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Valuing crowding in public transport: Implications for cost-benefit analysis

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ABSTRACT

This paper investigates the valuation of crowding in public transport trips and its implications in demand estimation and cost-benefit analysis. We use a choice-based stated preference survey where crowding levels are represented by means of specially designed pictures, and use these data to estimate flexible discrete choice models. We assume that the disutility associated with travelling under crowded conditions is proportional to travel time. Our results are consistent with and extend previous findings in the literature: passenger density has a significant effect on the utility of travelling by public transport; in fact, the marginal disutility of travel time in a crowded vehicle (6 standing-passengers/m^2) is 2.5 times higher than in a vehicle with available seats. We also compare the effects of different policies for improving bus operations, and the effect of adding crowding valuation in cost-benefit analysis. In doing that, we endogenise the crowding level as the result of the equilibrium between demand and supplied bus capacity. Our results indicate that important benefits may be accrued from policies designed to reduce crowding, and that ignoring crowding effects significantly overestimate the bus travel demand the benefits associated with pure travel time reductions.

1. Introduction

Fast growing transport needs are a common concern for urban areas in both the developed and developing worlds. To address this issue, many cities have already implemented improved high-capacity transit systems (BRT, tramway or Metro). Often these systems are designed using an engineering standard of six (and sometimes more) passengers/m^2 for the average supplied capacity. This design standard is an average across all vehicles of a service during the peak period, which is exceeded in a significant fraction of the operating buses/trains in some route segments. For instance, in Santiago, Chile, the average density across all trains in the most loaded segment during the morning peak hour exceeds 6 passengers/m^2. As many individuals are not willing to use the system under such crowded conditions, they choose travelling by car or shift to car as soon as it becomes available. This prevents public transport modal shares from growing, increasing congestion and emissions. Moreover, although passenger density below a maximum design threshold of say 6 passenger/m^2 may not be considered problematic at the design level, it is relevant because crowding may influence users' preferences even for low levels of passenger density.

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Crowdedness is usually left aside in most public transport demand models used for strategic planning. When planners evaluate transit network improvements, such as bus exclusive lanes, their goal is to increase the demand for public transport. Usually, this approach neglects the negative effects of crowding caused by the new induced demand. Notwithstanding, Tirachini et al. (2013) discussed its effects on operating speed, waiting time, travel time reliability, route and bus choice, and optimal levels of frequency, vehicle size and fare. The need for a more detailed understanding of crowding on travel decisions and its impact on project evaluation or cost-benefit analysis (CBA) is becoming an urgent priority. In this paper we focus on the valuation of crowding and its effect on mode-choice modelling. We estimate bus travel demand using a mode choice model that includes crowding effects and analyse the impact of using a wrong model, without crowding effects, in estimating demand and users benefits.

The general objectives of this paper are two: (i) to measure the willingness-to-pay (WTP) for crowding reductions in existing transit systems, and (ii) to study empirically the implications for CBA of making the demand for public transport endogenous with respect to the crowding level. The study is based on data from Santiago, Chile.

Most work addressing the valuation of crowding in public transport systems has used choice-based stated preference (SP) methods (e.g. Li and Hensher, 2011). But Guerra and Bocarejo (2013) and Haywood and Koning (2015) applied contingent valuation to find the willingness to pay (WTP) for reducing overcrowding in the Bogota bus system and in the Paris Metro system, respectively. Li and Hensher (2011) reviewed public transport crowding valuation research, focusing on studies conducted in the UK, USA, Australia and Israel. Most studies have used logit models with SP data from commuters, and focused mainly on in-vehicle congestion costs. Nevertheless, Douglas and Karpouzis (2005) also estimated crowding costs at the platform (related to waiting time) and in the access-way/entrance to train stations (related to walking time). The way crowding is represented in SP experiments is highly relevant. Wardman and Whelan (2011) suggest that passenger density is a better indicator of in-vehicle congestion, given that a same load factor may have different levels of crowding across different types of vehicles/wagons with varying seat composition.

Our study was performed within a mode choice SP framework. In the choice experiment respondents had to choose between two transport modes, which could be bus, Metro or car. Each alternative was described by a number of attributes (e.g. cost, travel time, waiting time), and one of them was related to crowding. Specifically, pictures depicting passenger densities on board of vehicles served to represent the level of crowding. Valuations were derived from the estimation of mixed logit (ML) models (Train, 2009) using these data.

To explore the effects of crowding valuation in CBA results, three transport policies - typically proposed for improving bus corridor operations - were modelled: increasing bus frequency, increasing vehicle capacity, and building exclusive bus lanes. We used the estimated modal choice model to solve the equilibrium problem for bus demand (induced by the dependence of the bus utility function on crowding levels that, in turn, depend on bus demand). By doing so, we identified the pure effect of each policy and the effect of endogenous crowding levels in CBA. We found, for instance, that increasing bus travel times overestimated demand and user benefits if the endogenous effect of crowding was not taken into account.

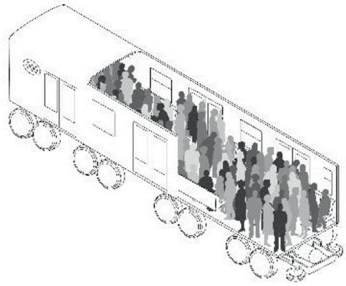
The rest of the paper is organised as follows. Section 2 presents the SP survey experimental design and the information collected. Section 3 discusses our discrete choice modelling approach and presents the main estimation results. Section 4 discusses the effect of including crowding on the cost-benefit analysis of three common measures to improve the performance of a bus corridor. Some final comments are given in Section 5.

2. Survey design

Prior to the experimental design, we conducted focus groups that served to define which attributes would be most important to consider and which could be their levels of variation. Alternatives were finally described by six attributes: transport mode, travel time, travel cost, average waiting time, waiting time variability (coefficient of variation), and crowding level inside the vehicle (bus or train).

The experimental design in SP surveys is represented by a matrix that summarizes the choice scenarios that respondents will have to face in the survey. In this matrix, columns represent the attributes of the alternatives, and rows represent different choice scenarios. There are several ways to define the design matrix. The more traditional (and more suitable matrix for linear models) consists in an orthogonal design, which ensures that all columns are orthogonal to each other (i.e. linear independent). This design minimizes the variance of the estimated parameters in the case of linear models. However, for nonlinear models and in particular for logit models, the levels of the variables (attributes) are not relevant, but the differences between them are. Therefore, the design is built orthogonal in differences (called optimal designs). For nonlinear models, where X is the matrix of independent variables, in general, the covariance matrix of estimated parameters (Ω) is not proportional to $(X'X)^{-1}$ as in the case of linear models. Moreover, Ω depends on the specific model to estimate.

Based on these considerations the so-called *efficient designs* (Rose and Bliemer, 2009; Ortúzar and Willumsen, 2011, Ch. 3) minimize Ω as function of the attribute levels in every choice scenario of the design. This means adjusting the design matrix to minimize Ω. To do so, Ω needs to be transformed to a scalar by some metric. Different metrics to transform Ω lead to different methods in the efficient design family. For instance, if the metric is the trace of the matrix, the design is called *A-efficient*; if the metric is the determinant of the matrix, the design is *D-efficient*. One difficulty of this type of designs is that Ω cannot always be derived analytically and requires numerical methods.

Attribute	Alternative A	Alternative B
Mode	Bus	Metro
Cost	Ch$ 590	Ch$ 650
In-vehicle travel time	25 min	15 min
Average waiting time	10 min	5 min
Waiting time range The bus or Metro may pass at any moment in this interval	Between 0 and 29 min	Waiting time is fixed
Occupancy The figure represents how crowded the bus or the train will be when arriving at the stop or station.		

Which alternative would you choose to make your trip?

○ Alternative A ○ Alternative B ○ I would not travel

Fig. 1. Example of SP choice scenario.

Our choice experiment was based on a *D-efficient design* (Bliemer and Rose, 2010) using Ngene (http://choice-metrics.com/). To find an efficient design we require *a priori* values of the parameters to be estimated. We used zero as prior values in the design for a preliminary survey conducted to obtain initial parameter estimates. These values were then used as priors for obtaining a new design, which was used in the final survey. Therefore, the survey was designed and applied in two stages. In what follows, we discuss the variables (and its levels) used in the designs. Fig. 1 shows an example of a SP choice scenario.

Alternative modes were presented based on their real availability in the reference trip reported by each individual. For example, if respondents reported using public transport, their choice scenarios only included bus and Metro as alternatives. If respondents declared using car, they were asked whether they could use public transport for the trip. If yes and if the respondent could use only bus, say, the choice scenarios included car and bus; otherwise, the choice scenarios included car, bus and Metro. Based on this "mode availability", three sets of choice experiments were built: one for individuals that could travel only by bus or Metro; another for individuals that could travel by car, bus or Metro; and another for individuals that could travel only by car or bus. The levels of the attributes were based on the actual levels reported by the respondents for their reference trips. The levels for travel time were pivoted on the actual travel time of the longest leg of the reference trip and took the values 80%, 100%, 120% and 130% of the actual travel time. Notwithstanding, in the final experimental design the minimum pivotal travel time was set to 20 min to avoid some very small variations.

The travel cost levels depended on the transport mode. For bus or Metro, the cost levels were Ch$ 590 or Ch$ 650,[1] the modes' single fares at the time. In turn, if the alternative was car, the travel cost levels were set either at the current levels experienced by the individuals, or with a 10% increment. The cost of using a car included expenditure in fuel, and was computed on the basis of travel time, average speed and average fuel consumption. If respondents paid for parking or for urban highway tolls in their reference trips, these values were added to the car travel cost.

[1] At the time of the survey 1 US$ = 530 Ch$ (Chilean pesos).

The average waiting time levels were considered different for every mode: zero for car, 5 or 10 min for bus, and 3 or 5 min for Metro. Headway regularity was classified as one of the most important attributes for participants of the focus groups; for this reason, we introduced waiting time reliability in the experimental design (as a measure of regularity), even though it is not the focus of our study. Waiting time reliability was presented as ... "the bus or Metro may pass at any moment in this interval" (see Fig. 1). Each interval was associated with a coefficient of variation, which was zero for car, and 0, 0.5, 0.7 and 1.0 for public transport. We did not consider travel time reliability because it was less relevant than waiting time reliability in Santiago. If we assume that the perception of uncertainty is the same for travel time and waiting time, we could use our estimates to value reliability of both types of time.

Crowding for bus and Metro were presented using six levels of standing passenger density by means of specially designed figures (see Table 1). Each figure was associated with a level of standing passenger density, starting at zero and increasing until 6.5 passengers/m^2. In the case of bus, the levels of passenger density were 0, 0.5, 1.0, 2.0, 3.5 and 6.0 passengers/m^2, and in the case of Metro, 0, 0.5, 2.0, 3.5, 5.0 and 6.5 passengers/m^2.

Finally, the SP experiment considered six hypothetical scenarios per respondent two alternatives and five attributes; all these values are well within the limits found by Caussade et al. (2005) for the Chilean case. Tables 2–4 summarize the final designs for the three mode availability cases.

The survey was implemented in laptops and applied face to face at the respondents' workplaces (it took 15–20 min to complete). All choice scenarios included a "non-purchase option" (I would not travel[2]), as recommended in the literature (Ortúzar and Willumsen, 2011). The survey form also included questions designed to obtain information about the respondent's characteristics (gender, age, car ownership and income), a reference trip to work, and attitudes towards comfort in public transport. The data sought for the reference trip was travel time, frequency, number of legs and, for every leg, mode, in-vehicle travel time, waiting time, comfort level (sit, standing with room around, standing with little room, standing in a quite crowding vehicle), and parking and toll costs if the trip had been by car. This information was used for pivoting the attributes presented in the choice scenarios.

3. Model formulation and estimation

3.1. Model specification

The framework for our model specification is random utility theory. In the context of the choice of transport mode, the theory can be summarized in the following assumptions about individual behaviour (Ortúzar and Willumsen, 2011, Chapter 7).

- There is a (finite) set of transport alternatives, mutually exclusive, for the individual's trip.
- Individual preferences for the alternatives can be represented by a utility function that depends on attributes of the alternatives and individual's characteristics.
- The mode that generates the highest utility among all available alternatives in the individual's choice set is selected.
- In the individual's utility function of every alternative, there are variables that the modeller cannot observe. This way, two individuals with the same choice set and the same observable characteristics may choose different transport modes.
- It is assumed that the unobservable individual component of every modal utility is randomly distributed in the population.

In practical terms, the theory involves defining a utility function for each mode, which depends on specific modal attributes, the traveller's characteristics and a random component with a certain distribution over the population. Analytically, the random utility of alternative m for individual i is written as $U(x_{mi}, z_i, e_{mi})$, where x_{mi} is a vector of observable attributes for mode m (travel time, cost, etc.) and individual i, z_i is a vector of observable characteristics of the individual i (income, age, sex, driver's license, etc.), and e_{mi} is the random component.

As we assume that individuals choose the alternative that maximizes their utility, then mode m is chosen if $U(x_{mi}, z_i, e_{mi}) \geqslant U(x_{ki}, z_i, e_{ki})$ for all modes k in the set of available modes of individual i. Since U is a random variable, we can write the probability that individual i chooses alternative m as Prob (i chooses m) = Prob ($U(x_{mi}, z_i, e_{mi}) \geqslant U(x_{ki}, z_i, e_{ki})$, for all k), and different models can be obtained according to assumptions made about the functional form of the utility and the probability distribution of the random components. In particular, the multinomial logit (MNL) model is obtained assuming that the random components are additively separable in the utility function, and identically and independently distributed Extreme Value Type I across alternatives and individuals (McFadden, 1974).

When individuals make repeated choices, the random component of modal utility is not independent from one choice occasion to another. To model this dependence, the random component of the utility of mode m for individual i in occasion t (e_{mit}) is decomposed into two terms such that $e_{mit} = u_{mi} + u_{mit}$. The random component u_{mi} is specific to individual i, and u_{mit} is specific to individual i and choice occasion t. This decomposition leads to an error components ML model (Revelt and Train, 1998; Walker et al., 2007; Train, 2009) if u_{mit} is identically and independently distributed Extreme Value Type I across

[2] Interpreted as "I would use another alternative" given that these were trips to work; we are grateful to an anonymous referee for having noted this.

Table 1
Passenger density and figures used to represent the level of crowding.

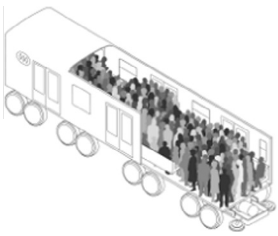
Nominal crowding level	Bus	Train
1		
2		
3		
4		
5		
6		

Table 2
Final experimental design for individuals that could travel by bus or Metro.

Block	Alternative A						Alternative B					
	Mode	Travel time (%)	Travel cost	Waiting time	W.T. coef. var.	Crowding level	Mode	Travel time (%)	Travel cost	Waiting time	W.T. coef. var.	Crowding level
1-1	Bus	100	590	10	0	4	Bus	130	590	5	0.5	2
1-2	Bus	100	590	10	0.7	1	Bus	120	590	5	0.7	4
1-3	Bus	100	590	10	1	3	Metro	80	650	5	0	4
1-4	Bus	100	650	5	0.7	3	Bus	120	590	10	1	6
1-5	Bus	100	590	5	0.5	6	Metro	130	590	3	0	3
1-6	Bus	100	650	5	0.7	2	Bus	80	650	10	0.5	3
2-1	Bus	100	590	5	0.5	5	Bus	100	590	5	1	1
2-2	Bus	100	590	10	0	2	Bus	100	590	5	0	6
2-3	Bus	100	650	5	0	1	Metro	120	650	10	0.7	5
2-4	Bus	100	650	10	1	5	Metro	130	590	5	0.5	1
2-5	Bus	100	590	10	1	6	Metro	80	650	3	0.5	2
2-6	Bus	100	650	5	0.5	4	Bus	100	650	10	0	5

Table 3
Final experimental design for individuals that could travel by car, bus or Metro.

Block	Alternative A						Alternative B					
	Mode	Travel time (%)	Travel cost[a]	Waiting time	W.T. coef. var.	Crowding level	Mode	Travel time (%)	Travel cost	Waiting time	W.T. coef. var.	Crowding level
1-1	Car	100	$1.0 * C$	0	0	1	Metro	130	650	5	0	1
1-2	Car	100	$1.0 * C$	0	0	1	Bus	80	650	10	0	3
1-3	Car	100	$1.0 * C$	0	0	1	Bus	100	590	10	0.5	5
1-4	Car	100	$1.1 * C$	0	0	1	Metro	120	590	3	0.5	4
1-5	Car	100	$1.1 * C$	0	0	1	Bus	120	650	5	1	1
1-6	Car	100	$1.1 * C$	0	0	1	Bus	100	590	5	0.5	6
2-1	Car	100	$1.1 * C$	0	0	1	Metro	100	590	3	0	5
2-2	Car	100	$1.0 * C$	0	0	1	Metro	80	650	5	0.5	2
2-3	Car	100	$1.1 * C$	0	0	1	Bus	80	590	10	0.7	4
2-4	Car	100	$1.0 * C$	0	0	1	Bus	130	650	5	0	2
2-5	Car	100	$1.0 * C$	0	0	1	Bus	120	650	10	1	6
2-6	Car	100	$1.1 * C$	0	0	1	Bus	130	590	5	0.7	3

[a] In this column C means the cost of the reference trip.

modes, individuals and choice occasions, and u_{mi} is, for example, normal distributed across individuals, but not necessarily across modes (Ortúzar and Willumsen, 2011, Section 7.6.2).

It is generally assumed that the utility function $U(x_{mi}, z_i, e_{mi}) = V(x_{mi}, z_i) + e_{mi}$ is additively separable and that its observable part $(V(x_{mi}, z_i))$ is linear in the modal attributes and independent of individual characteristics z_i. For example, if $V(c_m, t_m) = \alpha_m + \beta c_m + \gamma t_m$, where c_m is travel cost and t_m is travel time, then $-\beta$ is the marginal utility of income and γ is the marginal utility of travel-time savings (in simplified terms). The observable part of utility is not independent of z_i when the marginal valuations depend on individual characteristics, such that $V(c_m, t_m, z) = \alpha_m + \beta(z)\ c_m + \gamma(z)\ t_m$. This is the case when the marginal utility of income depends on individual income or if the modeller allows for systematic taste variations (Ortúzar and Willumsen, 2011, p. 279).

The marginal rate of substitution between money and time is defined as the subjective value of time (VT). This value can be calculated as the ratio between the parameters of time and cost (γ/β) in linear utility models (Gaudry et al., 1989). In this study, we postulated that the marginal utility of travel time depends linearly on the level of crowding in the vehicle (bus and Metro). This assumption is consistent with the time multipliers' approach adopted in similar studies reviewed by Li and Hensher (2011).[3] Following Haywood and Koning (2015), we write γ as a linear function of in-vehicle passenger density (d) as $\gamma\ (d) = \gamma_0 + \gamma_1\ d$. This specification captures the increasing discomfort for travelling in crowded conditions, and also implies that the total discomfort is proportional to travel time.

The variables used in the utility specification included only those presented in the experimental design (i.e., travel cost, in-vehicle travel time, average waiting time, range of waiting time, and level of crowding measured in passenger density). The utility specification for the model was specified as follows:

[3] Batarce et al. (2015) found a nonlinear effect of passenger density in travel time using mixed SP/RP data. Their utility function was specified with dummy variables to represent three levels (or ranges) of passenger density, because the RP data available used an approximate measure for it. In this paper, we used a linear utility specification for the passenger density effect, because the model was used for prediction and the equilibrium computation needed a continuous utility function in passenger density. In addition, estimation of a quadratic effect of passenger density in travel time resulted in non-significant parameters.

Table 4
Final experimental design for individuals that could travel by car or bus.

Block	Alternative A						Alternative B					
	Mode	Travel time (%)	Travel cost[a]	Waiting time	W.T. coef. var.	Crowding level	Mode	Travel time (%)	Travel cost	Waiting time	W.T. coef. var.	Crowding level
1-1	Car	100	$1.1 * C$	0	0	1	Bus	80	590	10	0.5	4
1-2	Car	100	$1.0 * C$	0	0	1	Bus	120	650	5	0.7	2
1-3	Car	100	$1.0 * C$	0	0	1	Bus	120	650	10	1	5
1-4	Car	100	$1.1 * C$	0	0	1	Bus	130	590	10	0.7	1
1-5	Car	100	$1.0 * C$	0	0	1	Bus	130	650	5	0	4
1-6	Car	100	$1.1 * C$	0	0	1	Bus	100	590	5	0.5	5
2-1	Car	100	$1.1 * C$	0	0	1	Bus	80	590	10	0.7	3
2-2	Car	100	$1.0 * C$	0	0	1	Bus	100	650	10	0	2
2-3	Car	100	$1.0 * C$	0	0	1	Bus	130	650	5	0.5	3
2-4	Car	100	$1.1 * C$	0	0	1	Bus	80	590	5	1	1
2-5	Car	100	$1.0 * C$	0	0	1	Bus	120	650	10	1	6
2-6	Car	100	$1.1 * C$	0	0	1	Bus	100	590	5	0	6

[a] In this column C means the cost of the reference trip.

$$V_{im} = \alpha_m + \beta c_m + [\gamma_0 + \gamma_1 d_m] t_m + \delta w_m + \varepsilon r_m \tag{1}$$

where c_m is the cost of mode m, t_m is travel time, d_m is standing-passenger density, w_m is waiting time, and r_m is the coefficient of the waiting time variation. One important assumption of this utility specification is that the value of time is the same across modes if the passenger density in public transport is equal to zero passenger/m^2. Then, the value of time as a function of passenger density (d) is given by:

$$VT(d) = \frac{(\gamma_0 + \gamma_1 d)}{\beta} \tag{2}$$

In addition, we considered systematic taste variations. For this, we wrote the parameters related to travel time (γ_0) and crowding (γ_1) as a linear function of individual characteristics. The variables considered as sources of taste variations were gender, age, income, and car ownership. The utility function for this model was specified as:

$$V_{im} = \alpha_m + \beta c_m + [\gamma_0(z_i) + \gamma_1(z_i) d_m] t_m + \delta w_m + \varepsilon r_m \tag{3}$$

with

$$\gamma_0(z_i) = \nu_0 + \sum_j \nu_j z_{ij} \tag{4}$$

and

$$\gamma_1(z_i) = \mu_0 + \sum_j \mu_j z_{ij} \tag{5}$$

In Eqs. (4) and (5), z_{ij} is the jth attribute of individual i, and ν_j and μ_j are parameters associated with attribute j. This specification allows us to control for personal characteristics influencing the marginal disutility of travel time and the crowding effect. Then, the value of time as function of passenger density (d) and individual characteristics (z) is given by:

$$VT(d, z) = \frac{\gamma_0(z) + \gamma_1(z) d}{\beta} \tag{6}$$

The next section presents our model estimation results. In addition to the ML model of Eq. (1), we estimated a (miss-specified) ML model without the effect of passenger density in the utility function. This model is used in Section 4 to analyse the bias introduced by the miss-specification in the rest of the parameters and the implications for CBA.

3.2. Estimation results

The estimation sample was composed of 3380 observations provided by 580 respondents of our SP survey, after discarding 100 observations (less than 3.0%) corresponding to choices of the outside-option. It comprises individuals surveyed using both the preliminary and final experimental designs. The number of respondents by type of design and some descriptive statistics of the sample are shown in Table 5. We also present the distribution of some key variables for travellers (that travel to work and are older than 18 years) from the most recent large-scale mobility survey in Santiago, collected in 2012 (SECTRA, 2014). The mean income and age distributions in the estimation sample are similar to those in the population of Santiago travellers to work, but gender and number of households with car differ in both samples. To control for possible biased parameter estimates, we introduced socioeconomic variables in a model with systematic taste variations.

The differences in design may imply that our four datasets (i.e., preliminary designs without and with car available, and final designs without and with car available) have different error variances. Therefore, we applied the mixed data estimation approach (Ben-Akiva and Morikawa, 1990; Ortúzar and Willumsen, 2011, Section 8.7.3), which makes sure that the scale parameter (inversely related to the error standard deviation) of the Extreme Value Type I distribution for the combined dataset is the same (Ben-Akiva et al., 1994). As a consequence, to estimate the models we allowed for different scale factors for each dataset and normalized the scale factor of the first (preliminary design without car) to one.

Table 6 summarizes the estimation results for our model and for the miss-specified model, estimated without passenger-density effects, to compare the results of omitting this variable in the rest of the parameters. The likelihood ratio test allows rejecting the hypothesis of null passenger-density effect on travel time disutility (H_0: $\gamma_1 = 0$, $LRT = 21.22$, p-value = 0.00). It is interesting to note that the four datasets seem to have the same error variance as the estimated scale factors are not statistically different from one.

The most significant difference between the ML model of Eq. (1) and the miss-specified ML model, is that the travel cost parameter increases by 40% (in absolute value) in the latter with respect to the well-specified model. This leads to a value of time for the miss-specified model of 2.40 US$/h, which is lower than that for the well-specified model at all levels of passenger density (see Table 7). Moreover, in the miss-specified model the car-specific constant doubles that of the well-specified model; this implies that in the former model the choice probability of car is less sensitive to changes in the level of service variables.

Regarding our best ML model, results indicate that crowding produces a significant increase in disutility (the marginal disutility increases 25% for each increment of one standing-passenger/m^2). A minute of travelling in high density condition

Table 5
Descriptive statistics of the sample and population of travellers in Santiago.

	Estimation sample		2012 Santiago Mobility Survey
Total respondents[a]	578		22,223
Experimental design			
Preliminary without car (dataset 1)	376	65%	–
Preliminary with car (dataset 2)	68	12%	–
Final without car (dataset 3)	92	16%	–
Final with car (dataset 4)	42	7%	–
Gender			
Women	363	63%	38%
Men	215	37%	62%
Age			
18–24	107	19%	11%
25–35	162	28%	28%
36–50	211	37%	35%
More than 50	98	17%	26%
Income (Ch$)	438,925		472,116
Household with car	56%		40%

[a] Respondents in the Santiago Mobility Survey correspond to a subsample of travellers that are older than 18 years and work, which is comparable with the estimation sample of this study.

Table 6
Model estimation results and implied subjective values of travel time.

Parameters	Miss-specified ML model		ML model Eq. (1)	
	Estimates	*t*-test[a]	Estimates	*t*-test[a]
Metro constant (α_{metro})	−0.4770	−4.70	−0.8440	−5.93
Car constant (α_{car})	2.1900	1.36	1.2900	1.53
Travel cost (β)	−0.0014	−1.85	−0.0010	−2.32
Travel time (γ_0)	−0.0293	−4.35	−0.0276	−3.97
Waiting time (δ)	−0.1510	−12.11	−0.1540	−12.33
Coefficient of variation of waiting time (ε)	−0.9150	−15.37	−0.8840	−14.86
Passenger density (γ_1)			−0.0070	−3.82
St. dev. panel error component Metro	1.0600	5.57	1.2200	6.16
St. dev. panel error component Car	2.8500	2.52	2.3600	3.73
Scale factor dataset 2	1.0600	0.13	1.3300	0.83
Scale factor dataset 3	0.9860	−0.10	0.8590	−1.06
Scale factor dataset 4	0.8290	−0.50	0.9690	−0.10
Log-*likelihood*	−1885.3		−1874.7	

[a] In the case of the scale factors, the test-t is for the hypothesis that the parameter is equal to one.

(6 passengers/m^2) produces a discomfort that is 2.5 times greater than that obtained at the lowest density condition (see Table 7), which is consistent with empirical evidence from other cities (Wardman, 2014).

To examine the impact of changes in passenger density in the demand for bus and car travel, Table 8 shows the own and cross passenger-density elasticities for both modes. They are given by the following expressions (see Ortúzar and Willumsen, 2011, p. 235):

$$\text{Bus-passenger-density elasticity of bus demand:} \quad \eta_{Bus,d} = (1 - P_{Bus}) \cdot \gamma_1 \cdot t_{Bus} \cdot d \tag{7}$$

$$\text{Bus-passenger-density elasticity of car demand:} \quad \eta_{Car,d} = -P_{Bus} \cdot \gamma_1 \cdot t_{Bus} \cdot d \tag{8}$$

where P_{Bus} is the bus share, t_{Bus} is in-vehicle travel time for bus, γ_1 is the estimated passenger-density parameter (see Table 8), and d is the standing-passenger density.

As the passenger-density elasticity depends on the specific travel time experienced by the user, the results are presented for the average in-vehicle travel time (28 min) in Santiago. In addition, since the elasticity depends on the modal share, we used the actual bus share in Santiago (41%). As expected, the elasticity increases with the crowding level. Although both the bus and car demands are relatively inelastic to passenger density in public transport, the demand for bus becomes significantly more elastic for high levels of crowding. For instance, an increment of 1% in passenger density when travelling at 1 passenger/m^2 reduces bus demand by 0.12% and increases car demand by 0.08%. But, when travelling at 6 passengers/m^2, an increment of 1% in density reduces bus demand by 0.69% and increases car demand by 0.48%.

Regarding systematic taste variations, Table 9 shows a model estimated with only the significant variables from the previous estimation. Note that in this case results suggest that dataset 3 (final design without car) appears to have different error variance than the rest. A likelihood ratio test (14.4) allows us to reject the hypothesis that the model with systematic taste variations is equivalent to the model of Eq. (1) at the 93% confidence level. In particular, gender, age and income are statistically significant. The effect of gender is that women perceive higher disutility than men for every minute travelling, independent of the level of crowding (μ_{gender}). This result is consistent with the focus groups carried out at the beginning of the study, where women expressed a strong aversion to unsafe travel conditions (risk of accident and robbery) in public transport. In Santiago, robbery and accidents are associated with travelling by bus independent of crowding conditions. Indeed, as accidents happen because of driver behaviour and traffic conditions, they are independent of the crowding level; robbery also occurs in different ways depending on the crowding level. The women participating in the focus groups expressed concern for sexual harassment with lower intensity (in words of the psychologist in charge) than for robbery, when they talked about crime perception in public transport. This could explain why the parameter of gender associated with crowding level was not statistically significant: aversion to travel in overcrowding conditions because of the risk of suffering sexual harassment is lower than expected.

The effect of age is to decrease the impact of crowding in the perceived travel time disutility. That is, for the same level of passenger density, older people perceive lower disutility than younger people.

Finally, the effect of personal income increases the impact of crowding in travel time disutility. This effect is also consistent with the results of the focus groups, where people from higher socioeconomic levels told us that comfort was more important than price when deciding their transport mode.

Table 7
Value of travel time (US$/h) and time multiplier.

Passenger density (standing-passenger/m^2)	Value of travel time miss-specified model	Value of travel time ML model Eq. (1)	Time multiplier ML model Eq. (1)
0	2.40	3.15	1.00
1	2.40	3.94	1.25
2	2.40	4.74	1.50
3	2.40	5.53	1.76
4	2.40	6.33	2.01
5	2.40	7.13	2.26
6	2.40	7.92	2.51

Table 8
Own passenger-density elasticity of demand for public transport and cross passenger-density elasticity of demand for car.

Passenger density (standing-passengers/m^2)	Bus own passenger-density elasticity	Car cross passenger-density elasticity
1	−0.12	0.08
2	−0.23	0.16
3	−0.35	0.24
4	−0.46	0.32
5	−0.58	0.40
6	−0.69	0.48

Table 9
Results for model with systematic taste variations according to Eqs. (3)–(5).

Parameters	Estimates	t-test[a]
Metro constant (α_{metro})	−0.8040	−5.58
Car constant (α_{car})	1.4400	1.51
Travel cost (β)	−0.0008	−1.75
Waiting time (δ)	−0.1540	−12.22
Coef. of variation of waiting time (ε)	−0.8880	−14.88
Systematic taste variations on travel time (γ_0)		
Constant (ν_0)	−0.0363	−1.81
Gender (woman) (ν_{gender})	−0.0259	−2.38
Age (between 36 and 50 years) (ν_{age2})	−0.0190	−1.81
Travel frequency (times/week) (ν_{freq})	0.0066	1.68
Systematic taste variations on crowding (γ_1)		
Constant (μ_0)	0.0072	0.63
Age (between 25 and 35 years) (μ_{age1})	0.0047	1.21
Age (between 36 and 50 years) (μ_{age2})	0.0073	1.96
Age (more than 50 years) (μ_{age3})	0.0091	2.11
Travel frequency (times/week) (μ_{freq})	−0.0026	−1.32
Income (million CL$) ($\mu_{income}$)	−0.0152	−2.37
St. dev. panel error component Metro	1.1500	5.52
St. dev. panel error component Car	2.2300	3.77
Scale factor data set 2	1.3000	0.81
Scale factor data set 3	0.7690	−1.79
Scale factor data set 4	0.8610	−0.58
Log-likelihood	−1867.5	
LRT w.r.t Model of Eq. (1) (p-value)	14.3	(0.07)

[a] In the case of the scale factors, the test-t is for the hypothesis that the parameter is equal to one.

4. Implications for cost-benefit analysis

In this section the impact of including the effect of overcrowding in the CBA of a project to improve public transport operations is discussed. For this, we consider the case of a bus corridor operated by a single bus line. Initially, buses operate on a street with mixed traffic (cars and buses), can accommodate 100 passengers and have a frequency of 15 buses/h. Total demand in the corridor is 5000 passengers/h, and the travel alternatives are bus and car. The analysed measures for improving the quality of public transport services are: (i) increasing the frequency to 20 buses/h, (ii) increasing capacity to 140 passengers/bus, and (iii) increasing operational speed by building a segregated busway.

Bus demand was estimated using the mode choice models in Table 7, that is, both the model that includes passenger-density effects and the miss-specified model, to analyse the impact of using the wrong model in estimating demand and benefits.

In addition, a simple model was developed to estimate the costs and benefits of changes in some operational features in the bus corridor given the total travel demand. This model simulates the operation of the system according to several variables related with the capacity supplied. In this way, it is possible to model different technologies (conventional bus, BRT, Metro) just by changing certain operating variables such as speed, capacity, frequency, or the coefficient of variation of the headway. A more complex model was developed by Tirachini et al. (2014) to define optimal policies, such as optimal frequency, taking into consideration crowding effects. Our focus is on the effect of crowding in CBA results. In particular, we used Chilean data to estimate costs and other relevant parameters for the analysis. It is worth noticing that in our cost-benefit analysis we only compared annual cost and benefits, and did not compute the present value of the net benefits in the time horizon of the project.

4.1. Operational model, cost and benefit measures

Fig. 2 shows a network representing a corridor of length L that is divided into N arcs or segments to distribute travel demand in the nodes joining the arcs. These nodes represent stops of origin and destination of the trips in the corridor.

4.1.1. Supply side of the model

The bus service operation is described by the frequency f (buses/h), the coefficient of variation of the bus headway υ_f, the average bus capacity k (passengers/bus), and the operational speed. The supplied capacity of trips at every stop is:

$$K = k \cdot f \quad \text{(trips/h)} \tag{9}$$

The operational speed in the corridor depends on the type of infrastructure (e.g. mixed traffic vs. segregated bus lanes) and the traffic level. We specified that a fraction a of any arc operates in mixed traffic lanes, and the remaining fraction $(1 - a)$ operates in segregated lanes. The average speed in arc s, is the weighted average of the speed assuming either type

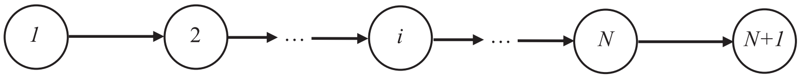


Fig. 2. Network representation of the corridor with N arcs.

Table 10
Demand distribution in the modelled network.

Demand (traveller/h)	Trip distance	Origin node	Destination node
444.4	14	1	8
444.4	14	2	9
444.4	12	3	9
444.4	12	4	10
444.4	10	5	10
444.4	10	6	11
444.4	8	7	11
444.4	6	8	11
444.4	4	9	11

of infrastructure. The operational speed of the buses in a mixed traffic road is independent of the car speed only when the car speed is higher than the bus speed. For low car speeds, we assumed a bottleneck and both buses and cars travel at the same speed. The dwell time due to passengers boarding and alighting was included in the operational speed. In addition, the circuit time of the buses included a fixed time due to operations at the extremes of the route.

The required fleet is determined by the operating frequency, the circuit time and the fraction of the fleet in operation. Likewise, the total distance driven by buses results from the frequency and length of the corridor. The fleet and run distance are relevant to compute the costs of the system.

Car travel supply is described by the road capacity in the corridor. We assumed two lanes with a total capacity of 1600 vehicles/h.[4] In the modelled arcs, car speed depends on the demand for car travel. To account for this, we assumed a BPR-type function for travel time with parameters calibrated to reproduce average speeds in Santiago. The expression for travel time in minutes is:

$$t_a = \frac{60 \cdot l_a}{v_0}\left[1 + c_1\left(\frac{\max\{0, Q_c - Q_e\}}{Q_a - Q_e}\right)^{c_2}\right] \tag{10}$$

where l_a is the length of arc a (km), v_0 is the free-flow speed in arc a (assumed equal to 33 km/h), Q_c is the car demand, Q_e is a congestion-starting flow (equal to 500 vehicles/h), and Q_a is the road capacity of arc a. c_1 and c_2 are the parameters assumed equal to 4.0 and 3.0, respectively. For car flows lower than the congestion-starting flow, travel time is equal to free-flow travel time. Car travel costs were estimated by assuming a fuel consumption of 10 km/lt, fuel price of 0.76 US$/lt, and parking cost of US$ 0.53.

4.1.2. Demand side of the model and equilibrium

Total travel demand was distributed uniformly among the first N nodes of the network (see Table 10). Bus travel demand was estimated with a binary logit model, the relevant variables of which were fare, travel and waiting time, the coefficient of variation of the headway, and the crowding level. At every node, users chose mode considering all level of service variables along the bus path. The bus utility (V_{ijb}) included the sum of the travel time disutility in every arc relevant for a trip between origin i and destination j, such that:

$$V_{ijb} = \alpha_b + \beta c_b + \sum_{l \in P\{i,j\}} (\gamma_0 + \gamma_1 d_b^l) t_b^l + \delta w_b \tag{11}$$

where d_b^l is the average bus passenger density in arc l, t_b^l is the travel time in arc l, and $P\{i,j\}$ is the set of arcs in the path from i to j. The expression for the car utility (V_{ijc}) is:

$$V_{ijc} = \alpha_c + \beta c_{ijc} + \sum_{l \in P\{i,j\}} \gamma_0 t_c^l \tag{12}$$

where c_{ijc} is the monetary cost of travelling by car between i and j, and t_c^l is the travel time in arc l given by Eq. (10). Using the utility functions of Eqs. (11) and (12), the bus travel demand with origin at node i and destination at j (Q_{ij}) is given by:

$$Q_{ij} = N_{ij}\frac{\exp(V_{ijb})}{\exp(V_{ijb}) + \exp(V_{ijc})} \tag{13}$$

[4] This capacity is consistent with 50% green light in traffic signals along the corridor, and with a exogenous car flow of 400 vehicles/h (users travelling from or to outside the corridor area) that reduces available capacity.

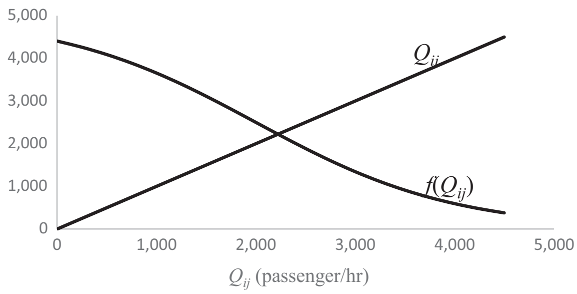


Fig. 3. Example of fixed-point equation for finding the equilibrium demand for bus travel.

where N_{ij} is total number of travellers between i and j.

It is worth noticing that the crowding level is the result of an equilibrium, because bus travel demand depends on passenger density, which in turn, depends on the same demand. Similarly, car travel demand depends on travel time, which in turn depends on car travel demand. For that reason, the simulation model needs to solve an equilibrium condition to estimate consistently the demand taking into account passenger-density and car congestion effects. The bus passenger density in any arc is determined by the ratio between passenger load and supplied capacity multiplied by the maximum passenger density acceptable for the vehicle under consideration (d_{max}). In turn, the maximum passenger density depends on the specified vehicle capacity, and both variables must be consistent. The passenger load in any arc is the sum of all the demand for bus travel with origin at upstream nodes and destination at downstream nodes. Then, bus passenger density is a function of the bus demand between several pairs of nodes. For arc l that connects nodes i and $i + 1$, the bus passenger-density is:

$$d_b^l = \frac{d_{max}}{K}\sum_{m=1}^{i}\sum_{n=i+1}^{N} Q_{m,n} \tag{14}$$

Car travel time may be written as function of total demand minus the demand for bus travel. Indeed, in any arc l connecting nodes i and $i + 1$, the total car flow is:

$$q_c^l = \sum_{m=1}^{i}\sum_{n=i+1}^{N}(N_{m,n} - Q_{m,n}) \tag{15}$$

Inserting Eqs. (14) and (15) into Eqs. (10)–(12), and then these equations into (13), we obtain a fixed-point equation of type $Q = f(Q)$, with f given by the function in the right-hand side of Eq. (13).

Fig. 3 shows this equation for the demand from i to j for fixed bus demands in the rest of the origin-destination pairs, and for a binary logit demand model. The existence of equilibrium is guaranteed because the right-hand side of Eq. (13) is a decreasing function of the bus demand.[5] Equilibrium is obtained by solving iteratively the fixed point equations for the bus demand for every origin-destination pair.

As bus travel time is obtained from the operating speed, it included the boarding and alighting times at stops. Even though boarding/alighting times depend on the demand for bus travel, this effect was not considered because it would require additional detailed assumptions (e.g., number of stops, distance between them, and number of bus doors). In addition, if travel time depends on bus travel demand, another equilibrium condition is introduced into the model, increasing its complexity beyond the scope of this research. As the focus of this paper was on the implications of crowding in CBA results, we did not model the effect of boarding or alighting passengers in travel time.

Waiting time was determined by the frequency and the coefficient of variation of the headway. The expression for the average waiting time is:

$$t_w = \frac{1}{2f}(1 + v_f^2) \tag{16}$$

This expression assumes that all passengers can board the first bus arriving at a stop. To consider the effect of insufficient bus capacity in waiting time, it would be necessary to introduce another equilibrium condition to the model. Therefore, to keep model tractability the passenger congestion effect at stops was also disregarded. Additionally, we assumed that passengers did not need to transfer across bus services to reach their destinations.

To simplify the equilibrium computation, we finally assumed that at every origin node all users travelled to the same destination node. The total demand distributed among nodes was 4000 travellers/h. In addition, we assumed different trip distances because the outcome of transport policies is probably different for individuals with different travel times. Table 10 shows the origin-destination structure of demand considered in the rest of this paper. This demand pattern is consistent with a residential zone around the first seven nodes of the network, a mixed land use zone around nodes 8 and 9, and a

[5] Batarce and Ivaldi (2014) present a formal proof for a demand function with similar congestion effects.

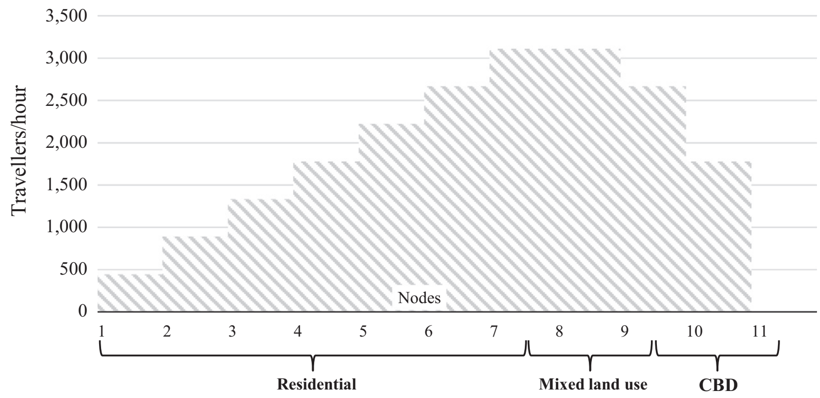


Fig. 4. Total demand distribution along the corridor.

CBD located around nodes 10 and 11 (see Fig. 4). More complex demand patterns are possible, but the adopted one is realistic enough to study the effects of crowding valuation on CBA results.

4.1.3. Operating costs, external costs and users' benefits

To evaluate policies, the model computes the total driven kilometres and operating costs for the estimated fleet. These include operating costs/km and capital costs (depreciation). The data on bus costs was obtained from Batarce and Galilea (2013) and SECTRA (2003), and the car-operating costs were estimated using data from MDS (2014). The external costs of bus and car were also included in the analysis (Rizzi and de la Maza, 2014) and comprise accidents, air pollution and noise. A summary of the bus operating variables and costs used in the computations is presented in Table 11. The results of one hour of operation are expanded to annual benefits using these values.

The benefits of the various policies were estimated using the compensating variation (*CV*). In the case of logit demand models, Small and Rosen (1981) derived an exact analytical expression for the *CV*. For changes in level of service that imply changes in the utility from V^0 to V^1 for M transportation modes the expression for the *CV* is:

$$CV = \frac{N}{\lambda}\left[\ln\sum_{m=1}^{M}\exp(V_m^1) - \ln\sum_{m=1}^{M}\exp(V_m^0)\right] \tag{17}$$

where the terms inside the brackets are the logsum or expected maximum utility (Williams, 1977); λ is the marginal utility of income, which equals the absolute value of the cost coefficient in the estimated discrete choice models, and N is the total number of travellers. We computed the *CV* for every node in the network and the total users' benefits are the sum of the *CV* across nodes.

The *CV* is independent of the order of changes introduced in the corridor. For instance, increasing frequency has two effects: to reduce waiting time and crowding. The benefits due to increasing frequency may be decomposed in the compensating variation for reducing waiting time plus that for reducing crowding, given new waiting times. Hence, to isolate the benefits due to changes on crowding conditions, the compensating variation was computed using this decomposition (see Table 12, row Users' benefits, columns 4 and 5).

4.2. Increasing capacity policies

We evaluated two policies for improving public transport capacity in the corridor: (i) to increase the average bus capacity and (ii) to increase the bus frequency. Both variables were increased by 40%, such that the new supplied capacity was 2100 passengers/h per arc once the policy was implemented.

The policy of increasing bus capacity, from 100 to 140 passengers/bus, produced significant user benefits (measured as compensating variation), which are higher than the costs (see Table 12, and for detailed results see Appendices A and B). Thus, cost-benefit analysis suggests that the policy should be implemented. The demand for bus travel increased by 8%, which is consistent with a policy designed to reduce car use. This analysis also considers the positive effects on congestion and pollution due to a reduction in car share. Indeed, the car driven kilometres fall, while the bus driven kilometres keep constant. If the occupancy rate is 1 passenger/car, this leads to a savings of around 1.6 million car kilometres per year, which corresponds to benefits of US$ 0.43 million due to the reduction in operation and external costs (accidents, air pollution and noise). As the only effect of increasing bus capacity is to reduce crowding in the buses, the CBA results based on the miss-specified model reject the implementation of this policy.

The policy of increasing bus frequency, from 15 to 21 buses/h, also produces significant benefits, which counterbalance its associated costs. The compensating variation was decomposed into the effect of waiting time reductions due to the frequency increase and the effect of crowding reductions due to average capacity increase (because of higher frequency);

Table 11
Operational variables of the simulation model.

Bus operation variables	
Corridor total demand (travellers)	4000
Bus corridor length (km)	20
Average trip length (km)	10
Operating speed in mixed traffic (km/h)	16
Operating speed in exclusive bus lanes (km/h)	22
Operation time at terminals (min)	30
Frequency (buses/h)	15
Coefficient of variation of headway	1.2
Operating costs	
Average bus operating costs	
12-meter-length bus (capacity 100 passengers/bus) (US$/km)	2.83
18-meter-length bus (capacity 140 passengers/bus) (US$/km)	3.54
Cost of buses	
12-meter-length bus (capacity 100 passengers/bus) (US$/bus)	180,000
18-meter-length bus (capacity 140 passengers/bus) (US$/bus)	240,000
Residual value of bus	20%
Lifetime of bus (years)	7
Car operating costs (US$/km)	0.15
External costs	
Bus	
12-meter-length bus (capacity 100 passengers/bus) (US$/km)	0.79
18-meter-length bus (capacity 140 passengers/bus) (US$/km)	0.90
Car (US$/km)	0.12
Infrastructure costs	
Investment costs of bus corridor (MUS$/km)	9.43
Annual capital cost of investment on infrastructure (MUS$/km)	1.01
Annual depreciation of investment on infrastructure (MUS$/km)	0.19
Parameters for expansion to annual costs and benefits	
Days per year	250
Length of demand peak (hours/day)	3
Length of operation peak (hours/day)	4

the former effect is around 52% of the latter. This points out to the relevance of crowding on user benefits. In fact, the policy is not socially worthy when considering only waiting time benefits (US$ 0.43 million) because of the high increment of the net costs (operation and external) associated with incrementing the frequency of the bus system (US$ 1.07 million). The crowding effect[6] produces not only more user benefits, but also cost reductions. The reduction of the car share (from 38% to 33%) implies a reduction in car driven kilometres, which is the source of savings in operating and external costs for the car. These savings compensate the increase in operating and external costs of the buses.

The CBA carried out with the miss-specified mode choice model rejects this policy. The cost of increasing the frequency is not counterbalanced by the users' benefits and the reduction of car costs. Indeed, the only source of benefits is the reduction of waiting time, as the model is insensitive to changes in passenger density. If we compare the waiting-time benefits obtained with both models, we see that the miss-specified model leads to lower benefits than the well-specified one. This is due to the bias in the cost parameter, which reduces the monetary value of the benefits (and the value of waiting time).

Comparing both policies, the total net benefits of increasing frequency are equal to the net benefits of increasing bus capacity. Thus, our results suggest that in this simplified corridor increasing frequency is as good as increasing bus size. It is remarkable that the latter policy is socially worthy, because standard CBA does not capture the benefits of operating larger buses. Complex transport models capture these benefits by modelling waiting time as a function of bus capacity (e.g. De Cea and Fernández, 1993). Reductions in waiting time occur because larger buses increase the probability of boarding the first arriving bus. However, explicit inclusion of crowding in the utility function (or in the modal shares model) allows us to measure the real impact of crowding on users' welfare with simple models using average busloads. In addition, the impact of crowding seems to be more significant than the impact of waiting time reductions.

4.3. Increasing bus speed

Another common policy used to improve the quality of public transport is to build bus corridors with exclusive lanes and, often, with stations with pre-boarding payment. These are key features of the Bus Rapid Transit (BRT) corridors being implemented in several cities worldwide (BRT Centre of Excellence et al., 2015). The goal of building bus lanes is to improve operating speeds and reduce travel times. We assumed that the project consisted of a bus corridor with exclusive lanes and 10 km length, located in the middle of the 20 km bus route. This increased bus speed from 16 km/h in mixed traffic to

[6] The crowding effect was measured with respect to the situation where waiting time was already reduced. Thus, it is the incremental effect over waiting time effect.

Table 12
Costs and benefits of policies for increasing bus capacity.

	Baseline case	Capacity increase	Frequency increase[a]		Frequency increase miss-specified model
			Waiting-time effect	Passenger-density effect	
Operating variables					
Fare (US$)	1.1	1.1	1.1		1.1
Frequency (buses/h)	15	15	21		21
Bus capacity (passengers)	100	140	100		100
Mean passenger density (pass./m^2)[b]	5.5	4.3	5.5	4.4	
Waiting time (min)	4.9	4.9	3.5		3.5
Bus travel time (min)	37.5	37.5	37.5		37.5
Car travel time (min)	25.2	21.0	23.3	20.1	20.9
Required bus fleet	46	46	64		64
Bus driven kilometres	600	600	840		840
Car driven kilometres	16,731	14,623	15,932	13,873	14,739
Bus share	60%	65%	62%	67%	62%
Annual costs and benefits					
Users' benefits (MUS$)[c]	−27.44	−26.46	−27.01	−26.18	−11.68
Bus operation costs (MUS$)	1.70	2.12	2.38		2.38
Capital cost of buses (MUS$)	0.95	1.26	1.32		1.32
Bus external costs (MUS$)	0.47	0.54	0.66		0.66
Car operating costs (MUS$)[d]	1.93	1.69	1.84	1.60	1.70
Car external costs (MUS$)[d]	1.52	1.32	1.44	1.26	1.33
Net benefits					
Compensating variation (MUS$)		0.98	0.43	0.82	0.27
Cost difference (MUS$)[d]		−0.37	−1.07	0.42	−1.05
Total net benefits (MUS$)		0.61	1.43		−0.78

[a] The effect of increasing frequency was decomposed into waiting time and passenger density effects and presented only when relevant for the variable in the first column.
[b] Passenger density is the weighted average by bus demand in each arc.
[c] Benefits were measured as the maximum expected utility divided by the marginal utility of income. The difference between these benefit measures equals the compensating variation. User benefits are negative as they represent the disutility of travelling. In the case of CBA with the miss-specified model, the users' benefits must be compared with the users' benefits of the baseline case computed with the same model; these benefits are MUS$ −11.95.
[d] With the miss-specified model, car costs must be compared with those of the baseline case computed with the same model; these costs are MUS$ −3.23. The difference with the well-specified model originates in the different modal shares by node, since the car-specific constant of the models were adjusted to reproduce the average modal share in Santiago.

22 km/h in the exclusive bus lanes (see Table 13, and for detailed results see Appendices A and B). These speeds are valid for Santiago de Chile and estimated with data from Muñoz et al. (2013). The infrastructure costs were estimated from a recent study of a bus corridor in Santiago (SECTRA, 2011).

We compared demand forecasts and user benefits obtained with the models that consider passenger-density on the travel time valuation with those of the traditional model. In the case of the model with passenger density effect, demand was estimated in two steps. In the first one, passenger-density was kept constant and equal to the level before the speed was increased. Therefore, the estimated demand and user benefits would be wrong at this step. In the second step, demand was estimated with the passenger-density at equilibrium. These results were compared with those obtained using the miss-specified model producing an incorrect demand forecast due to its biased parameters.

We also compared the user benefits computed by standard CBA to the benefits measured using the compensating variation. The standard CBA consists of computing total time-savings and valuing benefits by multiplying the time savings by the value of time, often called the *social value of time* (*SVT*). For instance, in the case of Chile the social value of time is fixed at 2.68 US$/h by the Ministry of Social Development (MDS, 2014).[7] Generally, this approach does not consider any effects of crowding on the value of time, and the benefits for reducing crowding are not included. The proposed comparison should shed some light on the benefit losses due to a constant value of time, independent of passenger density.

To be consistent with the estimated model, we assumed that the value of time increased linearly with passenger density. To compute the net benefits of travel time savings considering the crowding effect, we assumed that the total travel time spent in mode m was T_{0m} before the project and T_{1m} after the project implementation. Then, the net time benefits for bus users, ΔB_b, is given by:

$$\begin{aligned}\Delta B_b = B_{0b} - B_{1b} &= T_{1b}(VT + \gamma H_1) - T_{0b}(VT + \gamma H_0) \\ &= VT \cdot \Delta T_b + \gamma(T_{1b}H_1 - T_{0b}H_0)\end{aligned} \tag{18}$$

[7] It is worth noting that in Chile the *SVT* is not determined on the basis of WTP for travel time reductions, but corresponds to a weighted average of the value of work time (measured as the average wage rate) and the value of leisure (measured as a fraction of the value of work). This approach is valid under some specific assumptions on user behaviour (see, for instance, DeSerpa, 1971). In addition, the composition of the social value of time is an open question needing more empirical analysis (Mackie et al., 2001). Hence, there is no direct way to find equivalence between the value of time and *SVT*.

Table 13
Costs and benefits of improving speed in a bus corridor.

	Baseline case	Speed increase[a]		Speed increase miss-specified model
		Travel-time effect	Passenger-density effect	
Operating variables				
Fare (US$)	1.1	1.1		1.1
Frequency (buses/h)	15	15		15
Bus capacity (passengers)	100	100		100
Mean passenger density (pass./m^2)	5.5	5.5	5.9	–
Waiting time (min)	4.9	4.9		4.9
Bus travel time (min)	37.5	31.4		31.4
Car travel time (min)	27.3	20.4	21.3	20.9
Required bus fleet	46	40		40
Bus driven kilometres	600	600		600
Car driven kilometres	16,731	14,057	14,813	14,693
Bus share	60%	66%	64%	62%
Annual costs and benefits				
Users' benefits (MUS$)	−27.44	−26.36	−26.61	−11.70
Bus operation costs (MUS$)	1.70	1.70		1.70
Capital cost of buses (MUS$)	0.95	0.82		0.82
Bus external costs (MUS$)	0.47	0.47		0.47
Bus consumed travel time (h)	1,126,614	1,029,352	1,003,571	974,952
Car operation costs (MUS$)	−1.93	−1.63	−1.71	1.70
Car external costs (MUS$)	−1.52	−1.27	−1.34	1.33
Car consumed travel time (h)	503,160	350,092	384,100	395,447
Capital cost of infrastructure (MUS$)		7.47		7.47
Net benefits				
Compensating variation (MUS$)		1.08	−0.26	0.25
Operation and external cost savings (MUS$)		0.79	−0.22	0.32
Total net benefits (MUS$)[b]		1.39		0.58
Alternative measures of user benefits				
Time benefits with constant *SVT* (MUS$)		1.45	−0.05	1.17
Time benefits *SVT* with crowding effect (MUS$)		1.24	−0.27	0.96

[a] The effect of increasing speed is decomposed into travel time and passenger density effects and presented only when it is relevant for the variable in the first column.
[b] Net benefits correspond to user benefits measured with the compensating variation plus operational and external cost savings. The annual capital cost of infrastructure was not included.

In this expression, γ is the increment in the value of time associated with an increment in crowding (in this case, we assume $\gamma = 0.80$ US$/h for each extra passenger/m^2 as displayed in Table 7). *VT* can be associated with the value of time for a car user (or for a bus user in a bus with passenger density equal to zero), hereafter called the base level of value of time, while H_0 and H_1 are the bus passenger densities before and after project implementation respectively. Analogously, the net benefit for car users is:

$$\begin{aligned}\Delta B_c = B_{0c} - B_{1c} &= T_{1c} \cdot VT - T_{0c} \cdot VT \\ &= VT \cdot \Delta T_c\end{aligned} \tag{19}$$

Since the benefits of increasing bus speeds for the case of the value of time growing linearly with passenger density are compared with two cases where the value of time is constant (one uses a *SVT* from the correctly estimated model and another a *SVT* from the miss-specified model), we need a value of time for each of the latter cases such that the comparison is fair. We assumed that this constant value of time corresponded to the weighted average of the value of time for car and bus users immediately before the implementation of the project. Thus, we defined $SVT = s_{car}\,VT + s_{bus}\,VT(1 + \gamma\,H_0)$, where s_{car} and s_{bus} are the bus and car modal shares in the city (normalized to add one), and H_0 is the average bus passenger-density level in the baseline case.

Using the models in Table 6, this approach leads to a *SVT* equal to 5.9 (US$/h) in the case of the model with passenger-density effect, and of 2.4 (US$/h) in the case of the miss-specified model. Finally, our assumptions imply that the time benefits for the standard CBA are given by:

$$\Delta B_{CBA} = SVT(\Delta T_b + \Delta T_c) \tag{20}$$

It is worth noting that Eqs. (14)–(16) are valid only for very small (or no) changes in modal shares. A more general expression to measure the benefits of a policy is the rule-of-half (Jara-Diaz, 2007, Ch. 3), which is valid for any changes in modal shares. However, as Eqs. (14)–(16) are used in traditional CBA, we based our analysis on them.

Regarding demand modelling, our results show that in the first step of using the well-specified model (travel-time effect), demand is overestimated since it assumes that crowdedness is kept constant (66% versus 64%; see Table 13, under column Travel time effect); the procedure is similar to modelling demand without estimating the crowding effect. The bus demand estimated with the miss-specified model was lower than the final demand estimated with the model with passenger-density effect (62% versus 64%; see Table 13, last column), a result which is due to the low sensitivity of the miss-specified model to travel time (and the remaining level of service variables).

Regarding the composition of the benefits using the well-specified model, the travel time effect (the first step) leads to overestimation of both user benefits and cost savings. This is due to bus demand overestimation, leading to overestimating the reduction in car driven kilometres and their associated reduction of operation and external costs. The net user benefits are overestimated because the increment in crowdedness experienced by bus users is being neglected. But once the crowding effect is considered, user benefits and cost savings fall, and total net user benefits become about two thirds of the benefits due to the reduction of travel time alone. Finally, using the miss-specified model both user benefits and costs savings are underestimated since users changing from car to bus are underestimated.

Regarding the alternative measures of user benefits using the well-specified model (see Table 13, columns 3 and 4), user benefits are overestimated if travel time-savings are valued with constant *SVT* (Eq. (19)). The benefits due to the passenger-density effect were negative and represented only 3% of the travel time benefits. In fact, bus demand reduced from 66% to 64% due to the crowding effect. This fall of demand for bus trips arises when the equilibrium passenger-density is reached from the demand level estimated with travel time reductions only. In equilibrium, less users travel by bus, which increments road congestion and consumed travel time. This explains the negative net user benefits due to the passenger-density effect, which are consistent with the negative ones obtained when using the compensating variation or non-constant *SVT*, but in a lower magnitude. The difference is explained by the increase in crowding with respect to the baseline case that leads to a welfare loss for bus users. In conclusion, using a constant *SVT* to value travel time leads to an overestimation of user benefits.

If the social value of time considers the passenger-density effect, the time-savings benefits (Eqs. (17) and (18)) are somehow consistent with the benefits measured using the compensating variation; the benefits however were overestimated. In this case the loss of benefits due to the passenger-density effect represented 21% of the pure travel time-savings benefits (-0.27 versus 1.24).

In sum, the standard CBA with constant *SVT* results in greater user benefits (1.40 MUS$) than the other two approaches (the compensating variation: 0.83 MUS$, and the *SVT* with passenger-density effect: 0.97 MUS$). Thus, if computing net user benefits is considered the theoretically correct approach, then valuing time savings, with either crowding dependent *SVT* or constant *SVT*, is an inaccurate measure of user benefits.

So far, the capital cost of infrastructure for the bus corridor (MUS$ 7.47/year) has not been included in the CBA. To consider it we should expand the benefits from a daily peak period into the whole year, including off-peak operating hours. To do so, we used the expansion factors recommended by the Chilean National Transport Planning Agency (SECTRA). The factors are 2593 h/year for expanding user benefits and car costs, and 3797 h/year for expanding bus costs. Then, the annual net benefits, without including the cost of infrastructure, are MUS$ 4.35/year, which are insufficient to pay for it. Nevertheless, if two bus lines similar to the modelled one use the infrastructure, the project becomes socially worthy. In this case, the demand for buses increases to approximately 5100 passengers/h in the whole corridor and the total net benefits (including infrastructure) reaches MUS$ 1.24/year. This result is consistent with the recommendation for implementing bus corridors with central exclusive lanes from ITDP (2007, Ch. I).

Finally, regarding policy effectiveness, increasing bus speeds seems to be very effective in reducing car usage when crowding is not considered. However, after equilibrium is established, the final demand for bus trips is lower than the demand before equilibrium. Therefore, the crowding effect is key for the right evaluation of policies to promote public transport.

5. Final comments

This paper values the effect of crowding in public transport using data from a stated preference survey. The level of crowding was measured as in-vehicle standing passenger density and presented to respondents by means of appropriately designed pictures. We used flexible discrete choice models to value crowding and specified modal utility functions where passenger density increased the effect of travel time on utility. Thus, we assumed interactions between passenger density and travel time. The results show that crowding has a significant effect on the marginal utility of travel time. Indeed, the marginal disutility of travel time in a vehicle with 6 passengers/m^2 is 2.5 times greater than the marginal disutility in a vehicle with no standing passenger.

This study shows that the effect of crowding is similar to road congestion. The improvement in travel times for a bus line increases its demand. In turn, this new demand increases crowding and, consequently, the generalized cost of travel (travel disutility). These two effects have opposite signs and counterbalance, which may reduce the effectiveness of transport policies oriented to increase the operating speed of public transport without increasing capacity to avoid crowding. Two examples of this effect are the BRT system of Bogota and the Metro system of Santiago. Both systems offer a very fast travel experience compared with their alternatives, and attract very intense passenger flows (both reaching around 45,000 passengers/h-direction in their critical link-period). However, in both cases in-vehicle passenger density reaches values higher than 6 passengers/m^2. This high crowding prevents them to attract more demand coming from car users.

Our results can be used to include the cost of crowding (or congestion) in public transport, for cost-benefit analyses. Planners and policy makers might examine whether financing an increase in vehicle capacity to control for the negative effects of crowding is socially worthwhile. In this respect, the more consistent way of introducing crowding effects is to use the compensating variation to measure user benefits. If the official method consists of valuing travel time savings, the social value of time must depend on the level of crowding and, consequently, be different for car and public transport.

Finally, if users consider the level of crowding when choosing a public transport line or route, the final demand of each line will be the result of an equilibrium state. This equilibrium is similar to that in a road network with congestion. This implies that it is necessary to develop transit network assignment models that consider a similar effect to road congestion, but on bus routes. This is an interesting topic for future research.

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Appendix A. Simulation results by node

See Tables A.1–A.6.

Table A.1
Simulation results by node, baseline case.

Node	Bus share (%)	Car share (%)	Trip length (km)	Avg. bus travel time (min)	Avg. car travel time (min)	Avg. passenger density (passengers/m^2)	User benefits (MUS$)
1	59.6	40.4	14	52.5	31.2	4.01	−3.34
2	54.5	45.5	14	52.5	34.4	4.89	−3.42
3	56.0	44.0	12	45.0	30.7	5.37	−3.26
4	53.0	47.0	12	45.0	31.3	5.96	−3.29
5	56.2	43.8	10	37.5	27.6	6.36	−3.12
7	56.4	43.6	10	37.5	27.2	6.30	−3.11
8	61.7	38.3	8	30.0	22.0	6.38	−2.90
9	68.1	31.9	6	22.5	14.6	6.15	−2.63
10	75.1	24.9	4	15.0	7.8	5.62	−2.37
Total	60.1	39.9	10.0	37.5	25.2	5.67	−27.44

Table A.2
Simulation results by node, capacity increase case.

Node	Bus share (%)	Car share (%)	Trip length (km)	Avg. bus travel time (min)	Avg. car travel time (min)	Avg. passenger density (passengers/m^2)	User benefits (MUS$)
1	65.2	34.8	14	52.5	27.7	3.15	−3.24
2	60.1	39.9	14	52.5	29.0	3.83	−3.30
3	61.5	38.5	12	45.0	25.4	4.20	−3.13
4	58.6	41.4	12	45.0	25.5	4.65	−3.16
5	61.6	38.4	10	37.5	21.9	4.96	−2.99
7	61.9	38.1	10	37.5	21.8	4.89	−2.98
8	66.7	33.3	8	30.0	17.5	4.94	−2.79
9	72.4	27.6	6	22.5	12.4	4.75	−2.56
10	78.1	21.9	4	15.0	7.4	4.31	−2.33
Total	65.1	34.9	10.0	37.5	21.0	4.41	−26.46

Table A.3
Simulation results by node, frequency increase case, waiting-time effect.

Node	Bus share (%)	Car share (%)	Trip length (km)	Avg. bus travel time (min)	Avg. car travel time (min)	Avg. passenger density (passengers/m^2)	User benefits (MUS$)
1	62.5	37.5	14	52.5	31.2	2.87	−3.32
2	57.0	43.0	14	52.5	34.4	3.49	−3.41
3	58.7	41.3	12	45.0	30.7	3.83	−3.25
4	55.3	44.7	12	45.0	31.3	4.26	−3.28
5	58.9	41.1	10	37.5	27.6	4.54	−3.10
7	59.1	40.9	10	37.5	27.2	4.50	−3.09
8	64.8	35.2	8	30.0	22.0	4.56	−2.88
9	71.4	28.6	6	22.5	14.6	4.39	−2.61
10	78.2	21.8	4	15.0	7.8	4.01	−2.33
Total	62.9	37.1	10.0	37.5	25.2	4.05	−27.27

Table A.4
Simulation results by node, frequency increase case, passenger-density effect.

Node	Bus share (%)	Car share (%)	Trip length (km)	Avg. bus travel time (min)	Avg. car travel time (min)	Avg. passenger density (passengers/m^2)	User benefits (MUS$)
1	67.3	32.7	14	52.5	27.0	3.24	−3.21
2	61.8	38.2	14	52.5	27.9	3.94	−3.27
3	63.2	36.8	12	45.0	24.3	4.33	−3.10
4	60.1	39.9	12	45.0	24.4	4.79	−3.13
5	63.3	36.7	10	37.5	20.7	5.11	−2.95
7	63.7	36.3	10	37.5	20.6	5.04	−2.95
8	68.8	31.2	8	30.0	16.6	5.09	−2.75
9	74.8	25.2	6	22.5	11.9	4.89	−2.53
10	80.6	19.4	4	15.0	7.4	4.44	−2.29
Total	67.1	32.9	10.0	37.5	20.1	4.54	−26.18

Table A.5
Simulation results by node, case of bus speed increase, travel-time effect.

Node	Bus share (%)	Car share (%)	Trip length (km)	Avg. bus travel time (min)	Avg. car travel time (min)	Avg. passenger density (passengers/m^2)	User benefits (MUS$)
1	69.0	31.0	14	43.3	27.0	4.60	−3.20
2	63.7	36.3	14	42.3	28.1	5.56	−3.26
3	65.6	34.4	12	34.8	24.5	6.09	−3.09
4	60.7	39.3	12	35.8	24.7	6.67	−3.13
5	62.7	37.3	10	30.3	21.1	7.08	−2.96
7	60.8	39.2	10	32.4	21.0	6.89	−2.98
8	64.4	35.6	8	26.9	17.1	6.91	−2.79
9	68.8	31.2	6	21.5	12.3	6.57	−2.59
10	75.0	25.0	4	15.0	7.5	5.88	−2.36
Total	65.6	34.4	10.0	31.4	20.4	6.25	−26.36

Table A.6
Simulation results by node, case of bus speed increase, passenger-density effect.

Node	Bus share (%)	Car share (%)	Trip length (km)	Avg. bus travel time (min)	Avg. car travel time (min)	Avg. passenger density (passengers/m^2)	User benefits (MUS$)
1	66.5	33.5	14	43.3	27.8	4.44	−3.23
2	61.1	38.9	14	42.3	29.3	5.38	−3.30
3	63.3	36.7	12	34.8	25.7	5.89	−3.13
4	58.6	41.4	12	35.8	26.0	6.47	−3.16
5	61.0	39.0	10	30.3	22.4	6.87	−3.00
7	59.4	40.6	10	32.4	22.3	6.71	−3.01
8	63.3	36.7	8	26.9	18.1	6.75	−2.82
9	68.1	31.9	6	21.5	12.8	6.43	−2.60
10	74.7	25.3	4	15.0	7.6	5.78	−2.37
Total	64.0	36.0	10.0	31.4	21.3	6.08	−26.61

Appendix B. Simulation results by arc

See Tables B.1–B.6.

Table B.1
Simulation results by arc, baseline case.

Arc	Bus demand (passengers)	Car demand (passengers)	Bus passenger density (passengers/m^2)	Bus travel time (min)	Car travel time (min)	Car driven kilometres
1	265	180	1.1	7.5	3.6	359
2	507	382	2.0	7.5	3.6	764
3	756	577	3.0	7.5	3.6	1154
4	992	786	4.0	7.5	3.7	1572
5	1242	981	5.0	7.5	4.0	1961
6	1492	1174	6.0	7.5	5.2	2349
7	1767	1344	7.1	7.5	7.4	2689
8	1805	1306	7.2	7.5	6.8	2613
9	1647	1019	6.6	7.5	4.2	2039
10	1162	616	4.6	7.5	3.6	1232

Table B.2
Simulation results by arc, capacity increase case.

Arc	Bus demand (passengers)	Car demand (passengers)	Bus passenger density (passengers/m^2)	Bus travel time (min)	Car travel time (min)	Car driven kilometres
1	290	155	0.8	7.5	3.6	310
2	557	332	1.6	7.5	3.6	664
3	830	503	2.4	7.5	3.6	1007
4	1090	687	3.1	7.5	3.6	1375
5	1364	858	3.9	7.5	3.8	1716
6	1639	1027	4.7	7.5	4.2	2055
7	1936	1175	5.5	7.5	5.2	2351
8	1968	1143	5.6	7.5	4.9	2287
9	1774	892	5.1	7.5	3.8	1785
10	1240	537	3.5	7.5	3.6	1075

Table B.3
Simulation results by arc, frequency increase case, waiting-time effect.

Arc	Bus demand (passengers)	Car demand (passengers)	Bus passenger density (passengers/m^2)	Bus travel time (min)	Car travel time (min)	Car driven kilometres
1	278	167	1.1	7.5	3.6	333
2	531	358	2.0	7.5	3.6	715
3	792	541	3.0	7.5	3.6	1082
4	1038	740	4.0	7.5	3.7	1480
5	1300	923	5.0	7.5	4.0	1845
6	1562	1104	6.0	7.5	5.2	2209
7	1850	1261	7.1	7.5	7.4	2522
8	1889	1222	7.2	7.5	6.8	2443
9	1723	944	6.6	7.5	4.2	1888
10	1215	563	4.6	7.5	3.6	1125

Table B.4
Simulation results by arc, frequency increase case, passenger-density effect.

Arc	Bus demand (passengers)	Car demand (passengers)	Bus passenger density (passengers/m^2)	Bus travel time (min)	Car travel time (min)	Car driven kilometres
1	299	145	0.9	7.5	3.6	291
2	574	315	1.6	7.5	3.6	631
3	855	479	2.4	7.5	3.6	957
4	1122	656	3.2	7.5	3.6	1312
5	1403	819	4.0	7.5	3.7	1638
6	1686	981	4.8	7.5	4.0	1961
7	1992	1119	5.7	7.5	4.7	2238
8	2026	1086	5.8	7.5	4.5	2171
9	1828	838	5.2	7.5	3.7	1677
10	1280	498	3.7	7.5	3.6	996

Table B.5
Simulation results by arc, case of bus speed increase, travel-time effect.

Arc	Bus demand (passengers)	Car demand (passengers)	Bus passenger density (passengers/m^2)	Bus travel time (min)	Car travel time (min)	Car driven kilometres
1	307	138	1.1	7.5	3.6	275
2	590	299	2.0	7.5	3.6	598
3	882	452	3.0	6.5	3.6	904
4	1151	626	4.0	5.5	3.6	1253
5	1430	792	5.0	5.5	3.7	1584
6	1700	966	6.0	5.5	4.0	1933
7	1986	1125	7.1	5.5	4.8	2249
8	1985	1126	7.2	6.5	4.8	2252
9	1744	923	6.6	7.5	3.9	1845
10	1195	582	4.6	7.5	3.6	1165

Table B.6
Simulation results by arc, case of bus speed increase, passenger-density effect.

Arc	Bus demand (passengers)	Car demand (passengers)	Bus passenger density (passengers/m^2)	Bus travel time (min)	Car travel time (min)	Car driven kilometres
1	296	149	1.2	7.5	3.6	298
2	567	322	2.3	7.5	3.6	643
3	848	485	3.4	6.5	3.6	970
4	1109	669	4.4	5.5	3.6	1337
5	1380	842	5.5	5.5	3.7	1684
6	1644	1023	6.6	5.5	4.2	2045
7	1925	1186	7.7	5.5	5.3	2371
8	1932	1179	7.7	6.5	5.2	2357
9	1711	955	6.8	7.5	4.0	1911
10	1180	598	4.7	7.5	3.6	1196

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