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The effect of transport policies on car use: A bundling model with applications

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ABSTRACT

Borrowing from the bundling literature, the paper presents a novel model of vertical and horizontal differentiation applied to transport decisions: households differ in their preferences for transportation modes — cars vs public transport — and in the amount of travel. Using few observables, the model is then used to interpret and compute policy costs associated to the effects of two major transport policies: the driving restriction program introduced in Mexico-City in November of 1989 and the public transport reform carried out in Santiago-Chile in February of 2007. Both policies had the unintended impact of increasing the number of cars on the road; and their associated transport costs are estimated, respectively, to be about 5% and 9% of the value of the vehicle stock at the time of implementation.

1. Introduction

Air pollution and congestion remain serious problems in many cities around the world, particularly in emerging economies because of the steady increase in car use (EIU, 2010). This trend has also contributed to increasing carbon emissions. Latin American cities have experimented with different policies in an effort to contain such trend. In November of 1989, for example, authorities in Mexico City introduced Hoy-No-Circula (HNC), a program that restricted drivers from using their vehicles one weekday per week. More recently, in February of 2007, authorities in the city of Santiago-Chile embarked in a city-wide transportation reform, Transantiago (TS), with the idea of improving and increasing the use of public transport. As shown in Table 1,[1] other major efforts in Latin America are of the same type, either driving restrictions or reforms in public transportation; there is total absence, so far, of more market-oriented instruments such as road pricing and pollution taxes.[2]

Have these policies been effective in persuading drivers to give up their cars in favor of public transport, and hence, in reducing congestion and pollution? The problem with evaluating these policies is that it is not always easy to construct a counterfactual against which the performance of the policy can be contrasted upon (Small and Verhoef, 2007), and more so if we are interested not in the immediate or short-run effect of the policy but in its long-run effect, i.e., whether and how fast households adjust their stock of vehicles. In this paper we develop a novel, yet simple, model of a household's transportation-decision problem that can serve as theoretical framework for empirical applications.

The model distinguishes short from long-run impacts of a transportation policy that can take different forms.[3] In constructing the model we (partially) borrow from the bundling literature (e.g., Armstrong and Vickers, 2010), so we capture in a simple way the essential elements of a household's problem which are the allocation of existing vehicle capacity, if any, to competing uses (peak vs off-peak hours) and how that capacity is adjusted in response to a policy shock. Households are both horizontally and vertically differentiated: they differ in their preferences for transportation modes — cars vs public transport — and in the amount of travel. Some households will find it optimal to purchase the car-bundle (i.e., use the car for both peak and off-peak hours), others to rely exclusively on public transportation (bus-bundle), yet others to "two-stop shop" (e.g., car for peak travel and buses for off-peak travel).[4]

One of the advantages of the model is that it can be calibrated and utilized for policy simulations (including estimations of policy costs)

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[1] A description of the transport policies in the table can be found in Ide and Lizana (2011).

[2] The political economy of this absence is beyond the scope of the paper but it is nevertheless an interesting area for more research. Caffera (2011) touches on the issue but in the specific context of pollution control from industrial sources.

[3] Throughout the paper, we understand for short run the period right after a policy shock, say, first month, and long-run as the time it takes most agents to adjust their stock of vehicles as a response to the shock. There can be longer-run effects (e.g., changes in agents' location within the city) but our model does not consider them.

[4] Note that only the car-bundle comes with a discount because the same car can be used for both peak and off-peak travel.

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Table 1
Transport policies in Latin America.
Source: Ide and Lizana (2011).

Program	City	Start year	Type [a]	Scope
Restricción Vehicular	Santiago	1986	DR	Gradual
Hoy No Circula	Mexico D.F.	1989	DR	Drastic
Metrobus-Q	Quito	1995	PT	Gradual
Operação Rodizio	Sao Paulo	1996	DR	Gradual
Pico y Placa	Bogotá	1998	DR	Gradual
Transmilenio	Bogotá	2000	PT	Gradual
Pico y Placa	Medellín	2005	DR	Drastic
Metrobus	México D.F.	2005	PT	Gradual
Restricción Vehicular[b]	San José	2005	DR	Gradual
TranSantiago	Santiago	2007	PT	Drastic
Pico y Placa Quito	Quito	2010	DR	Drastic

[a] DR: driving restriction; PT: public transportation reform.
[b] The program suffered a temporary interruption in June–July of 2009.

using few observables at the city level, namely, the fraction of households owning either none, one, or more cars, the share of car trips at peak hours, the share at off-peak hours, and the ratio of peak trips over off-peak trips (we also need to make an assumption about the distribution of horizontal and vertical preferences in the population). Unlike other existing models (see, e.g., Basso and Silva (2013) and the references cited therein), our model is particularly well equipped to study the effects of policy interventions that affect car utilization such as driving restrictions. Existing models that aggregate preferences at the level of a representative agent (Parry and Small, 2009) or by income (Basso and Silva, 2013), would miss much or all of the action that our model captures, for example, that two households of similar income may have quite different responses.[5]

The model provides several results, which help interpret empirical findings. First, the model illustrates how little informative the shot-run impact of a policy can be. Take a driving restriction policy, for example, which the model captures with a reduction in vehicle capacity. The short-run impact (i.e., before any household has adjusted its stock of vehicles) is unambiguous and as expected, at least qualitatively: a reduction in car trips during both peak and off-peak hours. Depending on parameter values (e.g., price of cars), the long-run impact of the policy can go either way, however. If cars are relatively expensive, the reduction in car trips can remain in the long-run or even extend if enough households find it optimal to return their cars. Conversely, if cars are less expensive (or because households decide to buy older and cheaper cars to by-pass the restriction), the policy can result in an increase in the number of vehicles in the long-run. Similar arguments apply to a public transportation reform, which the model captures with a change in the variable cost of using public vis-à-vis private transportation. Regardless of the direction of the relative price change, its short-run effect on car use is likely to be small and hard to detect empirically.[6] The long-run effect, however, can be shown to be substantial in either direction.

Second, the model shows that policy impacts can vary widely among different income groups, which is important for policy design and evaluation. It shows, for example, that a driving restriction policy like HNC is likely to have its greatest impact in middle-income groups, where households were more likely to buy a second car, and lower in high- and low-income neighborhoods but for different reasons. High-income households have already sufficient car capacity to cope with the driving restriction while only a few low-income households own a car, and those that do, cannot afford a second one. A public transport reform like TS that increases the cost of using public transport uniformly across the city is also likely to have very heterogeneous impacts: lowest among the rich that relies less on public transport and highest among the poor.

The model also allows us to understand whether the effect of policy intervention on car use varies depending on the hours of the day — peak vs off-peak hours. This distinction is important when in the empirical application one may only be able to estimate policy impacts at peak hours. Finally, the model is useful for computing transport costs that policies impose on households due to changes in the relative prices of the different transportation options and see how much they change as households adjust to them over the long run.

Our model is then applied to two major policy interventions –HNC and TS– following the empirical results of our companion paper Gallego et al. (2013). Based on hourly concentration records of carbon monoxide, which comes primarily from vehicle exhaust, in Gallego et al. (2013) we document how household responses to both HNC and TS have been ultimately unfortunate — more cars on the road and higher pollution levels — but also remarkably similar in two important aspects: on how policy responses vary widely among income groups and on how fast households adjust their stock of vehicles, when they do. These empirical results are largely consistent with the regularities that our bundling model predicts both across time and income groups. We also use the model to compute the transportation costs associated to these two interventions. Despite some households adjusted to these policies by purchasing additional car capacity, the model shows that the costs inflicted by these policies remain largely unchanged in the long run. The reason for this latter is that households that decided to buy an additional (or first) car because of the policy were households that before the policy were not that far from buying that additional (or first) car anyway (they didn't do it before because buying a car is a lumpy investment). In the case of TS, these transport costs amount to approximately 9.5% of the value of the stock of vehicles in 2007 (or $126 million annually in 2007 U.S. dollars) and in the case of HNC these costs reach 5.3% of the stock value of the time.

The rest of the paper is organized as follows. Section 2 describes HNC and TS in more detail. The bundling model is presented in Section 3. The application of the model to HNC and TS –including a summary of the empirical strategy and results that are in our companion paper– is in Section 4. We conclude in Section 5.

2. Two major transport interventions

In this section we provide a brief description of the two transport interventions we will apply the model to: HNC and TS. While the two policies are of different nature — one affected the cost of purchasing a car by restricting its use while the other made its use relatively cheaper — and implemented in different cities, and almost 18 years apart, both amount to one-time drastic interventions like no other in the region in that they changed the relative prices of transport options at once and for the entire city.

2.1. HNC in Mexico-City

HNC was established on November 20 of 1989, as a response to record levels of air pollution and congestion in Mexico-City (Molina and Molina, 2002). The program banned every vehicle — except taxis, buses, ambulances, fire trucks and police cars — from driving one weekday per week, from 5 am to 8 pm, based on the last digit of its license

[5] The predictions of our model are even richer than that of Eskeland and Feyzioglu (1997) that was specifically designed to understand the effects of HNC. Their model predicts that households that would like to sell their cars because of the restriction must be of low income while the ones that would like to buy an extra car must of high income. The driving forces in our model are preferences for car vs public transport (which naturally is highly dependent on income but not exclusively) and amount of travel which can vary greatly across households.

[6] Litman (2011) explains that cross elasticities between public and private transportation are very low in the short-run (0.05). Furthermore, the 2006 Origin–destination survey for the city of Santiago (EOD-2006 for its initial in Spanish), for example, shows that most of the (passenger) cars in the city (799,811) must be already in use to cover an equivalent number of morning trips (706,518).

plate (GDF, 2004). The program was implemented all at once and the low cost of detecting non-compliers, the heavy fines, and high police control resulted in near universal compliance (Davis, 2008; Eskeland and Feyzioglu, 1997; Onursal and Gautam, 1997). In contrast, other driving restrictions in Latin America (see Table 1) have affected only a fraction of drivers (e.g., those using older cars) and under special circumstances (e.g., days of unusually high pollution).[7]

There is still the issue of whether some households could have moved forward the purchase (and use) of an additional car to right after the announcement of HNC (November 6) or even before that in anticipation of a possible increase in car prices because of HNC. There are several reasons to believe that this should not be a concern, namely, that the initial announcement of HNC had the program lasting until the end of February (and only then, the program was officially made permanent), that the effect of HNC on the stock of vehicles seems to have been rather modest,[8] and that there was not much time between the announcement and implementation so at best only very few households could have adjusted so quickly. Some believe that HNC had a good start (e.g., GDF, 2004; Onursal and Gautam, 1997), but most agree that over the longer term it lead instead to an increase in the number of vehicles on the road (e.g., Davis, 2008; Eskeland and Feyzioglu, 1997; Molina and Molina, 2002; Onursal and Gautam, 1997).

2.2. TS in Santiago-Chile

Nearly 18 years later, on February 10 of 2007, Chile's government implemented Transantiago (TS), with a similar motivation than HNC, that of persuading drivers to give up their cars, but with a different instrument: improving, supposedly, the quality of public transport. The old public transportation system was regarded as highly polluting, unsafe, and inefficient both in terms of travel time and cost (e.g., Briones, 2009; Muñoz et al., 2009).[9] TS was intended to remedy these problems at once and for the entire city. It involved a significant and sudden reduction in the number of buses, from roughly 7500 to 5500,[10] and a radical (centrally-planned) change in the design and number of routes more in line with a hub-and-spoke network where the existing subway system would play the role of a hub. The other public transport reforms in Table 1, most notably Transmilenio in Bogotá, have been more limited in scope and introduced gradually.

\While the original design of TS was expected to deliver significant reductions in congestion and pollution from fewer cars on the street,[11] its actual implementation has been recognized by many as a major policy failure (e.g., Briones, 2009) resulting in a significant and permanent increase in the cost of using public transport from the first day.[12] Commuting time increased, on average, from 77 to about 90 min (both ways), mainly because of the increase in the average travel time of public transport that went up by about 30% (from 102 to 133 min), which is the product of fewer buses (service frequency was reported to have dropped by 30% uniformly across the city) and transfers. In contrast, travel time of cars and taxis does not seem to have been affected nearly as much. The issue of anticipation to TS does not arise here despite the fact that its launch was announced several months in advance; this is simply because nobody anticipated the final outcome. This deterioration in service quality should have resulted in a switch towards alternative modes of transportation, e.g., cars, and hence, in an increase in emissions.

3. A model of car ownership and use

To understand a household response to policy shocks like HNC and TS, we develop a model that captures in a simple way two essential elements of a household's problem which are the allocation of existing vehicle capacity, which is lumpy, to competing uses (peak vs off-peak hours) and how that capacity is adjusted in response to the shock. The model is flexible and simple enough to accommodate to all sorts of policy interventions and income groups.[13]

3.1. Notation

There is a continuum of agents (households) of mass 1 that decide between two modes of transportation — polluting cars and public transport (e.g., 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).[14] Households differ in two ways: in their preferences for one mode of transportation over the other (horizontal differentiation) and in the quantity of transportation (e.g., km traveled, number of trips) they wish to consume (vertical differentiation). Horizontal preferences are captured with a two-dimensional Hotelling linear city. 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 $f(x^h,x^l)$.[15] Furthermore, the product differentiation (or transport cost) parameter is t^h for the peak and t^l for the off-peak. 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 number of (weekly) trips at peak and off-peak hours, respectively.[16] The density of (q^h,q^l) is denoted by $g(q^h,q^l)$.

A household is assumed to have a choice of owning zero, one, or two vehicles. Unlike public transportation (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 hours.[17] In turn, we assume that a household that owns two vehicles ($s = 2$) faces no capacity constraints.[18] The unit cost of using a car during peak hours is p_c^h and during off-peak hours is p_c^l (these costs include fuel, parking, etc., but also travel time, which depends on congestion, and any private cost associated to the probability of having an accident). The unit cost of taking a bus is p_b^i for $i = h,l$. These costs include travel time, transfers, density of bus stops, etc.,

[7] The driving restrictions in Medellín and Quito also appear quite comprehensive (e.g., Cantillo and Ortuzar, 2011).

[8] According to GDF (2004), of the total number of new cars sold in Mexico in 1990, 44.1% went to Mexico-City as opposed to 45.6% in 1989 and 46.5% in 1988.

[9] Most bus routes passed through the central business district connecting terminal points on the periphery, with average length of more than 60 km (counting both directions), so most passengers could travel almost anywhere in the city without transfers. Under TS, passengers are expected to transfer a few times before completing their journeys (Muñoz et al., 2009).

[10] See Briones (2009) for more details. More importantly for our analysis, the share of public transportation on CO emissions is only 3% (CONAMA, 2004), so such a reduction in the number of buses has virtually no effect on CO concentrations.

[11] DICTUC (2009) estimates that TS, as conceived by its architects, would have reduced CO concentrations by 15% by 2010.

[12] The Economist (Feb 7th, 2008) referred to TS as "…a model of how not to reform public transport".

[13] The model abstracts from longer-run considerations such as migration from and to the city.

[14] The empirical paper of de Grange and Troncoso (2011) also makes the distinction between peak and off-peak travel.

[15] Obviously this function may depend on income, but this is immaterial for what follows unless we believe policies can directly affect $f(\cdot)$, which we do not. They could, for example, if a policy introduces public transport in a place where it was absent before. But here we interested in changes in the quality, i.e., price, of an existing system.

[16] These inelastic and mode-independent demand assumptions are also in Basso and Silva (2013). But, as in Parry and Small (2009), 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 $\theta^i \in [0,1]$.

[17] Because of this capacity constraint, think of q^h and q^l as weekly quantities. This would accommodate, for example, a household with a single car that on a daily basis alternates its use between peak (commuting to work) and off-peak (shopping).

[18] Note that to study the impact of a driving restriction we cannot simply let $s \in \{0,1\}$ since households that already own a car may either want to buy an additional one or return the one they have.

and they also depend on congestion produced by car travel. The advantage of our model is that we do not need to be explicit about these costs, only about their difference, i.e., $\Delta p^i \equiv p^i_b - p^i_c$ for $i = h,l$, which simplifies the analysis greatly.[19] Our final assumption is that agents correctly anticipate the long-run effect of a policy intervention on these costs when making stock decisions. [20]

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 to be large enough that all types complete all their trips either by bus or car. A household's utility depends on whether vehicle capacity is binding or not. It is not binding if either (i) $s = 2$ or (ii) $s = 1$ and $q^h + q^l \leq k$, in which case the household's (net) utility as a function of its car stock is given by

$$u(\cdot|s) = \begin{cases} \upsilon - p^h_c q^h - p^l_c q^l - t^h x^h - t^l x^l & \text{if car for } h \text{ and } l \\ \upsilon - p^h_c q^h - p^l_b q^l - t^h x^h - t^l\left(1-x^l\right) & \text{if car for } h \text{ and bus for } l \\ \upsilon - p^h_b q^h - p^l_c q^l - t^h\left(1-x^h\right) - t^l x^l & \text{if bus for } h \text{ and car for } l \\ \upsilon - p^h_b q^h - p^l_b q^l - t^h\left(1-x^h\right) - t^l\left(1-x^l\right) & \text{if bus for } h \text{ and } l \end{cases} \quad (1)$$

Note that the fourth row in Eq. (1) also corresponds to the utility of a household that owns no vehicles.

On the other hand, the car capacity is (potentially) binding if $s = 1$ and $q^h + q^l > k$. Since now the household needs to rely on buses to complete one or both of its travel demands, there are two cases to consider. The first case — car specialization — is when the household allocates the entire car capacity k to satisfy $i = h,l$ and the bus to satisfy $j \neq i$. If so, its utility is

$$u(\cdot|s) = \upsilon - p^i_c min\left\{q^i, k\right\} - p^i_b max\left\{0, q^i - k\right\} - p^j_b q^j - t^i x^i - t^j\left(1-x^j\right). \quad (2)$$

If $q^i > k$, this household completes its demand for i trips with buses despite the fact that 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 ($q^i_2 > q^i_1 \geq k$) are equally likely to use and buy a single vehicle. In other words, if household 1 is indifferent between using (and buying) a single car or taking the bus for i-travel, household 2 is equally indifferent (having a larger demand does not make the single-car option more attractive because of the capacity constraint; it may eventually move the household to buy two vehicles).

The second case — car splitting — is when the household shares the car capacity between h and l. Letting $k^i \leq k$ denote the fraction of the capacity going to i and $k^j = k – k^i$ to j, the household's utility in this case is

$$u(\cdot|s) = \upsilon - p^i_c k^i - p^i_b\left(q^i - k^i\right) - p^j_c k^j - p^j_b\left(q^j - k^j\right) - t^i x^i - t^j x^j \quad (3)$$

where $k^i \leq q^i$ and $k^j \leq q^j$. Note, however, that if $\Delta p^i > \Delta p^j$, the household would like to allocate as much capacity as possible towards i-travel. But an allocation such as $k^j = 0$ and would invalidate Eq. (3) almost by construction since none of j demand would be satisfied with car trips. We solve this in a simple way; if the car capacity is to be shared, it is done proportional to the demands, i.e., $k^i = q^i k/(q^i + q^j)$ for both $i = h,l$.[21]

In deciding whether to own zero, one or two vehicles the household solves

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

where $max\ u(\cdot|s)$ is the utility from the best (short-run) transportation mix for a given stock $s \in \{0,1,2\}$ and r is the cost of buying a car, which can be made endogenous to the policy.[22] Implicit in Eq. (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 (e.g., Eberly, 1994).[23] We will come back to this issue below.

3.2. Short and long-run choices

We now compute a household's optimal use and ownership choices.[24] 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 Fig. 1, will at best consider buying and using a single vehicle; the ones that do are shown in Fig. 2(a) (for now, ignore the dotted lines in both Figs. 1 and 2 and the αs in Fig. 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. Fig. 2(a) 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 $x^i \leq \hat{x}^i - r/2t^i \equiv \tilde{x}^i(q^i)$, buy a vehicle despite the fact that 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., $\tilde{x}^i < x^i < \hat{x}^i$ for $i = h,l$, which also buy the car because of the "bundle discount" associated to it. The car-bundle discount is exactly equal to r.[25]

We can now use Fig. 2(a) to illustrate the short and long run effects of a public transport reform like TS. Suppose the policy means a slight deterioration of the quality of public transport during peak hours, which can be captured by an increase in $\Delta p^h/t^h$ of some small amount ε, as illustrated by the dotted line in the figure (note that consideration of a small amount ε is only to facilitate the exposition). 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) during peak hours from households in group A equal to

$$\Delta C^h_{SR}(A) \equiv \iint_A \varepsilon q^h \alpha^h_1\left(q^h, q^l\right) g\left(q^h, q^l\right) dq^l dq^h = \int_0^k \int_0^{k-q^h} \varepsilon q^h \alpha^h_1(\cdot) g(\cdot) dq^l dq^h > 0$$

[19] Take, for example, a transport policy that improves public transportation and, as a result, it also alleviates congestion. Our model captures these changes as reductions in both p^i_b and p^i_c. However, given the structure of the model, the household only cares about Δp^i. Note also that this formulation easily accommodates the fact that car trips are generally longer (or more numerous) than bus trips. In other words, by simply scaling Δp^i we can work with $q^i_{bus} = q^i$ and $q^i_{car} = \vartheta^i q^i$, where $\vartheta^i > 1$ (and equal to all agents). The model also accommodates, by simply adjusting Δp^i, increasing returns in public transport, e.g., that increasing ridership leads to a more frequent service. Note also that these costs are private costs, that is, they do not include, for example, pollution costs.

[20] One could easily relax this assumption in the model and allow that a fraction of consumers behave myopically, i.e., that believe costs will remain at their ex-ante values.

[21] We are informally saying that there may be decreasing marginal benefits in car use that justify an interior (splitting) solution. This latter is more reasonable if Δp^i is not too far apart from Δp^j, which is what we find in the calibrations.

[22] Note that if $r < min\{t^h,t^l\}$, households with strong preferences for cars, say $x^h = 0$ or $x^l = 0$, would buy a car even if $q^h = q^l \approx 0$.

[23] Transaction costs may come from sales fees, sales taxes, search costs or the lemons problem afflicting used vehicles.

[24] 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.

[25] 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.

where α_1^h (see the figure) is given by

$$\alpha_1^h\left(q^h, q^l\right) = \int_0^{\widetilde{x}^l\left(q^l\right)} f\left(\hat{x}^h\left(q^h\right), x^l\right) dx^l. \tag{5}$$

If the policy shock ε is permanent, there is an extra increase in car trips from additional car purchases, so the long-run effect of the policy upon group A during peak hours is equal to

$$\Delta C_{LR}^h(A) \equiv \iint_A \varepsilon q^h \left(\alpha_1^h + \alpha_2^h + \alpha_3^h\right) g(\cdot) dq^l dq^h$$

where $\alpha_2^h(q^h, q^l)$ is given by an expression similar to Eq. (5) and α_3^h by

$$\alpha_3^h\left(q^h, q^l\right) = \int_{\widetilde{x}^l\left(q^l\right)}^{\hat{x}^l\left(q^l\right)} f\left(\widetilde{x}^h\left(q^h\right) + \left[\hat{x}^l\left(q^l\right) - x^l\right] t^l / t^h, x^l\right) dx^l.$$

But because the policy also moves some households from the bus-bundle to the car-bundle, there is a long run effect during off-peak hours as well (despite the fact that the price of public transport has not changed there), which is equal to

$$\Delta C_{LR}^l(A) \equiv \iint_A \varepsilon q^l \alpha_3^h g(\cdot) dq^l dq^h.$$

Consider now households with $q^h + q^l > k$. There are four cases to study: groups B, C, D and E in Fig. 1. Like those in group A, households in group B buy at most one vehicle, $s \in \{0,1\}$, 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 $k^i = q^i k/(q^i + q^j)$ for $i = h,l$. Note that if $\Delta p^h \approx \Delta p^l = \Delta p$, then Eq. (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 Eq. (6) for a (single-purpose) vehicle is $q^i \leq k + r/\Delta p^i$ (see Fig. 1). The fraction of households in group B that effectively end up buying and using the car is shown in Fig. 2(b). Note that the car-bundle discount continues to be r despite the capacity constraint.

More interestingly, we can now use Fig. 2(b) to illustrate the short- and long-run effect of a second type of policy intervention: a driving restriction like HNC. Suppose the policy reduces car capacity k by a small amount ε (again, we restrict attention to small changes just to facilitate the exposition).[26] There are three 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. The second short-run effect, which is captured by the horizontal dotted line in the upper-left corner in the figure, is the reduction of car trips during off-peak hours from households that no longer consume the car-bundle. This drop amounts to $\iint_B \varepsilon(\Delta p^l k^l / 2t^l k) k^l \alpha_1^l g(\cdot) dq^l dq^h$. Similarly, the third short-run effect, which is captured by the vertical dotted line in the lower-right corner, is the reduction of car trips during peak from households that no longer consume the car-bundle and is equal to $\iint_B \varepsilon(\Delta p^h k^h / 2t^h k) k^h \alpha_1^h g(\cdot) dq^l dq^h$.

The driving restriction can also have an additional and "positive" effect on car travel in the long-run upon this group. For some households owning a car is no longer that attractive (although using it is, provided the car is available). In fact, if the resale price of a car is still r, a fraction of households in B would sell their cars, and hence, reduce their car trips, in both peak and off-peak, by $\iint_B \varepsilon(\Delta p^h k^h / 2t^h k) k^h (\alpha_2^h + \alpha_3^h) g(\cdot) dq^l dq^h$ and $\iint_B \varepsilon(\Delta p^l k^l / 2t^l k) k^l (\alpha_2^l + \alpha_3^l) g(\cdot) dq^l dq^h$, respectively.[27] However, if these households face a transaction cost equal to

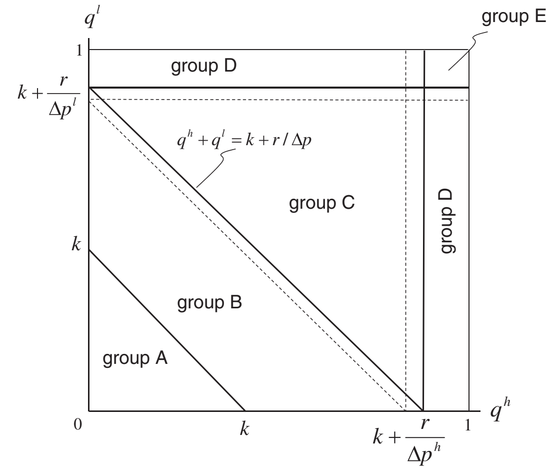

Fig. 1. Decision to own a vehicle based on vertical preferences.

$$\lambda \geq \varepsilon \frac{\Delta p^l}{r}, \tag{7}$$

none of these additional long-run benefits will accrue since no household will return a car at a resale price of $(1 - \lambda)r$.

Note that the presence of a transaction cost λ introduces an option value to the decision to invest in a car if households assign some probability to the possibility that either kind of policy is canceled in the future or substantially changed. This was to some extent the case in both HNC and TS. In the case of HNC, it was not clear at the time of implementation whether the authority would maintain the program after the winter months and in the case of TS some people thought that its bad start would only be temporary (after a month or two people realized that it was not). As formally shown in Appendix B, the introduction of an option value to the problem does not change our analysis in any fundamental way; it only makes investing in a car less attractive (i.e., the cost of a new car is r plus the cost of "killing" the option; r is a parameter that we calibrate so you may say that the cost of killing the option is included in it).

That the driving restriction reduces car travel (in the short-run and potentially in the long-run) extends to all other households in group B except to those close to the border $q^h + q^h = k - r/\Delta p$. As captured by the (downward) sloping dotted line in Fig. 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 by-passing the driving restriction altogether but what is worse, increasing car travel during both peak and off-peak hours.[28] Fig. 2(c) distinguishes precisely those households in group C that buy two vehicles from those that buy one and from those that buy none (to simplify the exposition, the figure focuses on the case in which $q^h, q^l \geq k$, say, subgroup C1).[29] 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 Fig. 2(c) depicts the effect of the driving restriction on group C1. The short-run effect is simply the drop by the amount ε of

[26] Note that a large reduction in k can also affect Δp from changes in congestion (but we omit that here).

[27] Note that α_3^h and α_3^l are related by $\Delta p^h k^h \alpha_3^h / t^h = \Delta p^l k^l \alpha_3^l / t^l$.

[28] Note that the same inward shift of the border $q^h + q^l = k + r/\Delta p$ would happen with a policy intervention that increases both Δp^l and Δp^h by ε.

[29] There are three more subgroups: C2, where $q^h, q^l < k$; C3, where $q^h < k$ and $q^l \geq k$; and C4, where $q^{hl} \geq k$ and $q^l < k$.

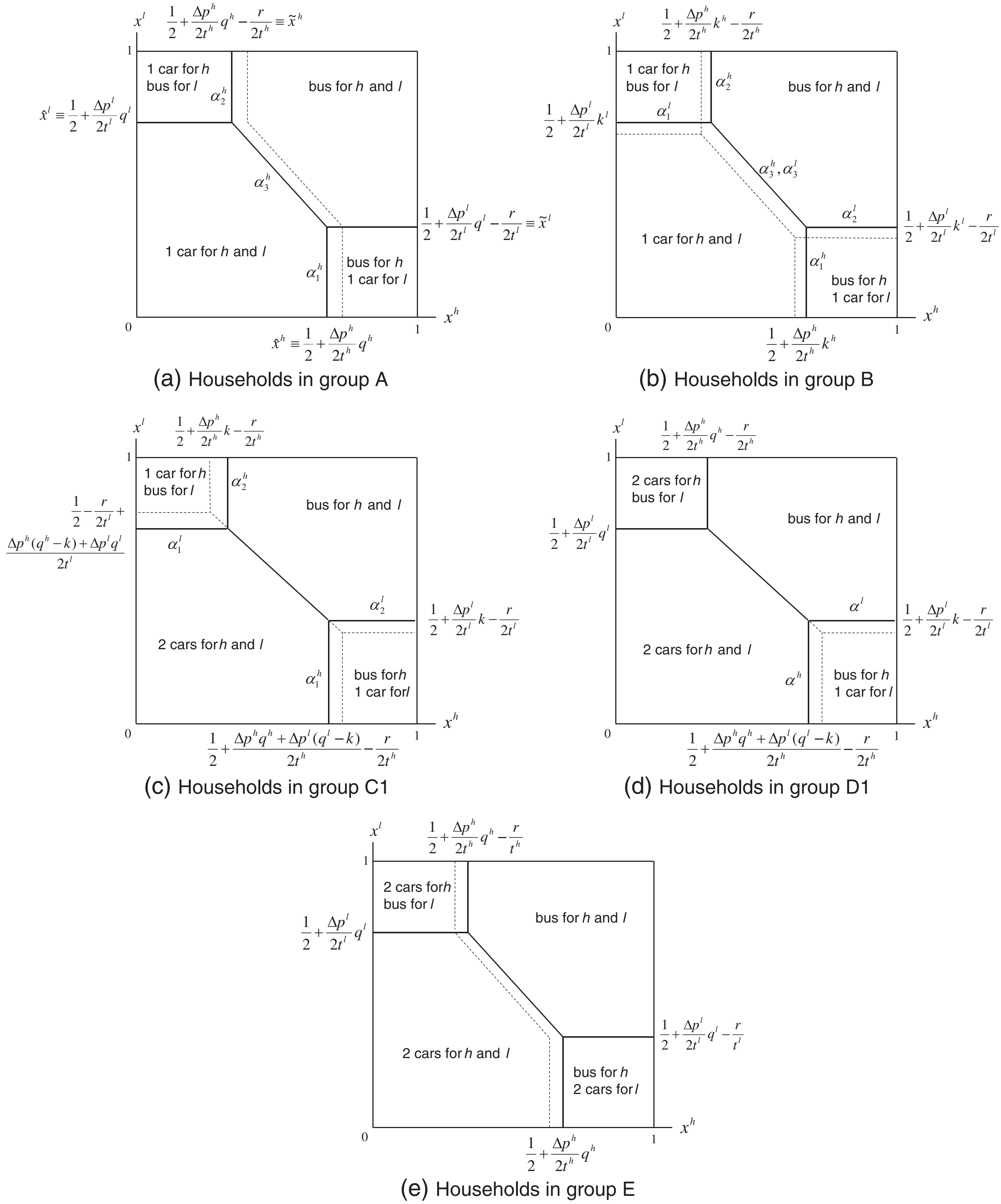

Fig. 2. (a). Households in group A. (b). Households in group B. (c). Households in group C1. (d). Households in group D1. (e). Households in group E.

car trips from the two-stop shoppers. The long-run effect can be divided into two parts. The first corresponds to the two-stop shoppers that would like to sell their cars if the resale price were to remain at r; if so, this would reduce car trips by $\iint_{C1}\varepsilon(\Delta p^h/2t^h)k\alpha_2^h g(\cdot)dq^l dq^h$ during peak and by $\iint_{C1}\varepsilon(\Delta p^l/2t^l)k\alpha_2^l g(\cdot)dq^l dq^h$ during off-peak. And the second part corresponds to two-stop shoppers that buy a second car; not only by-passing the driving restriction for their i trips but now also using the car for all of their j trips. This increase in car trips amounts to $\iint_{C1}\varepsilon(\Delta p^h/2t^h)q^h\alpha_1^h g(\cdot)dq^l dq^h$ during peak and $\iint_{C1}\varepsilon(\Delta p^l/2t^l)q^l\alpha_1^l g(\cdot)dq^l dq^h$ 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 Fig. 1, this adverse effect extends to households in group C that now belong to group D; a group in which households own either two vehicles, one or none. As shown in Fig. 2(d), the difference with group C is that some households in group D may buy two cars just for i-travel (again, the figure focus on the case in which $q^h \geq k + r/\Delta p^h$ and $k \leq q^l < k + r/\Delta p^l$, say, subgroup D1).[30] The effect of the driving restriction policy on the two-stop shoppers that have one car is the same as on the equivalent two-stop shoppers in C1. Finally, there is the group of households, group E, that because of their large demands own either two vehicles or none. As shown in Fig. 2(e), these households never face capacity restrictions (shortly we will come back to the dotted lines in the figure).[31]

4. Application to HNC and TS

We start the section with a brief description of the empirical findings of Gallego et al. (2013) and then move to the application of model to answer several questions raised by these findings about the behavioral responses that can explain the empirical results. For the application of the model we first calibrate the model for both cities using ex-ante (i.e., before the policy) information on car ownership and use and then proceed with several numerical exercises to answer questions and estimate policy costs.

4.1. Empirical findings

The empirical evaluation of GMS for HNC and TS is mainly based on hourly observations of concentration of carbon monoxide (CO), which are recorded by a network of several monitoring stations distributed over the two cities. Maps with the location of the monitoring stations are in Appendix A. As largely discussed in GMS, CO is found to be a very good proxy for vehicle use, particularly at (morning) peak hours, compared to alternative candidates like hourly records of traffic flows and of other pollutants.[32] Under stable meteorological conditions, like before and around the morning peak, rapid increases in vehicle use (and in CO emissions) are immediately reflected in changes in CO concentrations. Another reason to focus on CO at peak hours is that it allows us to study the response of different income groups by looking at the evolution of CO records from individual monitoring stations which happen to be located in neighborhoods of quite different incomes.

The empirical strategy in GMS is to compare CO records at (morning) peak hours two years before and after policy implementation. This is the equation that GMS estimate

$$y_t = \alpha_0 + \alpha_1 y_t^b + \alpha_2 t + \alpha_3 x_t + [\alpha_4 + \alpha_5(t - t_T)]A_t + \alpha_6 T_t(1 - A_t) + \varepsilon_t \quad (8)$$

where y_t is CO concentration in peak hour t in logs, y_t^b is the background pollution before the peak forms (which corresponds to pollution at night), t is intended to capture any pre-existing (linear) trend in pollution and car use, and x_t is a vector that includes fixed effects (hour of the day, day of the week and month of the year), hourly measures of weather variables including temperature, real humidity, precipitation, atmospheric pressure, wind speed and wind direction, and monthly economic covariates that may affect the decision to own and use a car such as real exchange rates and gasoline prices. The effect of the policy is captured with a linear function as follows: T_t is a dummy that takes the value of 1 after the policy, t_T is the time at which the policy gets implemented, A_t is an indicator function that takes the value of 1 during the adjustment phase which length is endogenously determined. Thus, the effect of the policy would be α_4 on impact (i.e., first day) and α_6 in the long-run, with a (constant) speed of transit from α_4 to α_6 of α_5. ε_t is the error term.

The results that GMS obtained from regressing Eq. (8) on average CO records for Mexico-City, as dependent variable, for the period Nov 1987 thru Nov 1991 are as follows: a reduction of 13% the day after implementation (α_4) and an increase of 11% over the long-run (α_6) which is reached about 12.5 months after implementation. On the other hand, the results of running Eq. (8) on CO records for 10 individual monitoring stations for which we have a complete series of data during the four-year window around policy implementation are summarized in Panel A of Table 2. Note that stations are ordered according to both location (i.e., sector) and the (relative) income level for the representative household living in the municipality (*delegación*) where the station is located (average income for the entire population has been normalized to 1). The results show a wide heterogeneity in responses to HNC with a very distinct pattern. The largest impacts are found in middle-income groups — with net increases in CO above 30% — and not nearly as large in lower-income (e.g., Xalostoc) and high-income groups (e.g., Plateros and Pedregal). One can say that the short-run reduction of 13% at the city-level is mostly driven by reductions in monitoring stations located in middle-income neighborhoods.

On the other hand, the results that GMS obtained from regressing Eq. (8) on average CO records for city of Santiago for the period Feb 2005 thru Feb 2009 are as follows: there is virtually no effect in the short run and a large and significant increase over the long run of about 27% that is reached after 7 months. Panel B of Table 2 also presents results with the effects of TS on 7 monitoring stations in Santiago (average income for the entire population has again been normalized to 1). Note that there is strong negative correlation between use of public transport and household income (the simple correlation is −0.90). This negative correlation explains why here policy responses to TS also vary significantly with income. While the short-term impact is found to be negligible in all parts of the city, the long-term impact is found to be decreasing with income from a high of about 40% in the poorest areas (e.g., Cerro Navia, El Bosque, Pudahuel) to 17% in the richest county.

We close this section with questions that these empirical findings raise and serve as motivation for the application of the model. What are the behavioral responses behind the empirical findings in GMS? In particular, can the long-run increase in CO be simply explained by more cars on the street or also by dirtier ones and/or more congestion? Can differences in income lead to such different effects? Do impacts at peak hours tell us anything about impacts at off-peak hours? Do most households adjust to these policies in the long-run, or only a few? Can we obtain an estimate of the short- and long-run transport costs inflicted by the policies using few observables like changes in the stock of cars?

4.2. Calibration

We first calibrate the model to parameter values that reflect the ex-ante (i.e., before the policy) situation of each city in terms of car

[30] There are three more subgroups: D2, where $q^h \geq k + r/\Delta p^h$ and $q^l < k$; D3, where $q^l \geq k + r/\Delta p^h$ and $k \leq q^h < k + r/\Delta p^l$; and D4, where $q^l \geq k + r/\Delta p^h$ and $q^h < k$.

[31] Note that the bundle discount for these households is $2r$ since they would buy two cars even if they are to be used only for i-travel.

[32] Mobile sources, and light vehicles in particular, are by far the main emitters of CO — 97% and 94%, respectively, at the time HNC and TS were implemented.

Table 2
Policy effects by monitoring stations.
Source: Gallego et al. (2013).

Station	Sector	Relative income	Short-run effect	Long-run effect	Difference LR-SR	Adjustment length	R^2	Obs.
Panel A: Mexico-City								
Xalostoc	NE	0.55	0.1196	0.1760	0.0564	12.5**	0.64	1222
Tlalnepantla	NW	0.50	−0.2132*	0.0760	0.2208*	9***	0.65	1474
I.M. del Petróleo	NW	0.53	−0.1781***	0.1598	0.3379***	14***	0.67	1209
M. Insurgentes	CE	0.70	−0.2458***	0.1427	0.3885***	15***	0.60	1473
Lagunilla	CE	0.71	−0.2821***	−0.0652	0.2169*	11***	0.62	1403
Merced	CE	0.84	−0.1527*	0.0807	0.2334***	12***	0.54	1588
Cerro Estrella	SE	0.54	−0.1781**	0.2037*	0.3818***	11.5***	0.33	1499
Taqueña	SE	1.41	−0.0948	0.2255**	0.3203***	15***	0.33	1381
Plateros	SW	1.99	−0.0331	−0.0331	0	0	0.58	1355
Pedegral	SW	1.99	−0.0338	0.1378	0.1716**	10.5***	0.59	1708
Panel B: Santiago								
El Bosque	S	0.53	−0.1246	0.202**	0.3266**	5.5**	0.55	1935
Cerro Navia	W	0.54	−0.0699	0.3979***	0.4678***	7***	0.73	1726
Pudahuel	W	0.65	−0.0568	0.3465***	0.4033***	7***	0.72	1813
Cerrillos	SW	0.81	−0.0715	0.3580**	0.4295**	9***	0.63	1492
Independencia	N	0.93	−0.0288	0.2915***	0.3203**	7***	0.62	1693
La Florida	SE	1.06	0.0013	0.3228***	0.3215**	5***	0.59	1887
Las Condes	NE	2.45	−0.0431	0.1663**	0.2094*	4.5***	0.48	1900

Levels of significance are reported as ***$p<0.01$, **$p<0.05$ and *$p<0.1$.

ownership and use. The car-ownership information includes the fraction of households that either own no cars ($s=0$), one car ($s=1$), or two (or more) cars ($s=2$). The car-use information, on the other hand, includes the share of car trips at peak hours (q^h_{car}/q^h), the share at off-peak (q^l_{car}/q^l), and the ratio of car trips at peak over car trips at off-peak (q^h_{car}/q^l_{car}). The ex-ante information is summarized in the first half of Table 2.[33] In all numerical exercises, we assume that households' preferences are drawn from uniform distributions, i.e., $f(x^h,x^l) = g(q^h,q^l) \equiv 1$.[34] The bottom half of Table 3 presents the calibration parameters obtained for each city.[35] The differences we observe are for the most part expected; for example, the higher use of cars in Santiago than in Mexico-City is consistent with a higher k and lower r and the lower congestion at off-peak hours is consistent with $\Delta p^l \equiv p^l_b - p^l_c > \Delta p^h \equiv p^h_b - p^h_c$ for both cities.

4.3. Policy simulations

As a first simulation exercise with the calibrated model, let us replicate the city-level empirical findings presented in Section 4.1 for HNC by decreasing car capacity k to 0.20 (all the other parameters remain unchanged). As shown in the first row of Panel A of Table 4, this HNC-like policy leads to a short-run decline in car use during peak hours (ΔC^h_{SR}) equal to the 13% reduction in CO concentrations. The most striking results are the long-run number (ΔC^h_{LR}) which is far from the empirical estimates (increase of CO of 11%). The long-run inconsistency can be explained by two assumptions in exercise A1 that are unlikely to hold in practice. First, in A1 all households have the option to return their cars at the original price r (according to the change in the stock of vehicles shown in the last columns of A1 and A2, households would like to return 13.3% of the current stock). If instead we assume that transaction/lemon costs are such that no household returns its car(s), i.e., Eq. (7) holds, exercise A2 shows that in the long run the policy leads to a net increase in the stock of vehicles of 4.1%, although still accompanied by a minor decline in car use (e.g., −2.7% in peak hours).

The second assumption in A1 is that the additional stock is equally polluting (and fuel-efficient) as the existing one, which we know from Eskeland and Feyzioglu (1997) is unlikely for HNC because of the import of older cars from adjacent regions. Thus, if we also let the additional stock be 2.4 times as polluting (and less fuel-efficient) as the existing ones,[36] the results in A3 match the long-run empirical estimates, which illustrates that they are consistent with the theory once we incorporate these more realistic assumptions. Even though the short-run gains are for most part undone, these exercises show for the case of HNC that this is much less due to increases in car use and congestion (actually they hardly changed with respect to the pre-HNC levels) than to the entry of older and more polluting cars.

Let us now use the model to study the response of different income groups and see how they match the empirical findings of Table 2. We can do this by simply varying r — which can be interpreted more generally as the price of cars relative to household income — so as to match ex-ante car use in different municipalities. Exercise A4 extends A3 to a higher-income neighborhood ($r = 0.25$) that exhibits an ex-ante car use of 70% during peak (q^h_{car}/q^h) and 74% during off peak (q^l_{car}/q^l). The effect of the policy is unsurprisingly small compared to the city average in A3 because these households have already sufficient car capacity to cope with the driving restriction (the long-run numbers go down to 0.6 and 0.7%, respectively, if we let the additional cars in this higher income neighborhood be equally dirty than the fleet average). In turn, exercise A5 looks at the other extreme by extending A3 to a lower-income neighborhood ($r = 1.3$) that exhibits an ex-ante car use of only 4%. The effects of the policy are again intuitive since these are households that at most have one car, so the driving restriction hits them hard in the short-run and only a few of them can afford a second car in the long-run. One reason the empirical estimates in poor Xalostoc do not reflect the large

[33] The ex-ante information for HNC was obtained as follows: car-ownership from INEGI (1989), q^i_{car}/q^i from Molina and Molina (2002, p. 227), and q^h_{car}/q^l_{car} from the EOD-2007 for Mexico-City. In the absence of more information, and based on what we know from EOD-2007 for Mexico-City and EOD-2006 for Santiago, we also assumed for HNC that $q^h_{car}/q^h = q^l_{car}/q^l$. All the ex-ante information for TS was obtained from the EOD-2006 for Santiago.

[34] We also experiment with triangular distributions but since we do not have a way to pick between different distributions based on the few observable we have we decided to maintain the uniform distribution.

[35] We used the same initial values in both calibrations: $\Delta p^h = \Delta p^l = t^h = t^l = r = 2k = 1$.

[36] Based on Beaton et al. (1992), who find that each additional year increases CO emissions by approximately 16%, a factor of 2.4 would suggest that the additional vehicles are on average 6 years older than the fleet average, which is perfectly reasonable since 8% of the gasoline fleet in 1989 is at least 20 years old (Molina and Molina, 2002).

Table 3
Calibration.

Targets	HNC	TS	Parameters	HNC	TS
$s = 0$	0.71	0.62	Δp^h	0.91	0.91
$s = 1$	0.23	0.30	Δp^l	1.01	1.23
$s = 2$	0.06	0.08	t^h	0.95	1.22
q^h_{car}/q^h	0.16	0.31	t^l	0.90	1.20
q^l_{car}/q^l	0.16	0.32	k	0.29	0.40
q^h_{car}/q^l_{car}	0.98	0.85	r	0.98	0.95

Table 4
Simulations.

Exercise	ΔC^h_{SR}	ΔC^l_{SR}	ΔC^h_{LR}	ΔC^l_{LR}	Δ stock
Panel A: HNC					
A1	−12.5%	−12.1%	−8.3%	−8.1%	−9.2%
A2	−12.5%	−12.1%	−2.7%	−2.0%	4.1%
A3	−12.5%	−12.1%	11.0%	12.1%	4.1%
A4	−1.7%	−1.7%	3.9%	4.2%	3.0%
A5	−20.4%	−20.6%	2.3%	3.0%	2.6%
Panel B: TS					
B1	0.0%	0.3%	27.8%	28.1%	18.4%
B2	4.5%	−4.4%	28.2%	−0.1%	11.5%
B3	0.0%	0.0%	9.1%	9.1%	6.0%
B4	0.2%	−0.1%	11.2%	7.6%	6.0%
B5	0.2%	−0.1%	27.5%	9.1%	6.0%
B6	1.7%	0.5%	17.2%	0.3%	1.5%
B7	0.1%	−0.1%	40.7%	10.1%	10.6%
B8	−0.6%	0.4%	−15.2%	−8.5%	−7.9%

reduction of car use in the short run is partly because cars contribution to CO in such poor areas is likely minor relative to the contribution of other sources not affected by HNC (i.e., taxis, buses).[37]

We now turn to TS. Recall that the model captures a TS-like policy with changes in Δp^h and/or Δp^l. The first exercise in Panel B of Table 4 (exercise B1) considers a TS-like policy that inflicts a uniform deterioration of 20% in the relative quality of the public transport, i.e., Δp^h and Δp^l go up by that amount in the long-run, so that short and long-run effects ($\Delta C^{i=h,l}_{SR}$ and $\Delta C^{i=h,l}_{LR}$, respectively) are equal to empirical estimates for peak hours (no impact and 27% increase, respectively).[38] Since we do not have empirical estimates for off-peak hours, one may start asking, for example, what kind of TS-like policy could simultaneously generate sizeable effects at peak and virtually none at off peak (some observers indicated that the deterioration in the quality of service is restricted to peak hours). Exercise B2 considers such possibility; the relative quality of public transport must deteriorate by 68% at peak and improve by 56% at off-peak.[39] But such a pronounced asymmetric change in quality is unlikely since peak and off-peak services are supplied by the same system. Survey reports of the time indicate that while service quality has deteriorated at all times, it has deteriorated the most at peak hours. This is not entirely surprising due to the more frequent subway service at off-peak hours prompted by the same TS.

Exercise B1 also shows a big increase in the stock of vehicles of 18.4%, which is way above the empirical finding of GMS of 5 to 8%. The next two exercises consider changes in Δp^h and Δp^l that can produce stock variations more in line with this empirical finding, say, of 6%. In B3 we let both Δp^h and Δp^l raise by 6.7% while in B4 we allow for an uneven deterioration in quality by letting Δp^h raise by 12% and Δp^l only by 3.15%. But now, car use (or CO) during peak hours is below the empirical estimate of 27% in either case. There are two factors, however, that neither B3 nor B4 account for. Unlike in HNC, the increase in car use could have very well generated additional congestion, more so if at peak hours streets already presented some degree of saturation at the time the policy was implemented.[40] While the effect of additional congestion on car use is already captured by our model with smaller than otherwise increases in Δp^h and Δp^l, the effect on CO is not. The second factor, based on an increase in trade of used car, is the possible arrival of older and more polluting cars. Exercise B5 extends B4 to incorporate both of these corrections. First, we let the additional vehicles be 24% more polluting than existing ones (consistent with the increase in trade of used cars reported in Gallego et al. (2013), this captures that a third of the additional stock corresponds to used cars, some of which quite old),[41] and second (and consistent with the changes in traffic flows reported in GMS), we let the extra congestion reduce the average speed at peak hours by 8%, which, according to Robertson et al. (1998), should increase CO emissions by a factor of 1.12. With these corrections, the long-run change in CO concentrations at peak hours returns to 28%.

The next two rows of Panel B present the predictions for the effects of TS on households with different income levels (recall that service quality went down similarly across the city, so all parameters are as in B5 except r). Thus, exercise B6 extends B5 to a high-income neighborhood ($r = 0.1$) that displays an ex-ante car use of 72% during peak and 81% during off peak. The short run effect is still very small — somehow positive during peak hours because of the excess capacity — but the long-run effect is considerably smaller than the city average, i.e., the one in B5, and close to the empirical estimate of 17% for Las Condes that is in Table 2. This is simply because households in this neighborhood rarely use public transportation. Exercise B7, on the other hand, extends B5 to a lower-income neighborhood ($r = 1.5$) that has an ex-ante car use of 8%. Again, the short-run effect is negligible but the long-run effect is substantial (40.7%), which again, is consistent with the findings reported in Table 2 for low-income counties such as El Bosque, Cerro Navia and Pudahuel.

Although it seems evident that the long run increases in CO must come from additional cars, the model helps clarify that in the case of HNC they happen to emit significantly more than the fleet average and in the case of TS they add to the existing congestion. The model also confirms, in direction and magnitude, the empirical finding that policy impacts vary widely among different income groups. But the model also shows, as the empirical evidence does, how little informative the short-run or immediate impact of a policy, whether is HNC or TS, can be. Exercise B8 illustrates this further for a TS-like policy. A policy that improves the quality of the public transport by 22% during peak hours has virtually no impact in the short run, just like in B1, but leads to a 15% reduction in car use (and CO) in the long run — consisted with what DICTUC (2009) projected for the "original design" of TS. This can be seen in Fig. 2(e), where the dotted line captures a policy shock that reduces Δp^h. The short-run response includes only those households in the upper left corner that no longer use the car at peak hours. Instead,

[37] From Onursal and Gautam (1997) and GDF(2004) one obtains that 70% of the CO emitted in the city was subject to HNC. Given that CO records do not vary much across monitoring stations (particularly at peak hours) and that car use in poor areas is about one-fourth of city-average, cars contribution to CO in these areas should be about 18%.

[38] These short-run numbers confirm that families that own a car use it to a maximum extent and only complement it with buses when they are capacity constrained (see also fn. 6).

[39] Note that exercise B2 assumes the presence of transaction costs; otherwise, it is impossible to generate zero impact at off-peak if we let households return their cars at the original price as a response to the improvement of public transport at off-peak.

[40] This seems to be the case according to the relatively low average speeds (20 km/h) reported in SDG (2005). The latter also predicts that the average speed, including peak and off-peak hours, should fall by approximately 10% between 2005 and 2010.

[41] This correction increases the change in CO at peak from 11.2% to 13.8%. More precisely, we are assuming that a third of the additional stock corresponds to used cars that are 8 years older than the fleet average and two thirds to new cars that are 10 years newer than this average. According to ANAC (Chile's National Automobile Association), the stock in 2007 was on average 10.4 years old and a 22% of it was at least 20 years old.

Table 5
Transport costs inflicted by HNC and TS.

Costs	HNC	TS	ratio TS/HNC
Short-run	5.47%	9.68%	1.8
Short-run (corrected)	5.47%	15.35%	2.8
Long-run	5.29%	9.50%	1.8
Long-run (corrected)	5.29%	15.08%	2.9
Long-run ($\lambda = 0$)	4.71%	15.08%	3.2

Table 6
Transport costs as a function of income.

Income group	HNC		TS	
	SR	LR	SR	LR
Low	2.29%	2.25%	12.30%	12.21%
Middle	5.47%	5.29%	9.68%	9.50%
High	3.27%	2.73%	3.39%	3.29%

the long-run response includes the latter households plus the ones that abandon the two-car bundle.

4.4. Estimation of transport costs

It is clear from both the empirical results reported in Table 2 that both policies not only failed to accomplished their main (long-run) purpose — persuade drivers to give up their cars in favor of public transport — but also worse, they induced drivers to buy additional cars (and in many cases more polluting ones). We conclude the paper with an exercise that uses the model to compute the transport costs that these policies have imposed on households by changing the relative prices of the transportation options. Note that since we abstract from the policy costs associated to pollution changes, our welfare analysis is far from complete.

Costs are expected to be higher in the short-run when agents have little margin of adjustment and lower in the long-run as the margin of adjustment widens. Based on the large difference between the short- and long-run CO impacts found for both HNC and TS (24 and 27% at peak hours, respectively), one may argue that despite the fact that these policies did not work as intended, a large fraction of households were nevertheless able to accommodate to them. And if so, the long-run costs associated to these ineffective policies are perhaps not that large.

An estimate of these transport costs can be obtained with the help of the model. Given the functional forms adopted in Eqs. (1)–(4), welfare costs are obtained directly as the difference between ex-ante and ex-post household's utilities (i.e., agents' willingness to pay to avoid the policies). But before we can compute these costs we must agree on the most likely effects attributable to these policies as described, for example, by some of the exercises in Table 4. Based on the CO empirical findings described above, the additional evidence in GMS regarding gasoline sales, car registrations, car purchases, etc., as well as results (not shown) from additional runs of the model, we believe that the numbers in exercise A3/B5 capture reasonably well the impacts of HNC/TS at the city level.

Consequently, Table 5 presents transport costs imposed by HNC and TS based, respectively, on exercises A3 and B5. Cost figures have been normalized by the annual value of the ex-ante existing stock of cars in the corresponding city, that is, $r\Sigma_i s_i^0$, where s_i^0 is household i's ex-ante vehicle stock. The first row of the table indicates that in the short run HNC made households in Mexico-City bear losses equivalent, on aggregate, to 5.5% of the value of the current stock. The short-run fig. in the case of TS is even higher, 9.7%, which would amount, in annual terms, to $129 million (in 2007 U.S. dollars).[42]

We cannot immediately read from the first row in Table 5 that TS was 1.8 times costlier than HNC in the short-run because stock values, relative to total surplus, are not the same. One possible correction is to normalize the ex-ante total surplus in each economy to the same number (by simply adjusting the gross utility v), which is the same as to normalize losses in TS by the stock value in Mexico-City. The second row of the table shows that with this correction TS becomes 2.8 times costlier. The next two rows in the table show that this cost difference extends to the long run; but more importantly, that the long-run losses are surprisingly close to the short-run ones. One possible explanation is that only a few households accommodated to the shocks after all. This seems to be the case in both policies. In fact, the model indicates that only 6.2% of the households that owned a single car before HNC decided to buy a second one and that only 3.1% of all households in Santiago decided to buy a car (or an extra one) because of TS.

But this is not the full story. Even if a policy prompts a much larger response in terms of additional cars on the street, the long-run losses are still likely to be slightly smaller than the short-run losses. As we increase the policy shock, not only we increase the number of households adjusting to the shock but also the costs borne by those that do not adjust.[43] Overall, these numbers indicate that the long-run flexibility does not provide much of a cost alleviation. Consequently, any cost-benefit analysis may well abstract from long-run adjustment considerations. Large part of the reason for this latter is that households that decided to buy an additional (or first) car because of the policy were households that before the policy were not that far from buying that additional (or first) car anyway; they didn't do it before only because buying a car is a lumpy investment.

Given the heterogeneous CO responses reported in Table 2 and supported by the numerical results of the model, it is unlikely that the transport costs in Table 5 are distributed evenly among households of varying incomes. We again use the model to shed some light on this. Table 6 reports welfare costs for three groups of households: high-income (as portrayed by exercises A4 and B6 in Table 4), middle-income or city-average (numbers are in Table 5), and low-income (as portrayed by exercises A5 and B7). Not surprisingly, middle-income households suffer the most in HNC; many of them own a single car but only a few can afford a second one to by-pass the driving restriction. TS, on the other hand, appears fairly regressive with low-income households being hit, on average, 3.6 times as bad as high-income ones.

5. Concluding remarks

We have developed a theoretical "bundling" model that characterizes the short and long-run impacts of different transportation policies

[42] This number, which may be even slightly higher since p_c^i was kept constant in the analysis despite some increase in congestion, is the product of three variables: $r = 1404$ (see below), $\Sigma_i s_i^0 = 0.945$ million (from INE) and 9.7% (from the model). r was constructed as follows: the average vehicle in the city of Santiago in 2006/2007 was US$6556 in value (from www.sii.cl) and 10.4 years old (from ANAC, see fn. 79). And following conversations with ANAC, we then assumed an annual depreciation for such car of $983 (15%) that divided by 0.7, to account for a 30% additional spending in insurance, taxes, registration and some maintenance, leads to the number above (a similar number is obtained using a 2006 household survey). Unfortunately, we cannot carry out a similar exercise for HNC because of lack of comparable information for 1989. If we use the numbers reported in Davis (2008, p. 78), which are based on a 2005 household survey, we obtain a short run cost for HNC of $132 million annually (in 2006 U.S. dollars); figure that may be seen as an upper bound since the average value of a car running in 1989 was clearly lower than one in 2005.

[43] Take for instance exercise B1 in Table 4. The long-run response is quite large, a 18.4% increase in the stock; yet the difference between short- and long-run losses is again small: 27.6 vs 26.1%. Note that this small difference also extends to "good" policies. For example, the short-run (transport) gains in B8 amount to 13.2% while the long-run gains to 13.6%.

and for different income groups. The model captures in a simple way the essential elements of a household's decision problem which are the allocation of existing vehicle capacity, if any, to competing uses (peak vs off-peak hours) and how that capacity is adjusted in response to a policy shock. The model was then applied to two major transportation policies –HNC in Mexico-City and TS in Santiago– to illustrate precisely how it can be of great complement in empirical analysis. One of the advantages of the model is that it can be calibrated and utilized for policy simulations (including estimations of policy costs) using few observables at the city level, namely, the fraction of households owning either none, one, or more cars, the share of car trips at peak hours, the share at off-peak hours, and the ratio of peak trips over off-peak trips. Its main limitation is that it also need to make an assumption about the distribution of horizontal and vertical preferences in the population (in this paper we assume a uniform distribution for convenience, so future work should relax that assumption with more detailed household data).

We learned from HNC that driving restriction policies can be effective in reducing congestion and pollution but only in the short-run. As these policies appear politically feasible — they have been applied in quite a few cities in Latin America (see Table 1) and elsewhere (e.g., Beijing, Tianjin) — and are relatively easy to enforce. Yet, there is more to be understood on how to design them in a way that the short-run gains are not wiped out by the long-run losses associated to the purchase of additional (higher-emitting) vehicles. We should look for the best way to combine a permanent ban on older vehicles and a sporadic one on newer vehicles to attack a limited number of episodes/days of bad pollution. Note that the model shows that a permanent ban can also work as intended as far as older, higher polluting vehicles are under strict control, i.e., prohibition of their import into the city and gradual retirement of existing ones.

The TS experience, on the other hand, showed how rapidly commuters can abandon public transport in favor of cars after a (permanent) deterioration in the quality of service. But even more successful public transport reforms (e.g., Transmilenio in Bogotá) indicate that it is challenging to persuade drivers to give up their cars. We believe that there is a lot more to learn on how commuters decide between public and private transportation and the role different instruments — including road pricing and pollution/gasoline taxes — play in that decision. This is particularly important in cities that exhibit a fast increasing motorization rate, not only for dealing with local problems such as urban air pollution and congestion, but also, with the global problem of carbon emissions.

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Appendix A. Location of monitoring stations

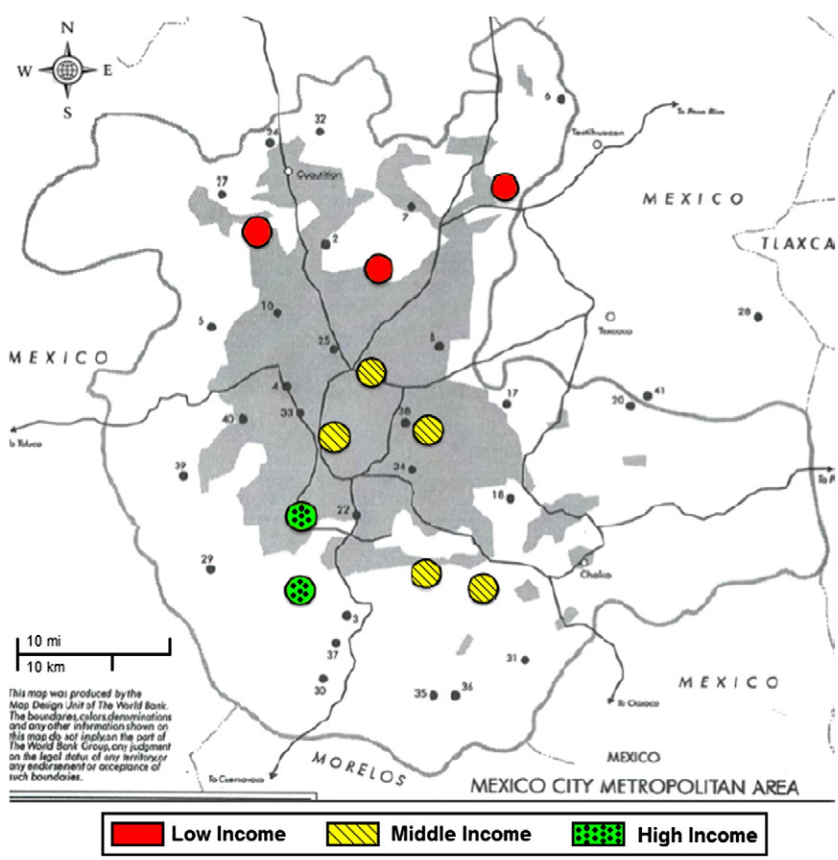

Fig. 1. Monitoring Stations in Mexico-City.

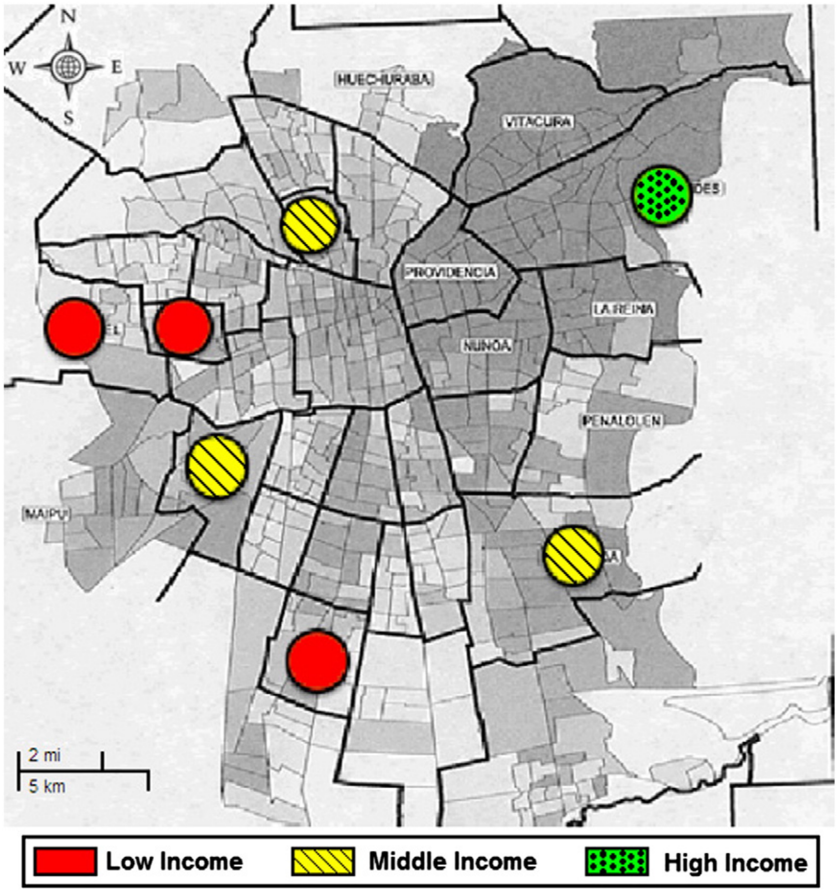

Fig. 2. Monitoring Stations in Santiago.

Appendix B. Option value

Suppose there is a probability $\phi < 1$ that the enacted policy (e.g., HNC, TS) is canceled in the future, say at time T. The relevant discount factor is $\delta < 1$. The cost of car is r and the lemon cost is λ, so the resale price of the car is $(1 - \lambda)r$. A household has four investment options: (i) invest in the car today and sell it at T if the authority decides to cancel the policy, (ii) wait until T and buy the car only if the authority decides to keep the policy in place, (iii) never invest in a car, and (iv) invest in the car today and keep it at T regardless of whether the authority decides to cancel the policy or not.

Because of the irreversibility and uncertainty there is an option value of waiting (or an additional cost if the car is bought today). This is only relevant for those that are indifferent between options (i) and (ii). Households that go for (iii) are far from buying the car anyway, so the policy doesn't affect them at all. Households that go for (iv) are those for whom the policy is sufficiently important that they are willing to kill the option anyway (there may be none if λ is big enough).

Let Δu be the utility gain from buying a car. The expected (additional) utility from following option (i) is

$$E[\Delta U_I] = \Delta u - r + \delta\{\phi[(1-\lambda)r - \Delta u] + (1-\phi)\times 0\}.$$

One may be tempted to conclude that all households for which $E[\Delta U] \geq 0$, or Δu is equal or greater than the cutoff

$$\widehat{\Delta u}_I = r\left(1 + \frac{\delta\phi\lambda}{1-\delta\phi}\right) > r$$

should buy the car. This is not correct because we need to add the cost of "killing" the option of waiting. To do this, we need to compute the expected additional utility from following option (ii):

$$E[\Delta U_{II}] = 0 + \delta\{\phi \times 0 + (1-\phi)(\Delta u - r)\}.$$

The utility cutoff that makes $E[\Delta U_I] = E[\Delta U_{II}]$ is

$$\widehat{\Delta u}_{I/II} = r\left(1 + \frac{\delta\phi\lambda}{1-\delta}\right) > \widehat{\Delta u}_I$$

so the difference

$$\widehat{\Delta u}_{I/II} - \widehat{\Delta u}_I = r\frac{\delta^2\phi(1-\phi)\lambda}{(1-\delta)(1-\delta\phi)}$$

is the cost of killing the option. This cost is increasing in λ and decreasing or increasing in ϕ depending on whether

$$\frac{1}{\phi} \lesseqgtr 1 + \sqrt{1-\delta}.$$

More importantly, a household follow (i) only if

$$\Delta u \geq \widehat{\Delta u}_{I/II}.$$

This result can be easily taken to the analysis in Fig. 2. For example, take the indifferent household in Fig. 2(a) (the case of a TS-like policy captured by a shift of relative prices from $\Delta p/2t$ to $\Delta p/2t + \varepsilon$). For some households to go for investment option (i) we require now

$$\varepsilon q^h \geq r \frac{\delta \phi \lambda}{1-\delta} > 0.$$

Note that when $\lambda = 0$, there will be always some households buying the car even if ε is very small. However as λ increases the policy intervention must be big enough. Note that if $\phi = 0$, the λ parameter becomes irrelevant since there is never the option to think about returning the car, i.e., we go back to basic analysis that is discussed in the main text.

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