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Environmental repercussions of parking demand management strategies using a constrained logit model

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A R T I C L E I N F O

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A B S T R A C T

In order to select the correct mobility strategy, individuals' choice behavior must be studied, and their reactions in response to strategies must be predicted. Upon exploring aspects subject to constraints, our results included walking distance, parking rates, search time and parking availability. We have identified scenarios in which simulation outputs of environmental parking mobility strategies differ significantly when using the Constrained Multi-Nominal Logit (CMNL) when compared with the widely used Multi-Nominal Logit (MNL). With the CMNL model growing in popularity, it is worth considering environmental mobility strategy repercussions in this context with the incorporation of relevant constraints.

1. Introduction

Managing parking demand is a crucial issue for any transportation administration seeking to balance the use of urban areas. The response of drivers to parking demand management measures depends mainly on the drivers 'preferences; therefore (dis)incentives are used to achieve specific goals regarding traffic conditions and air quality.

In the literature, road transportation is often blamed for a significant portion of air pollution in the urban environment (O'Mahony et al., 2000). It is common for vehicular fleets within cities to increase at a speed unmatched by road infrastructure growth. This often leads to tariff differentiation and a shortage of parking spaces.

Pedestrians, infrastructure and vehicles coexist in urban areas, especially in central business districts (CBD)–wherein the first two are generally affected by the latter. These are high density areas with high rise buildings that often obstruct the dilution of pollutants through natural ventilation. According to Gallagher et al. (2011), increases in pollutant levels are largely associated with on-street parking in urban areas. In the context of parking and congestion, attention must be drawn to pedestrians, as they are directly exposed to traffic emissions.

Efforts to revert such trends are the basis of policy, transportation demand management strategies, the purpose of various smartphone applications, and the topic of many scientific articles. The success of these measures depends on modelers' knowledge of driver/parker behavior.

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2. Literature review

Scientific literature has presented four identifiable alternatives to mitigate near-road air quality: efficient vehicle design, urban planning strategies, city breathability, and transportation demand management (TDM) policies, including technology applications. This section presents a collection of papers selected to comprehensively address the following topics: pollution caused by transportation, alternative fuel vehicles and low-emission (greenhouse gas) cars, urban repercussions, mobility management, and discrete choice models used to evaluate parking strategies.

2.1. Pollution caused by urban traffic

More than ever, air pollution in dense city centers and increasing numbers of vehicles are some of the major challenges of sustainable city development. Such problems are aggravated in CBDs by tall buildings surrounding narrow streets, which cause reductions in ventilation effectiveness, leading to high concentrations of pollutants (Ng and Chau, 2014).

The distribution of pollutants within street canyons and densely built-up areas has been studied as fluid dynamics: defining the role of street width, building heights, wind direction and velocity, roof geometry of buildings, tree planting and building packing density. Ventilation, then, is presented by Buccolieri et al. (2010) as a measure of city breathability (Neophytou and Britter, 2005) in terms of pollutant concentration. This knowledge is primarily useful in growing areas within cities in which the wind flow over and through might allow the removal of pollutants and encourage ventilation (Panagiotou et al., 2013).

Exposure to high levels of noise generated by transportation is the cause of physical and psychological disorders; however, pollutant emissions resulting from fuel combustion (NOx, SO_2 and CO) and the use of internal combustion engines contribute to an increased risk of death from cardiopulmonary causes and non-allergic respiratory symptoms or allergies (European Environment Agency, 2013). Other effects are linked to changes in the formation of reactive oxygen species, antioxidant defenses and to non-allergic inflammatory processes (World Health Organization, 2006). According to Morrowa et al. (2010), vehicles also emit greenhouse air pollutants such as CO_2 and CH_4.

2.2. Low-pollution vehicles and conventional vehicles

The authors Goli and Shireen (2014) foresee the near future as a pollution free environment full of electric vehicles (EV) and plug-in hybrid electric vehicles (PHEV) with rechargeable batteries and charging stations. These vehicles have more efficient fuel and engines to reduce pollutant emissions and gain stability of the combustion process (Armas et al., 2012; Valentino et al., 2012).

Words such as "future" and "potential" are often used to describe these vehicles in terms of fuel consumption and emissions (Litman, 2005; Duvall, 2007; Tulpulea et al., 2013); however, Hackbarth and Madlener (2013) have identified the most sensitive group for the adoption of alternative fuel vehicles as younger, well-educated, and environmentally conscious car buyers, who have the ability to plug-in their car at home. In spite of the efforts made to increase the number of low-greenhouse gas cars (green cars) on-street (Jovanović et al., 2014), Hackbarth and Madlener (2013) state that conventional vehicles will maintain their dominance. Consequently, in order to address pollution caused by transportation, we must rely mainly on strategic urban planning and transportation demand management.

2.3. Strategic Urban Environmental Planning

Transportation Demand Management (TDM) is sometimes referred to as Mobility Management in order to focus on specific objectives. TDM defines strategies for reducing traffic congestion, vehicle energy consumption and pollution emissions, improving traffic safety and public health and providing parking management solutions to parking problems (VTPI, 2013).

Special attention must be paid to the management of parking demand-supply, considering parking facilities as special elements within the transport infrastructure often chosen by drivers based on location and convenience (e.g.: cost and walking distance to destination). The process of searching for a free parking space is not effective; in fact, it can be seen as a collection of inefficient processes in which time and fuel are wasted and CO_2 is produced (Shoup, 2007). Arnott and Inci (2006) describe downtown parking, alluding to traffic congestion and saturated on-street alternatives, and Arnott (2006) presents detailed information about drivers cruising for parking, described as "traffic parasite," capable of increasing traffic by 25–40% (Giuffrè et al., 2012). Evidently, Strategic Urban Environmental Planning is an important tool to address urban environmental issues of a multi-sectorial nature, in a systematic and calculated manner, in order to cope with air pollution generated by vehicles and traffic congestion (The World Bank, 2011).

2.4. Parking policy measures

Among the set of urban planning strategies, there is a group called soft policy measures, which refers to measures designed to motivate individuals to voluntarily change their travel behavior towards sustainable mobility (Richter et al., 2009), such as car sharing, car clubs, travel awareness campaigns or personalized travel planning, all aimed at reducing car use and pollution. The other group of hard policy measures includes physical improvements of infrastructure, congestion charging, or control of road space. Guzman et al. (2014) show how different innovative mobility policies, or a combination of measures in transport strategy design (NICHES, 2007), can be used to achieve sustainability in complex city dynamic environments. This can be achieved through time saving and reduction of greenhouse gas emissions (NOx, PM10), resulting in health benefits due to better air quality.

There has been an emergence of interactive dynamic technology applications that help reduce vehicle emissions. Parking information guidance on-street features (such as VMS described by Thompson et al., 2001) and off-street parking availability and guidance Apps, like Parkopedia Parking (Parkopedia, 2014), ParkMe (2014) or VoicePark (2013), are modern strategies used to reduce driving distance in the search for parking spaces. However, when it comes to defining parking policy, strategies or measures, decision makers often rely on behavioral models.

2.5. Behavioral models to evaluate parking strategies

An example of TDM in parking was developed by Nelson-Nygaard Consulting Associates (2011): a list of strategies evaluated or reinvented to address parking problems of the present and the future. The current study analyzed a university campus; however, its model is useful in many city areas where understanding behavior is crucial in estimating environmental repercussions. Further examples include:

- Using pricing to reduce and redistribute parking demand (Ma et al., 2013; Simićević et al., 2013; Habibian and Kermanshah, 2013; Azari et al., 2013; Hensher and King, 2001).
- Promoting carpooling and ride sharing (Efthymiou et al., 2013; Su and Zhou, 2012).
- Using technology to direct drivers to available parking spaces (Thompson et al., 2001; Li et al., 2012; Bekhora and Albert, 2014).
- Shared use of existing private and city parking Establishing fees based on daily-monthly use (Li et al., 2007; Kelly and Clinch, 2009).

In order to define strategies properly, effects must be estimated and predicted. Discrete choice models have been used to evaluate and propose TDM strategies regarding parking issues; they are perhaps the most common tools used to predict and analyze individual choices for one alternative among a set of mutually exclusionary options, finite and known by the choice maker (Manski, 1977). According to this theory, rational individuals select the alternative with the highest utility (Block and Marschak, 1960). The probability of choosing is the following:

$$P_i = P(V_i \geqslant V_j;\ \forall j \in A) \tag{1}$$

where A is the set of possible alternatives. The utility V_i has two components: one observable and deterministic, $\widehat{V}_i$, e.g.: cost, wait time, walking distance, etc., and a random component e_i which represents the observer's incapability to capture the preferences of the decision maker, such as:

$$\mathrm{V_i} = \widehat{\mathrm{V}}_\mathrm{i} + \mathrm{e_i} \tag{2}$$

$$\mathrm{P_i} = \frac{\exp(\mu \widehat{\mathrm{V}}_\mathrm{i})}{\sum_{\mathrm{j}\in\mathrm{A}} \exp(\mu \widehat{\mathrm{V}}_\mathrm{j})} \tag{3}$$

when e_i is Gumbel distributed with parameter of scale μ (iid) the probability of choosing alternative i can be described as a Multi-nominal Logit (MNL) in Eq. (3).

2.6. Attributes in parking choice models to assess environmental repercussions

Hunt and Teply (1993) used logit models to study the behavior of drivers going to work in a CBD, considering parking facilities such as garages, surface lots and special parking provided by employers as off-street alternatives, grouped and distinct from on-street areas. Lamb (1996) studied motorists' choices among parking facilities when travelling towards specific destinations in a city, discovering a strong pattern: drivers behaved as if they were minimizing a linear combination of driving distance (normally increasing emissions), walking distance and parking fee.

Teknomo and Hokao (1997) analyzed parkers' behaviors by choosing a parking location in Surbaya (Indonesia) in the CBD, as Hensher and King (2001) did. The latter analyzed parking demand and responsiveness to supply, pricing and location in the Sydney CBD (Australia), focusing on the role of pricing and supply according to time of day, influencing decisions on whether to drive or park in the CBD.

Thompson et al. (2001) focused on the optimization of parking guidance and information systems (PGI) display configurations, as PGI operators had difficulties determining the best parking availability information to reduce the number of engines emitting gas pollutants, while queuing in line before entering a parking facility during periods of high demand. Caicedo (2010) proposed a real-time parking information management strategy to reduce search time and vehicle displacement, considering that the time spent searching for free parking spaces produces environmental pollution.

Mei and Tian (2011) went further on PGI configuration recommendations, incorporating drivers' perceptions of waiting times at car parks to predict the influence of PGI signs on the overall performance of the traffic system. Ma et al. (2013) analyzed parking behavior finding location and charge as the most important decision making factors. Azari et al. (2013) studied parking behavior under parking and cordon pricing policy, specifically travelers' responsiveness to congestion pricing in deciding whether to drive or park in the CBD. Finally, the study of Simićević et al. (2013) shows that parking prices affect car usage, while time limitations determine the type of parking used (on-street or off-street); moreover, due to distinctions among parkers, strategies might target specific user categories.

2.7. Review summary, motivation and paper structure

Urban traffic congestion is a growing problem for cities in which traffic demand has increased rapidly and/or road capacity has decreased (Shi et al., 2014). Congestion comes along with automobile air and noise pollution, which lead to physical and psychological disorders, generating a growing problem in city centers, particularly during rush hour (Mbuligwe and Kassenga, 1997). A massive low-pollution vehicular fleet might be a solution; however, in spite of efforts to increase the amount of these vehicles on-street, conventional vehicles will likely maintain their dominance. For this reason, Strategic Urban Environmental Planning and parking policy measures are essential.

Parkers' behavior in parking strategies is often modeled by means of logit models, with the MNL used most commonly. All the references presented in Section 2.6 consistently selected a set of attributes to describe parking choices, e.g.: walking time (or distance), parking fare (or charge), searching time (or wait time), and availability, among others. Such attributes successfully explain strategies which aim to modify the demand response of drivers in choosing the most convenient parking type or parking site (see detailed information in Table 1).

On the other hand, Constrained Logit (CL) is a choice behavior model that has recently gained the attention of researchers, due to its ability to incorporate endogenous constraints of decision makers, e.g.: maximum price, maximum walking time in transport mode choice, and exogenous constraints such as regulations or supply capacity in individuals' preferences in the context of discrete choice (Martínez et al., 2009). Castro et al. (2013) studied the Constrained Multinomial Logit (CMNL) model and recommended it as an appropriate model for specific applications (e.g.: model split). Additionally, interesting results were found on the marginal rates of substitution in restricted environments.

In reference to curb parking, a recent study by Zhang and Zhu (2015) integrated pricing restrictions in order to manage parking demand; the authors confirmed that using a model with restrictions was more accurate than the traditional MNL model. Not surprisingly, CMNL models are being used more commonly, and for innovative applications; such as for route choice for metro systems (Herrera, 2014), optimal price in telecommunication (Pérez et al., 2016), locations for schools (Castillo-López and López-Ospina, 2015), choice of residential location and living place (Martínez and Donoso, 2010; López-Ospina et al., 2016), and consumers' food choices (Ding et al., 2012).

With the CMNL model growing in popularity, it is worth considering environmental mobility strategy repercussions in this context with the incorporation of relevant constraints. Our motivation was to focus on the environmental repercussions of parking demand management, using a constrained logit model, as there is currently a lack of research in this regard. This research consists of five sections. The first two sections present the introduction and literature review; Section 3 uses a constrained logit model to explain parkers' choice behavior; Section 4 includes a description of test cases and scenarios, defined to estimate demand share repercussion with the inclusion of restrictions; finally, Section 5 focuses specifically on the study of search times (a) with capacity constraints and occupancy rate, and (b) without capacity constraints, as an effort to transform results into environmental repercussions.

3. Modeling parking choice

3.1. Constrained multi-nominal logit features

One of the most important underlying assumptions of discrete choice models is that decision makers follow a compensatory behavior strategy = wherein different variations of attribute values lead to a given level of utility. In some choice contexts, the compensatory assumption is not evident (i.e.: when characteristics of goods are defined by thresholds imposed by the decision maker), and the number of feasible alternatives under consideration must be reduced.

Based on the work of Swait (2001), Cascetta and Papola (2001) and Martínez et al. (2009), we assume that utility can be separated into two components: one compensatory and another non-compensatory, for the purpose of highlighting the feasibility of the alternative. The constrained utility is the following:

$$V_i = \widehat{V}_i + \frac{1}{\mu}\ln(\phi_i(x_i)) + e_i \tag{4}$$

where $\frac{1}{\mu}\ln(\phi_i(x_i))$ is a cut-off (or penalty) function imposed on i by the choice maker and μ is a scale parameter. The penalty, introduced with a logarithm function, allows a smooth transition between the compensatory and non-compensatory components; consequently, restrictions imposed to specific attributes can be moderately skipped. Again, if e_i is (iid) Gumbel distributed, the probability of choosing i is the following:

Table 1
Discrete choice models in parking.

Reference	Year	Choice subject	Model	Attributes												
				Walk (time/ distance)	Fare	Search or wait time	Time limitation in red zone	Car dependency	Purpose work	Position[a]	Winter provision[b]	Cordon cost	Hours of operation	O/D Distance[c]	Availability	VMS-Parking distance
Hunt and Teply	1993	Type	NL[d]	x	x	x				x	x					
Lamb	1996	Site	MNL	x	x									x		
Teknomo and Hokao	1997	Site	MNL	x	x	x										
Hensher and King	2001	Type-zone	NL	x	x								x			
Thompson et al.	2001	Site	MNL	x	x	x								x	x	
Caicedo	2010	Site	MNL	x	x	x									x	
Mei and Tian	2011	Site	MNL	x	x	x									x	X
Ma et al.	2013	Site	MNL	x	x											
Simićević et al.	2013	Type-zone	MNL		x		x	x	x							
Azari et al.	2013	Type	MNL	x	x	x						x				
Relative frequency	–	–	–	0.9	1.0	0.6	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.2	0.3	0.1

[a] Position relative to the trip from home to work and/or from work to home.
[b] Type of winter provision.
[c] Distance from the person's trip origin to the parking facility.
[d] For further details about the Nested Logit (NL) please refer to the source.

$$P_i = \frac{\phi_i(x_i)\exp(\mu \widehat{V}_i)}{\sum_{j \in A} \phi_j(x_j)\exp(\mu \widehat{V}_j)} \tag{5}$$

The CMNL can consider both upper (e.g.: budget, maximum walking distance tolerated or maximum time desired to spend searching for free spaces), and lower limit restrictions (e.g.: minimum availability required, depth measured from surface level or lighting), denoted $\phi_i^U(x_i)$ and $\phi_i^L(x_i)$ respectively. The latter constraints are defined by the following binomial logit:

$$\phi_{ik}^U = \frac{1}{1 + \exp(z_k(x_{ik} - b_k + \rho_k))} \tag{6}$$

$$\phi_{ik}^L = \frac{1}{1 + \exp(z_k(a_k - x_{ik} + \rho_k))} \tag{7}$$

where k is the attribute under consideration, b_k and a_k are the upper and lower values of characteristic k in order to constrain one alternative; z_k is the scale parameter of the binomial logit model, x_{ik} is the value of attribute k and ρ_k is a parameter, defined as follows:

$$\rho_k = \frac{1}{z_k} \ln\left(\frac{1 - \eta_k}{\eta_k}\right) \tag{8}$$

where η_k is a value associated to the proportion of individuals that violates restrictions imposed on attribute k. Note that when parameter η_k approaches extreme values such as 0 or 1, ρ_k becomes undefined; this is caused by the nature of binomial logit models, which only cover deterministic choices (i.e.: the probability is either 0 or 1) when variables under consideration tend to positive/negative infinite.

In order to incorporate many constraints, a global cut-off is defined as the multiplication of cut-off functions related to each attribute, assuming that constraints are independent. In the same way, it is possible to define system constraints as choice capacities related to maximum supply or regulations (Martínez et al., 2009).

As defined by Bierlaire et al. (2010), the CMNL model can be understood as a heuristic or practical approach to examining constraints. Castro et al. (2013) estimated CMNL model parameters by maximizing the probability of options, using synthetic and real data of travel time and access time. Not only were significant differences found in terms of elasticity (as attribute thresholds are activated), but also that CMNL models performed better than MNL.

3.2. The CMNL parking model proposed to contrast environmental repercussions

Although every analyzed situation differs, some attributes have been constantly considered in modeling decision making used in TDM strategies: walking distance – used in 9/10 of references in Table 1; search time or wait time – used in 6/10; and fare, used in all references consulted due to its ability to regulate demand when the cost is correct, or to increase congestion when parking is free. A particularly notable attribute is availability; it appears in only three of the prior references, but not because it lacks importance. The reason is because only within recent years has availability information become "available" to drivers.

All attributes described in the last paragraph are subject to a restriction. In fact, some have been restricted and empirically analyzed, such as by Castro et al. (2013). For example, a driver does not want to spend more than a certain amount of time searching for a free parking spot. Next, a driver does not want to walk more that a fixed distance between parking and destination. Parking cost can be restricted, too, as well as the number of spaces available. However, this last attribute is closely related to perception of search time.

Based on previous descriptions, the proposed utility function of the alternative i from the viewpoint of individual h, V_{hi}, is the following:

$$V_{hi} = \alpha f_i + \beta w_{ih} + \varepsilon_{ih} \tag{9}$$

where f_i is the parking charge and w_{ih} is walking distance. This operates under the assumption that α and β take the same value for all individuals; however, endogenous levels of attributes associated with maximum willingness to walk are variable, as is the maximum willingness to pay.

Finally, demand in alternative i, a_i, is described as follows:

$$a_i = \sum_h p_{ih} = \sum_h \frac{\exp(\alpha f_i + \beta w_{ih})}{\sum_j \exp(\alpha f_j + \beta w_{jh})} \tag{10}$$

3.3. Endogenous constraints

The following section describes three endogenous constraints proposed to better explain parking choices.

3.3.1. Walking distance constraint

Each decision maker has a maximum willingness to walk, w_h^{max}, towards their final destination. The cut-off function is described as follows:

$$\varphi_{hw_i} = \frac{1}{1 + \exp(z_{hw}(w_{ih} - w_h^{max} + \rho_{hw}))} \tag{11}$$

Then, the choice probability of selecting alternative i is written as follows:

$$p_{ih} = \frac{\varphi_{hw_i}\exp(\alpha f_i + \beta w_{ih})}{\sum_j \varphi_{hw_j}\exp(\alpha f_j + \beta w_{jh})} \tag{12}$$

3.3.2. Fare constraint

Each decision maker has a maximum willingness to pay for parking, $\mathrm{w}_\mathrm{h}^{\mathrm{max}}$. The cut-off function is described as follows:

$$\varphi_{hf_i} = \frac{1}{1 + \exp(z_{hf}(f_i - f_h^{max} + \rho_{hf}))} \tag{13}$$

Hence, the choice probability is written as follows:

$$p_{ih} = \frac{\varphi_{hf_i}\exp(\alpha f_i + \beta w_{ih})}{\sum_j \varphi_{hf_j}\exp(\alpha f_j + \beta w_{jh})} \tag{14}$$

Both cut-off functions φ_{hw_i} and φ_{hf_i} depend on values of parameters ρ_{hw} and ρ_{hf}. These parameters allow consideration of more flexible constraints in such a way that certain level of membership exists, involving violation constraints.

4. Test scenarios

This section covers the following topics: scenarios, demand share results and environmental repercussions.

4.1. Simulation background

A city (or a zone of a fictional city) with 10×10 micro-areas was generated to estimate demand share of parking garages, considering decision makers' endogenous constraints associated with walking time and fare. Each square in Fig. 1 characterizes the desirability of a location, where activities such as work or leisure take place. Parkers' demand of spaces was simulated to represent 1000 drivers, whose micro-area of destination is randomly assigned; and destination is described as pair of coordinates (v_i, j_i), where, $1 \leqslant v_i,\ j_i \leqslant 10$.

Since capacity restriction is evaluated in detail in Section 5.2, in the early stage we assume that the supply of parking garages have sufficient capacity to manage demand. Yellow squares in Fig. 1 represent 5, 7, 10 or 16 parking alternatives at specific micro-areas. Finally, we assume that parking supply consists solely of parking garages.

Maximum willingness to pay for parking garages, f_h^{max}, and maximum willingness to walk, w_h^{max}, were randomly generated between the interval values described in Table 2.

Clearly, the lower the value of w_h^{max}, the fewer options available to each individual, because he/she is not willing to walk more – which is represented in the model by means of smooth cut-off functions in Eq. (11). On the other hand, the lower the maximum willingness of an individual to pay, the less probable they are to use expensive parking garages, Eqs. (11) and (13), therefore limiting their number of options for parking.

Individual walking distance, w_{ih}, from parking garage i to the destination of individual h, was obtained as follows: $45 + |v_i - v_h| + |j_i - j_h|$; whenever destination and parking garage coincide on the same square, individuals will walk 45 m, otherwise Manhattan distances will be considered. The parameters used in the simulations, presented in Table 3, are based on empirical and theoretical experiences.

4.2. Results

The first scenario analyzed the demand share using a MNL model; in the second scenario, the fare restriction was included. Walking-distance restriction was included in the third scenario, and both fare and walking-distance restrictions were included in the fourth scenario.

Graphical results for each scenario are presented in Fig. 2a–d. The blue[1] lines that represent the base scenario and the green lines that represent walking distance restrictions seem to follow a similar (almost parallel) pattern: red and violet lines, representing fare restrictions. Fare and walking-distance restrictions also seem to follow a similar but more "dramatic" pattern when compared with the green and blue lines.

[1] For interpretation of color in Figs. 2 and 7, the reader is referred to the web version of this article.

Zones	1	2	3	4	5	6	7	8	9	10
1	1	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	2	0
3	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0
7	0	0	3	0	0	4	0	0	0	0
8	0	0	0	0	5	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0

Scenario 1: 5 parking alternatives

Zones	1	2	3	4	5	6	7	8	9	10
1	0	0	0	0	0	0	0	0	0	1
2	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0
5	2	0	0	0	0	0	3	0	0	0
6	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0
8	4	5	0	0	6	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	7
10	0	0	0	0	0	0	0	0	0	0

Scenario 2: 7 parking alternatives

Zones	1	2	3	4	5	6	7	8	9	10
1	0	0	0	0	0	0	0	0	1	0
2	0	0	0	0	0	0	0	0	0	0
3	2	0	0	0	0	0	0	0	0	0
4	0	0	0	0	3	0	0	0	0	0
5	0	0	0	0	0	0	0	0	4	0
6	0	0	0	0	5	0	0	0	0	0
7	0	6	0	0	0	0	0	0	0	7
8	0	0	0	0	0	0	0	0	0	0
9	0	0	0	8	0	0	9	0	0	0
10	0	0	0	0	0	10	0	0	0	0

Scenario 3: 10 parking alternatives

Zones	1	2	3	4	5	6	7	8	9	10
1	0	0	0	0	0	0	1	0	2	0
2	0	0	0	3	0	4	0	0	0	0
3	0	0	0	0	0	0	0	5	0	0
4	6	0	0	0	7	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0
6	0	0	0	8	0	0	0	0	0	0
7	0	0	0	0	9	0	0	0	10	0
8	0	0	0	0	0	11	0	0	0	0
9	0	0	0	0	0	0	0	12	0	0
10	13	0	14	0	0	15	0	0	0	16

Scenario 4: 16 parking alternatives

Fig. 1. Scenarios defined with spatial location of parking supply. Note: Yellow squares represent parking locations. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 2
Parameters used to describe driver's preferences.

Description	f_h^{max} (CLP[a])	w_h^{max} (m)
Maximum value	5500	410
Minimum value	4500	164
Average	5004	286
Mean	5000	300

[a] CLP is an acronym for Chilean Pesos, where 570 CLP = 1 USD.

Table 3
Parameters used in the simulations.

Parameters	Description	Value
α	Parking charge	−0.00100
β	Walking distance	−0.00750
z_{hw}	Cut-off parameter of scale for walking distance	1.20000
z_{hf}	Cut-off parameter scale for parking charge	1.20000
ρ_{hw}	Flexibility constraint of walking distance	1.83103
ρ_{hf}	Flexibility constraint of parking charge	1.83103

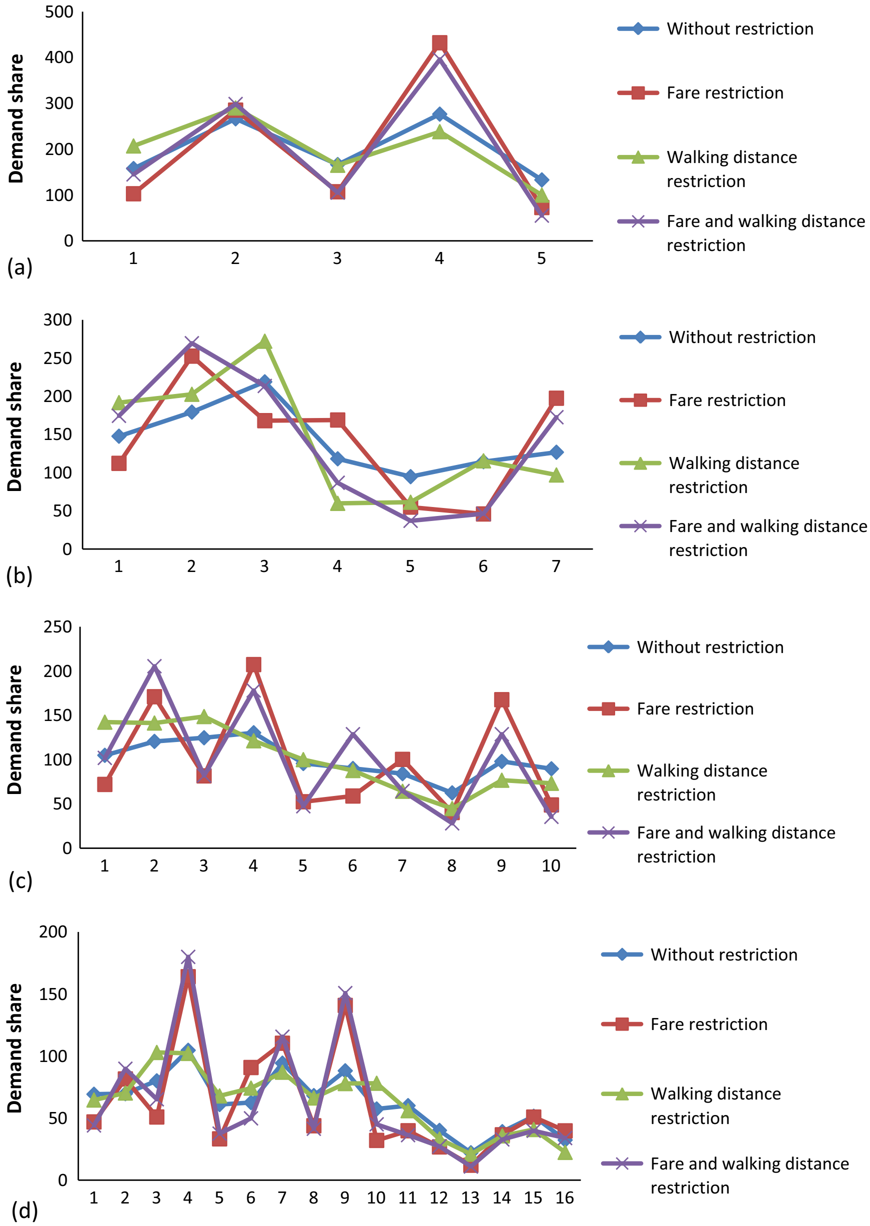

Fig. 2. Demand share representation in scenarios.

The peaks highlight behavior of parkers when they reveal specific preferences for the least expensive facilities.

Restrictions can be categorized as active or passive. For example, the walking-distance restriction becomes more passive as supply increases. The more parking facilities available, the less distance parkers walk. This can be confirmed when comparing the separation of blue and green lines in Fig. 2(a) and (d). However, the latter performance is not followed by red and violet lines. Each figure shows evidence on how fare restriction remains active as parking alternatives (i.e.: supply) increase.

We were also interested in discovering if restriction effects can be superimposed, resulting in an amplified effect. Demand share results (as proportions), were Z-tested in order to find statistical differences between all scenarios, which lead to six comparisons, due to six possible combinations.

Table 4 only shows values and cells in color when Test-Z results indicate that demand is not significantly different among the scenarios compared. The table confirms that blue and green lines in Fig. 2a–d (21% of differences according to Test-Z), as well as red and violet lines (26% of differences according to Test-Z), follow similar patterns. On the other hand, the most significant differences were found comparing the base scenario (NR) and the fare restriction (FR).

Table 4
Prueba Z de diferencia de proporciones para 6 combinaciones posibles.

	Comparission 1	Comparission 2	Comparission 3	Comparission 4	Comparission 5	Comparission 6
Escenarios	NR - FR	FR - WR	WR - F&WR	NR - WR	NR - F&WR	FR - F&WR
5 parking alternatives					0.80	
	-0.95	-0.24	-0.42	-1.18	-1.60	-0.66
				0.09		0.14
				1.96		1.64
						1.61
7 parking alternatives			1.00		-1.62	
				-1.33		-0.86
					0.29	
		-0.61				1.91
				-0.08		-0.03
						1.43
10 parking alternatives					0.21	
		1.83		-1.38		
				-1.56		-0.03
				0.61		1.66
				-0.33		0.52
				0.18		
	-1.25		-0.03	1.69	1.67	
		-0.50		1.76		1.50
				1.68		
				1.34		1.50
16 parking alternatives		-1.72		0.42		0.30
	-1.00	0.96	-1.61	-0.05	-1.66	-0.66
				-1.78	1.28	-1.36
				0.18		-0.95
				-0.63		-0.51
		1.35		-1.03	1.23	
	-1.18	1.75		0.57	-1.55	-0.37
				0.17		0.27
				0.83		-0.63
				-1.85	1.26	-1.50
		-1.69		0.39		0.41
	1.66	-0.84	0.77	0.83	1.59	-0.07
	1.73	-1.56	1.78	0.17	1.95	0.22
	0.30	0.11	0.35	0.40	0.75	0.46
	0.07	1.07	0.11	1.14	1.25	1.19
	-0.89		-1.56	1.36	-0.20	0.69
Percentage of significant differences in Test-Z	76%	66%	76%	21%	58%	26%

NR: no restrictions, FR: fare restriction, WR: walking-distance restriction, F&WR: fare and walking-distance restriction.

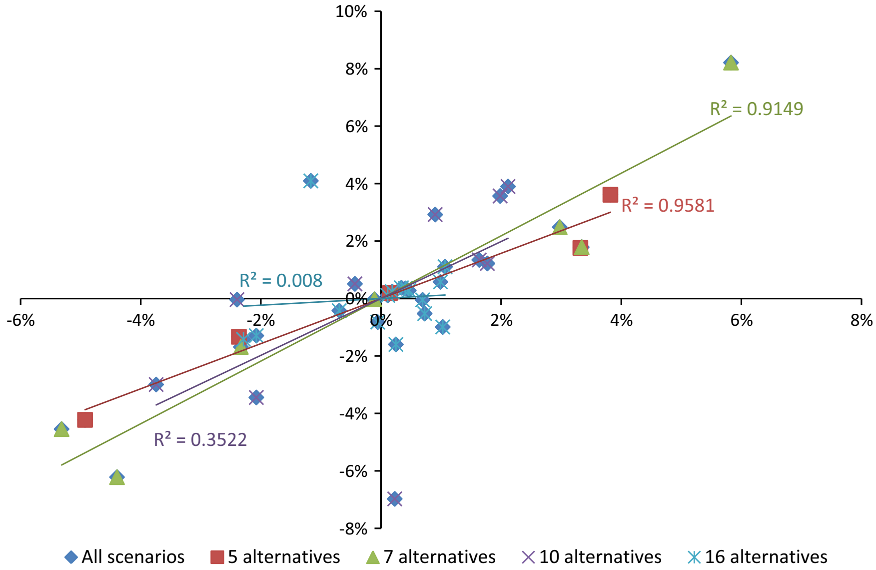

Fig. 3. Adding properties of restrictions.

In terms of consistency, significant differences were found while comparing fare restriction and walking-distance restriction (WR) separately, i.e.: comparison 2 or 3. However, comparisons 4 (NR - WR) and 6 (FR – R&WR) were notable, as they allow exploration of whether the effect of a single restriction can be isolated. For example, Fig. 3 is plotting comparison 4 (NR - WR) in the X-axis and comparison 6 (FR – R&WR) in the Y-axis; interestingly, this figure indicates that in low-supply scenarios (e.g.: 5 and 7 parking alternatives) some amplifying effect can be observed: first, walking restriction is practically added to fare restriction, and second, they move in the "same" direction – correlation coefficients range from 0.91 to 0.96. These behaviors cannot be observed in scenarios with 10 and 16 parking alternatives, likely caused by activeness of passiveness of each restriction.

5. Environmental repercussions based on search time and CO_2 emissions

5.1. Search times without capacity constraints

The terms "static capacity" and "rotation" must be introduced. The first refers to the maximum number of cars simultaneously parked in each facility, and the second refers to number of times each parking space is used in operating days. Table 5 summarizes one of our first approaches evaluating the inclusion of restrictions in behavior, and the effects measured in terms of search time, when static capacity is 300 and rotation is 1.3. The last four rows conclude that WR and F&WR lead to consistent and higher search times. The highest search time values are obtained when fare is restricted, meaning that parkers are willing to spend more time searching for low-cost parking alternatives. The confidence interval for the lower limit of FR was also the lowest, thereby preventing the conclusion that search times were always higher compared to the base scenario – however, we that confidence interval of the lower limits ranged from 1.57 to 1.58, which is practically the same.

Further analysis indicates that the effect of including fare restrictions (in terms of search time increases) in decision making is minimal when the ratio of the zone of utilization (i.e.: arrivals divided by parking capacity and by rotation) is low, and becomes more evident when the ratio is high. The highest value was computed considering five parking facilities of 300 spaces and 2.5 rotations. It is also interesting that an exponential function seems to be appropriate for describing this trend (see the correlation coefficient presented in Fig. 4).

Fig. 5 is the result of our efforts to transform the results from this section into environmental repercussions. In order to prepare that figure, it was assumed that 55% of the city's vehicular fleet is composed of gasoline engine vehicles and the remaining used diesel (Querol, 2014), vehicles searching for a space drive at 16.1 km/h; gasoline engine vehicles emit 232.78 g/km and diesel engine vehicles emit 222.93 g/km (Generalitat de Catalunya, 2011); and that there are, on average, 200 working days per year. According to Fig. 5, when a city's parking ratio of utilization reaches 29%, the underestimation of emissions is more than 3 tons/year of CO_2; however, when it reaches 51%, the underestimation of emissions is more than 10 tons/year of CO_2.

Table 5
Average utilization and search times results in different scenarios.

Arrivals/capacity/rotation	Daily occupation average (%)				Search times (min)			
	NR	FR	WR	F&WR	NR	FR	WR	F&WR
51% due to 5 parking alternatives	0.40	0.26	0.53	0.37	1.72	1.59	1.90	1.69
	0.68	0.73	0.74	0.77	2.17	2.28	2.30	2.36
	0.43	0.27	0.42	0.27	1.75	1.60	1.75	1.60
	0.71	1.11	0.61	1.02	2.23	3.36	2.03	3.05
	0.34	0.19	0.26	0.14	1.66	1.54	1.59	1.52
37% due to 7 parking alternatives	0.38	0.29	0.49	0.45	1.70	1.61	1.84	1.78
	0.46	0.65	0.52	0.69	1.79	2.10	1.88	2.19
	0.56	0.43	0.70	0.55	1.95	1.76	2.20	1.92
	0.30	0.43	0.15	0.22	1.62	1.76	1.53	1.56
	0.24	0.14	0.16	0.10	1.58	1.52	1.53	1.51
	0.29	0.12	0.30	0.12	1.61	1.52	1.62	1.52
	0.32	0.51	0.25	0.44	1.64	1.86	1.58	1.77
26% due to 10 parking alternatives	0.27	0.18	0.36	0.26	1.60	1.54	1.68	1.59
	0.31	0.44	0.36	0.53	1.63	1.77	1.68	1.89
	0.32	0.21	0.38	0.21	1.64	1.56	1.70	1.56
	0.33	0.53	0.31	0.46	1.65	1.90	1.63	1.79
	0.25	0.13	0.26	0.12	1.58	1.52	1.59	1.52
	0.23	0.15	0.22	0.33	1.57	1.53	1.57	1.65
	0.22	0.26	0.16	0.17	1.56	1.59	1.53	1.53
	0.16	0.10	0.11	0.07	1.53	1.51	1.52	1.51
	0.25	0.43	0.20	0.33	1.58	1.75	1.55	1.65
	0.23	0.13	0.19	0.09	1.57	1.52	1.54	1.51
16% due to 16 parking alternatives	0.18	0.12	0.17	0.11	1.54	1.52	1.53	1.52
	0.18	0.21	0.18	0.23	1.54	1.56	1.54	1.57
	0.21	0.13	0.26	0.17	1.55	1.52	1.59	1.53
	0.27	0.42	0.26	0.46	1.59	1.74	1.59	1.80
	0.16	0.09	0.17	0.10	1.53	1.51	1.54	1.51
	0.16	0.23	0.19	0.13	1.53	1.57	1.55	1.52
	0.24	0.28	0.22	0.30	1.58	1.61	1.56	1.62
	0.17	0.11	0.17	0.11	1.54	1.52	1.54	1.51
	0.23	0.36	0.20	0.39	1.57	1.68	1.55	1.70
	0.15	0.08	0.20	0.12	1.53	1.51	1.55	1.52
	0.15	0.10	0.14	0.09	1.53	1.51	1.53	1.51
	0.10	0.07	0.08	0.07	1.51	1.51	1.51	1.51
	0.06	0.03	0.05	0.03	1.50	1.50	1.50	1.50
	0.10	0.09	0.09	0.08	1.51	1.51	1.51	1.51
	0.13	0.13	0.10	0.10	1.52	1.52	1.51	1.51
	0.08	0.10	0.06	0.09	1.51	1.51	1.50	1.51
Average	–	–	–	–	1.63	1.67	1.64	1.67
Standard deviation	–	–	–	–	0.16	0.33	0.19	0.30
Interval of confidence lower limit	–	–	–	–	1.58	1.57	1.58	1.58
Interval of confidence upper limit	–	–	–	–	1.68	1.78	1.70	1.77

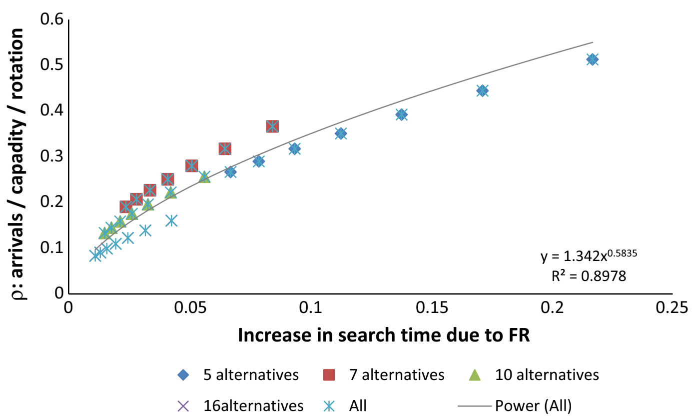

Fig. 4. Search time repercussions due to zone's utilization ratio.

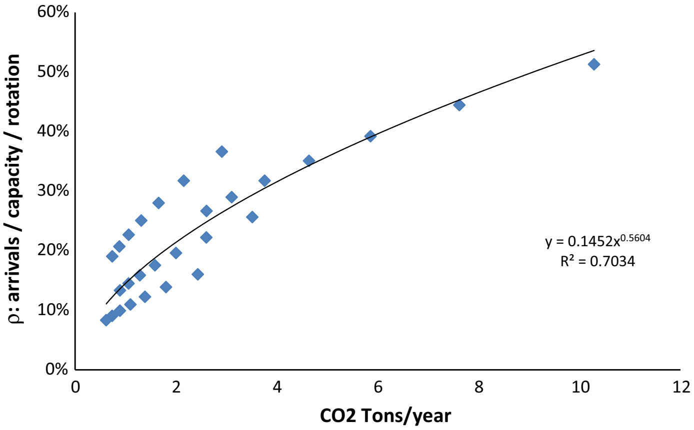

Fig. 5. Underestimation of CO_2 emissions due to zone's utilization ratio.

5.2. Search times with capacity constraints and occupancy rate

In this section, high occupancy rate will be penalized based on the hypothesis that higher levels of congestion will result in higher search times. Fig. 6 shows a logistic function representing the level of penalty that, once applied to search time, affects the probability of choosing one alternative. Fig. 6 is related to static capacity restrictions and the dissuading response of demand when real-time information alerts that availability is low.

The use of constrained models allows incorporation of a smooth and differentiable transition between stages, when search times are strongly affected by occupancy rate and when they are not. Moreover, the use of search time or availability constraints implies externalities due to other drivers' decisions, i.e.: drivers' preferences for a particular alternative affecting other drivers' probability of choosing the same alternative.

Mathematically, the penalty is written as follows:

$$V_{hi} = \alpha f_i + \beta w_{hi} + \frac{1}{\mu}\ln(\varphi_{hC_i}) + \varepsilon_{hi} \tag{15}$$

where C_i is the capacity of alternative i, and φ_{hC_i} is defined as follows:

$$\varphi_{hC_i} = \frac{1}{1 + \exp(z_{hC_i}(a_i - C_i + \rho h_i))} \tag{16}$$

The values of z_{hC_i} and ρ_{hC_i} are used to introduce penalties due to occupancy rates. Since demand in alternative i is affected by its static capacity, the result is a non-linear problem of a fixed point system of equations:

$$a_i = \sum_h p_{ih} = \sum_h \frac{\varphi_{hC_i}\exp(\alpha f_i + \beta w_{ih})}{\sum_j \varphi_{hCj}\exp(\alpha f_j + \beta w_{jh})} \tag{17}$$

where demand assignment in alternative i, a_i depends on φ_{hC_i} and φ_{hC_i} depends on a_i, $\forall h$.

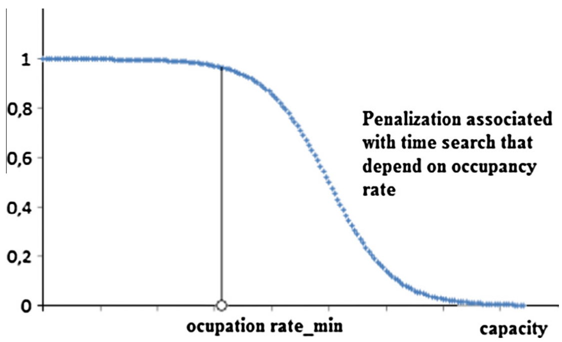

Fig. 6. Search time and occupancy penalization.

Table 6
Parameters used to perform capacity restriction and occupancy rate analysis.

Parameter	Occupation threshold	
	40%	70%
z_{hC_i}	0.06	0.09
ρh_i	160	50

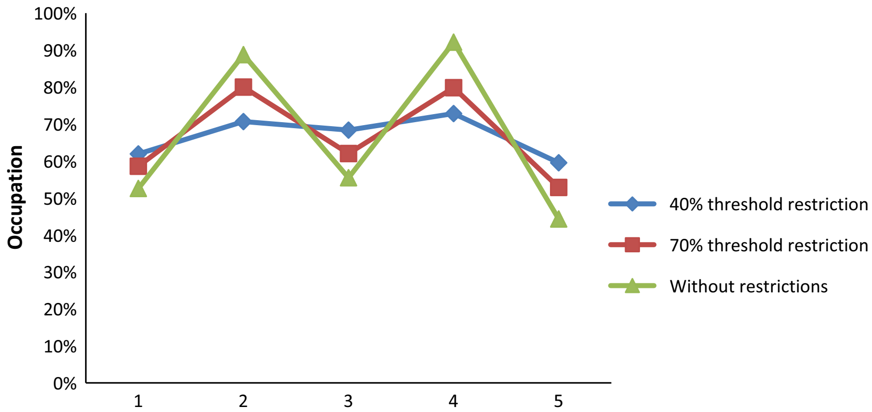

Fig. 7. Different occupancy restrictions results.

In Martínez et al. (2009) the convergence of the system of equations described in Eq. (17) is not only proven, but applied to similar problems that deal with choices of housing or schools. Table 6 shows the set of parameters defined to model the cut-off function (Eq. (16)), meaning that 40% or 70% utilization rates are considered thresholds from which the penalty associated to search times becomes effective.

Thus, Fig. 2 shows that the inclusion of restrictions of walking distance and fare resulted in different demand share results; in fact, search times are higher due to parker's preferences. However, Fig. 7 shows that choices are more efficient when occupancy restrictions are included, meaning when drivers depend on information regarding availability.

The inclusion of capacity restrictions allows an analysis of parkers' behavior in terms of time windows, which is typical in multi-period simulations or dynamic environments. The reader must note that, in contrast to the exercise presented in Section 5.1, wherein arrivals were considered throughout an operational day, static capacity restrictions allow representations of arrivals per hour. The green line in Fig. 7 is associated to an average of 2.33 min spent by each driver searching for free spaces, a figure that decreases to 2.2 and 2.15 min as capacity restrictions (i.e.: search time penalty) are included. In practice, this optimization can be supported by all kinds of user aid: VMS, parking guidance systems, real-time information on websites or Smartphones, etc. Using the same assumptions described in the last paragraph of Section 5.1, 5.7–7.6% reduction of CO_2 emissions can be achieved.

6. Conclusions

In order to simplify the analysis and come to a conclusion, we assumed that this fictional city's parking supply consists solely of parking garages; on-street/off-street parking differentiation was not considered.

From a macro viewpoint, the number of arrivals in all scenarios is the same; hence, we studied the resulting effect of using one model (MNL) or over another (CMNL). In our tests, a closer view of what is happening within each parking facility indicates that search times are higher when walking distance and fare restrictions are included in the model. Facilities that satisfy most of the restrictions set by drivers (i.e.: walking convenience or charge) contend with more demand, therefore higher occupation that increases search time.

The model also confirms that parking user aid technology (e.g.: VMS, parking guidance systems, real-time information on websites, Smartphone applications), incorporated as an active occupancy restriction, plays a significant role in correcting the inefficiencies of choice making. Hence, modern cities, or "smart" cities, have the advantage of technology.

We cannot confidently suggest that environmental repercussions of parking choices have been underestimated, or that they can be counterbalanced. More testing is required, including different scenarios, alternatives and cities. Our intention was to present one of the first applications of a CMNL in which parking choice was restricted, yielding searching times 1.1–5.7% higher. For example, if parking behaviors and environmental repercussions of parking congestion within a city have been forecasted using an MNL model, a restricted model may better explain the behavior of parkers, and externalities may require recalculation. Additionally, if the city does not offer drivers any kind of ITS parking-oriented features to counteract inefficiencies, environmental repercussions of parking choices may be underestimated. Finally, the answer to the question of underestimations of environmental repercussions of parking depends on model accuracy, parking demand–supply ratio and available technology.

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