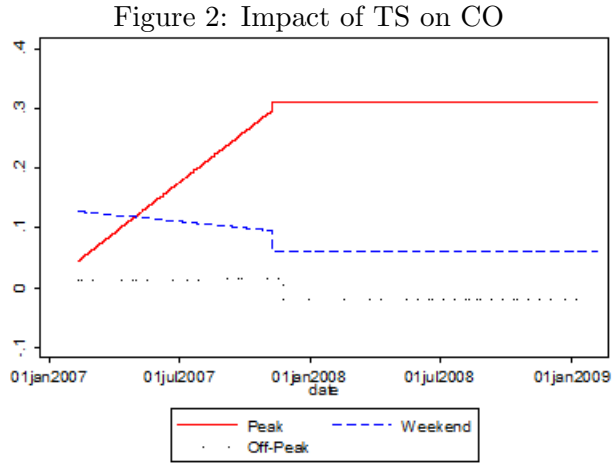

Table 4: Effect of HNC on CO

	Peak	Off-Peak	Weekend
Short-run	0.195**	0.042	0.246*
	(0.098)	(0.112)	(0.141)
Policy trend	1.07e-05	-1.13e-05	-4.13e-05
	(2.34e-05)	(2.80e-05)	(2.84e-05)
(Policy trend)^2	1.24e-09	4.82e-10	2.91e-09
	(1.51e-09)	(1.78e-09)	(2.11e-09)

C Additional evidence in Santiago

1. Gasoline sales
2. Taxi Permit Price
3. Car registrations and transactions
4. Car Traffic

C.1 Gasonline sales

Monthly gasoline sales data in Santiago are regressed against gasoline prices, other economic activity variables and the country's gasoline consumption behavior (build from the data on gasoline sales in Chile, excluding Santiago). A simple least squares estimate using a dummy variable equal to 1 after the program was implemented.

Table 5: Effect of TS on Gasoline Sales

	(1)	(2)
1(Date>Jan 2007)*Santiago	0.058***	0.048**
	(0.018)	(0.016)

C.2 Taxi permit price

We compiled classified advertisements of taxi prices and taxi permit prices in Santiago for the period January 2004 to November 2010. Since most taxis in Santiago are sold with its permit attached, our approach was to substract the taxi's price (which includes the permit) from the equivalent-car's price, leaving a probably biased estimate of the permit price. This bias comes, among other things, from the fact that the vehicles we are comparing not necessarily have the same value since taxi's have more use. Since we do not expect the bias to change from before to after the implementation of TranSantiago, this methodology should therefore allow an unbiased estimator of the TranSantiago effect on taxi permit price. More than 360 permit prices were obtained using this methodology. In addition, 60 taxi permits advertisements were found along the period examined.

Figure 3 plots the permit prices, along with a monthly mean and median. The first graph includes all permit prices, and the second only the ones that were directly advertised as permit prices (i.e. unbiased permit price observations). The trajectory of the observations in the second graph (real permit prices) is very similar to the mean and median trajectory of all permit prices (graphed in both figures).

The figure clearly shows a significant impact of the policy on permit prices, along with some adaptation during the first year. Regressions in table 6 corroborate the former with several specifications that control for the amount of permits available in Santiago (the authority fixes the number of permits), a time-trend and year-of-fabrication and/or model fixed effects; coefficients reported are the dummy equal to 1 after the TranSantiago was implemented.

Figure 3: Taxi Permit Price

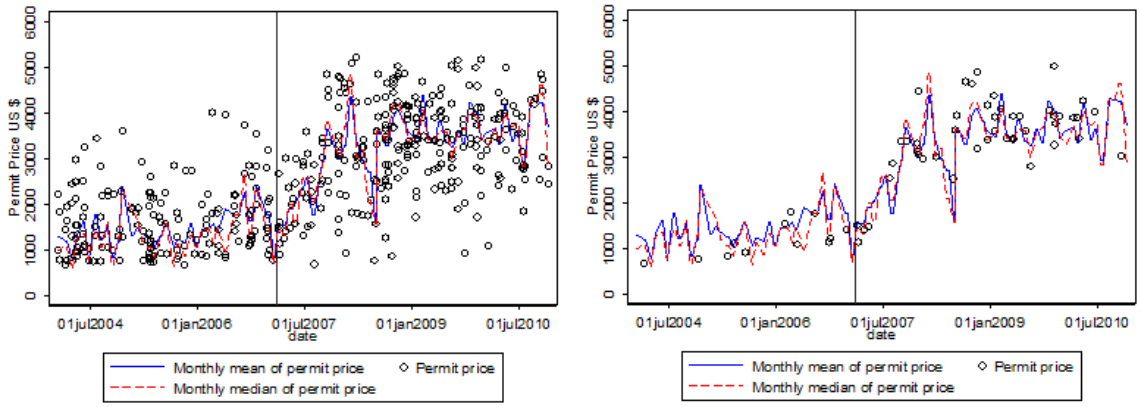

Table 6: Effect of TS on Taxi Permit Price

	Monthly Mean
OLS	1.025***
	(0.063)
OLS w/permit	0.750***
	(0.086)
OLS w/permit and trends	1.156***
	(0.245)
OLS w/permit and year-fe	0.533***
	(0.116)
OLS w/permit and model-fe	0.811***
	(0.124)
OLS w/permit and model-year-fe	0.516***
	(0.180)
OLS w/permit, trends and model-year-fe	0.817**
	(0.3978)

Clusterd s.e. by month-year

C.3 Car registrations and transfers

Monthly data on car first registrations (new cars) and car transfers (used cars) in Chile by region is analyzed in order to understand the impact of the TranSantiago on the dynamics of the car ownership. A difference-in-difference approach is used to compared the behavior of household in Santiago and other regions, before and after the implementation of the program. TranSantiago coefficient represents the long-run impact of the program. When controlling for the particular behavior of the first months, registrations show a significant increase while transfers do not.

Table 7: Effect of TS on Car Registration and Transfers

	Transfers			Registration		
	(1)	(2)	(3)	(4)	(5)	(6)
TranSantiago	2,406.6***	1,028.5	-272.5	3,078.5***	2,201.1**	2,421.2**
	(503.119)	(1,035.4)	(1,230.7)	(473.9)	(969.4)	(1,037.2)
Month1			1,889.8***			2,989.0***
			(674.6)			(568.3)
Month2			2,594.7***			-316.3
			(647.6)			(540.8)
Month3			1,032.4			-1,644.2***
			(622.2)			(515.7)
Month4			2,778.7***			-560.4
			(598.7)			(493.3)
Month5			1,438.1**			-1,212.0**
			(577.3)			(473.9)
Month6			-702.0			-1,876.8***
			(558.2)			(458.1)
Regional-Monthly Fixed Effect	No	Yes	Yes	No	Yes	Yes
Observations	624	624	624	624	624	624

Clusterd s.e. by month-year

C.4 Car Traffic

Preliminary data on car traffic in several streets in Santiago is displayed in the three following figures. Residuals from a regression containing fixed effects (hour of the day, day of the week, month of the year) and several dummies that characterize events in Santiago other than TranSantiago are plotted for before and after the program's start, for three different day times. Graphs suggest an irregular behavior of traffic after the TranSantiago implementation, with an average positive effect.

Figure 4: Impact of TS on Traffic