University Transportation Research Center - Region 2

Final Report

Using Visual Information to Determine the Subjective Valuation of Public Space for Transportation: Application to Subway Crowding Costs in NYC

Performing Organization: Cornell University

November 2017

Sponsor:
University Transportation Research Center - Region 2

University Transportation Research Center - Region 2

The Region 2 University Transportation Research Center (UTRC) is one of ten original University Transportation Centers established in 1987 by the U.S. Congress. These Centers were established with the recognition that transportation plays a key role in the nation's economy and the quality of life of its citizens. University faculty members provide a critical link in resolving our national and regional transportation problems while training the professionals who address our transportation systems and their customers on a daily basis.

The UTRC was established in order to support research, education and the transfer of technology in the field of transportation. The theme of the Center is "Planning and Managing Regional Transportation Systems in a Changing World." Presently, under the direction of Dr. Camille Kamga, the UTRC represents USDOT Region II, including New York, New Jersey, Puerto Rico and the U.S. Virgin Islands. Functioning as a consortium of twelve major Universities throughout the region, UTRC is located at the CUNY Institute for Transportation Systems at The City College of New York, the lead institution of the consortium. The Center, through its consortium, an Agency-Industry Council and its Director and Staff, supports research, education, and technology transfer under its theme. UTRC's three main goals are:

Research

The research program objectives are (1) to develop a theme based transportation research program that is responsive to the needs of regional transportation organizations and stakeholders, and (2) to conduct that program in cooperation with the partners. The program includes both studies that are identified with research partners of projects targeted to the theme, and targeted, short-term projects. The program develops competitive proposals, which are evaluated to insure the mostresponsive UTRC team conducts the work. The research program is responsive to the UTRC theme: "Planning and Managing Regional Transportation Systems in a Changing World." The complex transportation system of transit and infrastructure, and the rapidly changing environment impacts the nation's largest city and metropolitan area. The New York/New Jersey Metropolitan has over 19 million people, 600,000 businesses and 9 million workers. The Region's intermodal and multimodal systems must serve all customers and stakeholders within the region and globally.Under the current grant, the new research projects and the ongoing research projects concentrate the program efforts on the categories of Transportation Systems Performance and Information Infrastructure to provide needed services to the New Jersey Department of Transportation, New York City Department of Transportation, New York Metropolitan Transportation Council , New York State Department of Transportation, and the New York State Energy and Research Development Authorityand others, all while enhancing the center's theme.

Education and Workforce Development

The modern professional must combine the technical skills of engineering and planning with knowledge of economics, environmental science, management, finance, and law as well as negotiation skills, psychology and sociology. And, she/he must be computer literate, wired to the web, and knowledgeable about advances in information technology. UTRC's education and training efforts provide a multidisciplinary program of course work and experiential learning to train students and provide advanced training or retraining of practitioners to plan and manage regional transportation systems. UTRC must meet the need to educate the undergraduate and graduate student with a foundation of transportation fundamentals that allows for solving complex problems in a world much more dynamic than even a decade ago. Simultaneously, the demand for continuing education is growing – either because of professional license requirements or because the workplace demands it – and provides the opportunity to combine State of Practice education with tailored ways of delivering content.

Technology Transfer

UTRC's Technology Transfer Program goes beyond what might be considered "traditional" technology transfer activities. Its main objectives are (1) to increase the awareness and level of information concerning transportation issues facing Region 2; (2) to improve the knowledge base and approach to problem solving of the region's transportation workforce, from those operating the systems to those at the most senior level of managing the system; and by doing so, to improve the overall professional capability of the transportation workforce; (3) to stimulate discussion and debate concerning the integration of new technologies into our culture, our work and our transportation systems; (4) to provide the more traditional but extremely important job of disseminating research and project reports, studies, analysis and use of tools to the education, research and practicing community both nationally and internationally; and (5) to provide unbiased information and testimony to decision-makers concerning regional transportation issues consistent with the UTRC theme.

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16. Abstract

The objective of this project is to explore the role of visual information in determining the users' subjective valuation of multidimensional trip attributes that are relevant in decision-making, but are neglected in standard travel demand models. More specifically, this project aims at analyzing overcrowding perceptions in discrete choice experiments, with the use of visualization of passenger density in subway cars. Data will be collected in New York City, but a pretest with a small sample size will be performed with international collaborators in the subway system of Santiago, Chile.

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1 Background

Subway demand in NYC has been on the rise, reaching 1.8 billion trips in 2014. Overcrowding delays have extended to non-peak hours and weekends; weekend overcrowding delays grew 141.2% in 2014-2015 (weekday overcrowding delays increased 65.3% during the same period; NY Daily News, 2015). In addition to delays, nonmonetary crowding costs include discomfort and a loss in security that play against overall perceptions of public transportation. In fact, subway crime has also been on the rise (NY Daily News, 2015). The evaluation of projects such as investment in open gangway cars (MTA is planning to spend $52.4 million on 10 of these cars; Wired, 2016), which are expected to increase capacity up to 10%, requires correct measurement of crowding externalities.

2 Objectives

The objective of this project is to explore the role of visual information in determining the users' subjective valuation of multidimensional trip attributes that are relevant in decision-making, but are neglected in standard travel demand models. More specifically, this project aims at analyzing overcrowding perceptions in discrete choice experiments, with the use of visualization of passenger density in subway cars. Data will be collected in New York City, but a pretest with a small sample size will be performed with international collaborators in the subway system of Santiago, Chile.

3 Introduction

Livable and sustainable communities need transportation options that are affordable; efficient in their use of public space, operation (travel time, frequency), and energy use; accessible, reliable, comfortable, secure, and safe; and that exhibit high-levels of quality of service. However, standard demand models focus almost exclusively on the valuation of instrumental tradeoffs between direct monetary costs and time (as measured by the 'value of time', or VOT). Consequently, transportation planning – including the design of transit systems and of bicycling infrastructure – neglects the role of those extended attributes that explain transportation decisions beyond VOT. In fact, VOT fails to explain demand situations where people may choose a subway/transit route that takes longer but is less crowded. In addition, travel demand estimates coming from models that omit variables such as crowding, convenience, comfort, security, and overall quality are biased, potentially leading to incorrect forecasts and decisions. Although the consequences of omitting relevant attributes is well known within transportation modelers and practitioners, it is the inherent difficulty of measuring qualitative attributes that explains their omission.

The project thus aims at better understanding the subjective valuation of subway crowding **passenger congestion in both trains and platforms** in NYC.

In this project, visual information is exploited to determine the users' economic valuation of hard-to-illustrate, multidimensional trip attributes. Furthermore, seat availability, passenger density, and crowding perceptions have significant behavioral and operational impacts, including effects on waiting and in-vehicle times (Milkovits, 2008; Tirachini, 2013), travel time variability, vehicle and route choices

(Leurent and Liu, 2009; Raveau et al., 2011), passenger satisfaction and wellbeing, and on the optimal determination of fares (crowding externalities increase the marginal cost of traveling; see Kraus, 1991), frequency (Jara-Díaz and Gschwender, 2003), and vehicle size (number of seats per hour).

This project implements discrete choice experiments with qualitative experimental attributes for crowding and related externalities, which are contextualized in the form of visuals.

Using visual information in stated preference studies is an emerging topic in discrete choice analysis, but there are several challenges in the selection of visual information and in the construction of quantitative measures from the images for model estimation and inference. In particular, this project aims at analyzing the sensitivity of the model estimates to alternative ways of representing passenger density.

Results from this project are relevant to the USDOT goals of livable communities and environmental sustainability, as well as to the UTRC focus areas 1 and 3.

4 Synthesis of Literature Review

The consideration of quality-of-service (QoS) of transit systems (e.g., accessibility, reliability, comfort, convenience, safety, security) is not only key for economic and engineering design of their operation (for a review see Litman, 2008) but also for better addressing issues of urban sustainability, inequality, and mobility. For instance, perceived safety, comfort, and ease of access may create incentives for the use of public spaces (Khisty, 1994; Shriver, 1997) and of travel modes where exposure to the environment is higher, such as transit, walking, or cycling (Antonakos, 1994; Zacharias, 2001; Hunt and Abraham, 2007). However, these QoS attributes are multidimensional, users perceive them in a qualitative manner, and require special methods for their correct measurement (such as hybrid choice models that integrate perceptions into demand; see Daziano, 2015; Walker and Ben-Akiva, 2002; Daziano, 2012; and Hurtubia, 2014).

Regarding QoS, passenger crowding (in transit access-ways, stations/platforms, and vehicle) has been determined to be one of the main determinants of travel mode choice. As reviewed by Tirachini (2012), a large set of factors have been associated with high levels of crowding, including perceptions of risk to personal safety and security (Cox et al., 2006; Katz and Rahman, 2010), propensity to arrive late at work (Mohd Mahudin et al., 2011), and a possible loss in productivity for passengers that work while sitting on a train (Fickling et al., 2008; Gripsrud and Hjorthol, 2012), stress and feelings of exhaustion (Lundberg, 1976; Mohd Mahudin et al., 2011; 2012), a feeling of invasion of privacy (Wardman and Whelan, 2011), potential ill-health (Cox et al., 2006; Mohd Mahudin et al., 2011), and increased anxiety (Cheng, 2010). The few travel demand models that include user sensitivity to crowding are usually specified in terms of load factors, probability of finding an available seat, and density of standees (Douglas and Karpouzis, 2005; Kim et al., 2009; Whelan and Crockett, 2009; Hensher et al., 2011a; Fröhlich et al., 2012). Using these specifications, it has been shown that the VOT for both waiting and in-vehicle times increases with the number of people in stations and vehicles, inducing a crowding externality or crowding cost. From a design perspective, the inclusion or omission of the crowding cost influences the optimal values of service frequency, vehicle size and fare level, among other supply side variables (Kraus, 1991; Jara-Díaz and Gschwender, 2003; Tirachini et al., 2010a; 2010b). Using discrete choice models, it is possible to estimate a crowding multiplier (CM), which is the ratio of the VOT under crowded conditions to the VOT under uncrowded conditions (see Whelan and Crockett, 2009).

QoS visualization in discrete choice experiments has recently emerged as an alternative to text descriptions of qualitative attributes (Strazzera, 2010; Hensher et al, 2011). The idea is to include images that explicitly show the physical features of the experimental conditions in each choice scenario. For example, in the specific case of crowding, Hensher et al. (2011) used as experimental attributes bird?s-eye views (2-D diagrams) of different levels of occupancy for bus and train. Although the use of visual information is promising, there are several challenges that need to be addressed, including the design of the image itself, behavioral bias in processing the image, and the translation of the attributes in the image to quantitative measures that can be used for model estimation.

5 Summary of Work Performed

5.1 Preliminary Case Study in Santiago of Chile (Tirachini et al., 2017)

As case study of the methodology derived as part of this project, we analyzed crowding perceptions in the subway (Metro) system of Santiago, Chile. This case study was published in Transportation Research Part A (Tirachini et al., 2017); the full paper can be read in Appendix.

In sum, a sample of N=413 respondents (210 online surveys, 203 face-to-face surveys) among users of the Metro system of Santiago was used to analyze three types of crowding visualization, namely: i) text, ii) 2D diagrams (bird's-eye view), and iii) photos taken inside a metro car (edited with a photo edition software, if necessary, to match with the exact number of persons required for a particular passenger density level). A basic Multinomial Logit (MNL) model, a Latent Class (LC) model and a Mixed Logit (ML) model were estimated and crowding multipliers were computed for each of these models, considering the three types of crowding representation. Estimates did not reveal significant effects of the differing crowding representations. The conclusion is that there is no evidence for preferring one type of visualization over the others in discrete choice experiments for crowding valuation purposes.

5.2 Main Case Study in New York City

5.2.1 Survey Instrument

The survey instrument was implemented online using the Qualtrics platform. The instrument was designed considering the following sections:

1. **Screening**: only adults living in the New York City metro area (in the specific counties of Kings, Queens, New York, Bronx, and Richmond), that regularly commute and frequently take the subway were invited to complete the survey.
2. **Background information**: regarding household and personal income and household composition
3. **Last subway trip**: a series of questions aimed at collection information about the last subway trip of the respondent, including purpose, time of the day, day of the week, frequency, areas of origin and destination, subway line or lines used, length of the trip, combination with other modes, trip cost, overall satisfaction
4. **Crowding evaluation**: frequency of experience of differing crowding conditions, ratings of crowding levels in terms of comfort and security.
5. **Discrete choice experiment**: as detailed below.
6. **Sociodemographics**: standard sociodemographics including gender, ethnicity, age, and education.

The discrete choice experiment presented static online choice scenarios focused on in-subway-car time. The use of images was used in the form of bird's-eye views of

Figure 1: Crowding levels

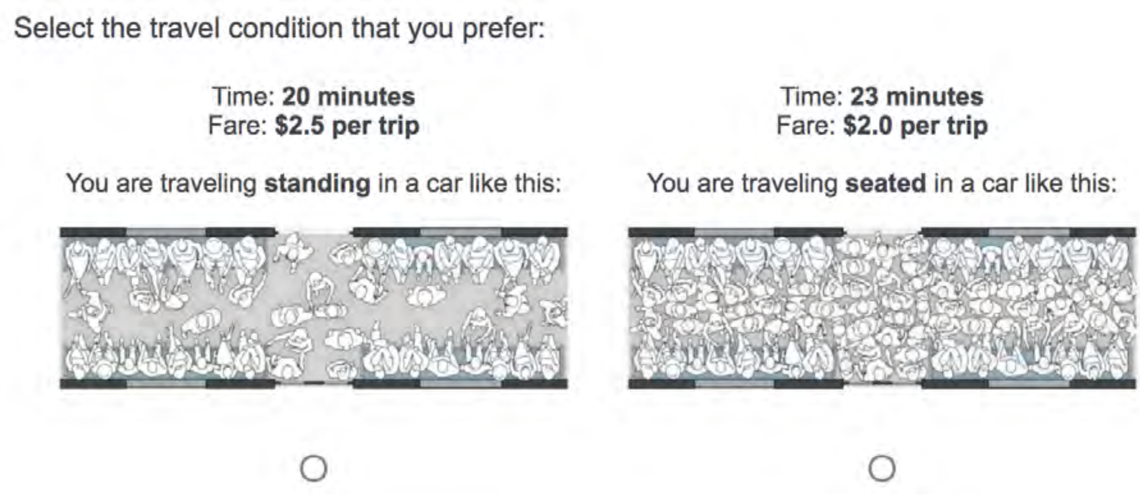
Crowding Level	Density Equivalent	Diagram
1	0 standees	
2	1 pass/sq-m	
3	2 pass/sq-m	
4	4 pass/sq-m	
5	6 pass/sq-m (Technical Capacity)	

trains to schematically represent the experimental crowding conditions (Fig 1.)

5 levels of crowding were considered, with corresponding passenger densities ranging from zero to technical capacity (6 passengers per square-meter). Dimensions of the cross section of the train correspond to an average subway car.

The attributes followed those considered in the case study in Santiago, namely: travel time, passenger density, and whether the passenger would travel standing or seated. In addition to these attributes, travel cost was also considered so that estimates of the valuation of travel time savings could be derived.

Figure 2: Discrete choice experiment sample



An efficient design was ran in the software NGene to generate the hypothetical choice scenarios to present to the respondents. Figure 2 presents a sample of a hypothetical choice scenarios as presented in the survey.

5.2.2 Sample

We surveyed 1849 users of the New York City subway to understand the effect of crowding in their travel decisions (Cox et al., 2006; Raveau et al., 2014; Tirachini et al., 2017). The following series of graphs summarizes composition of the sample, including gender (Fig. 3), marital status (Fig. 4), employment (Fig. 5), gender (Fig. 3), personal income (Fig. 6), household income (Fig. 7), and actual frequency of subway use (Fig. 8).

Figure 3: Gender

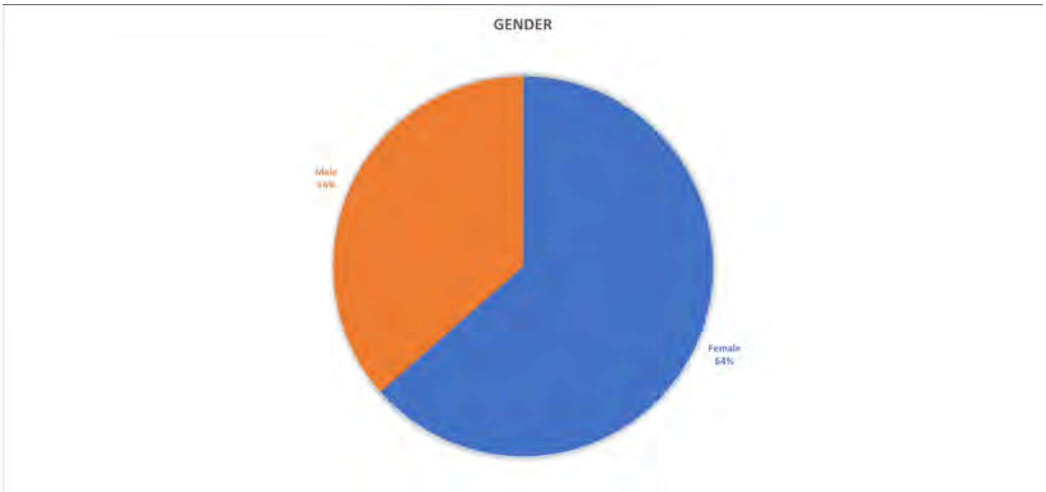


Figure 4: Marital Status

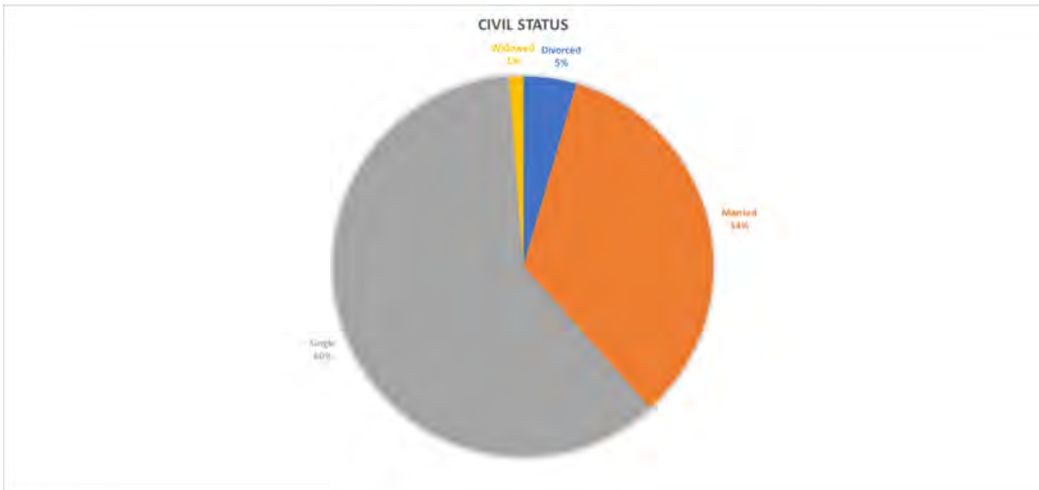


Figure 5: Employment

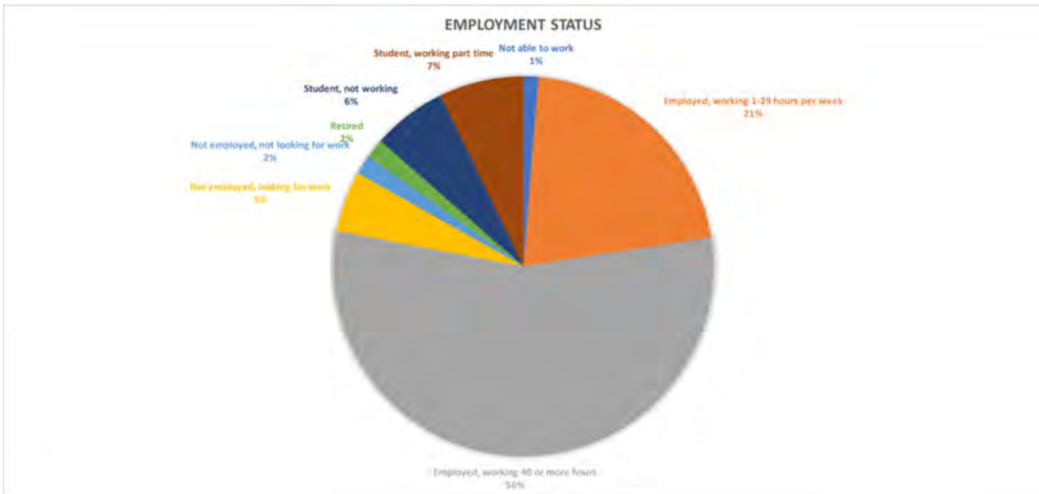


Figure 6: Personal Income

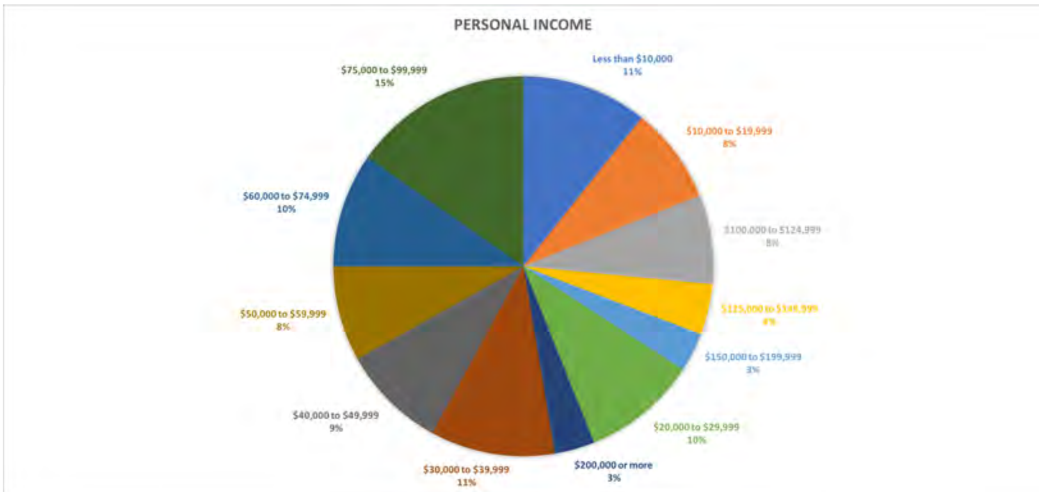


Figure 7: Household Income

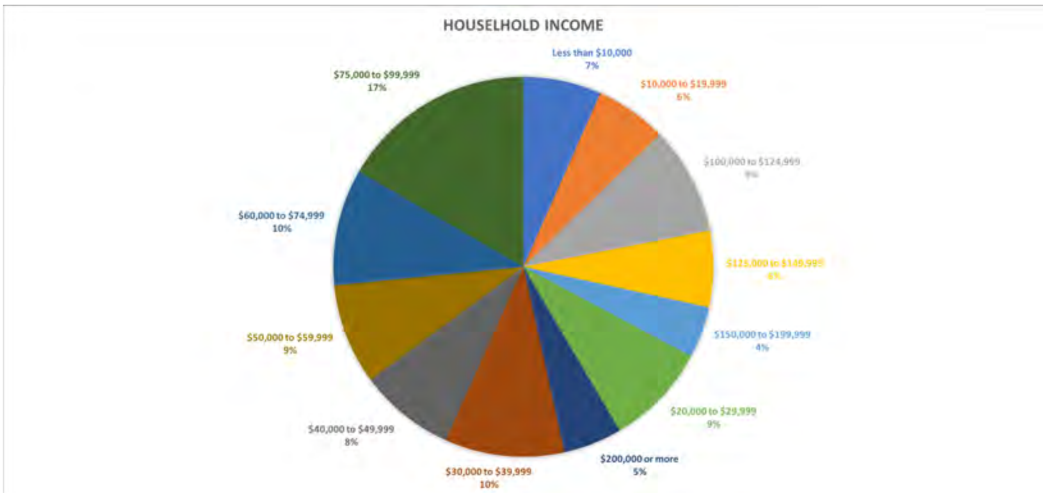
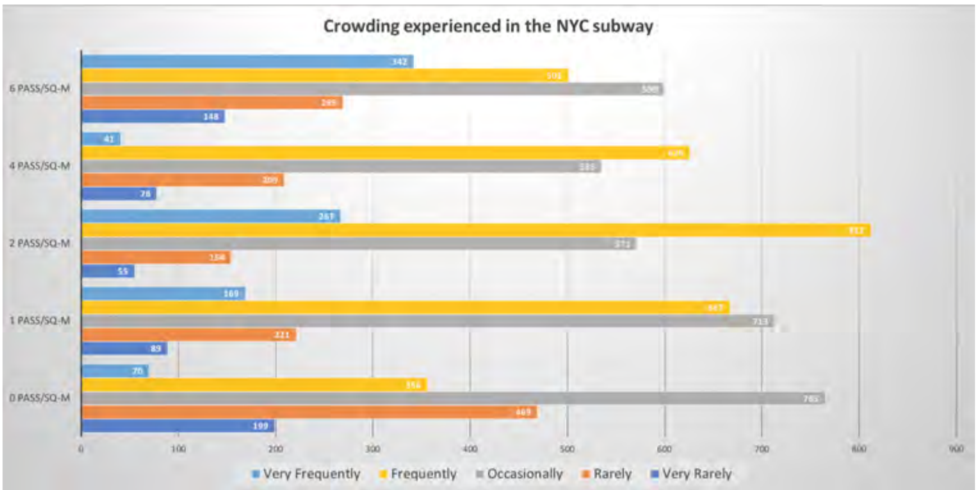


Figure 8: Frequency of Subway Crowding



5.3 Models for New York City

In the crowding choice experiment within the survey, each respondent chose an alternative from a set of two hypothetical, unlabeled subway routes, with a maximum of 6 choice situations (See Figure 1). Each route was described in terms of:

1. travel time (TT) in minutes,
2. travel cost (TC) in dollars per trip,
3. passenger density or occupancy level (OL) in passengers per square meter, and
4. an indicator whether the passenger would travel standing (STAND), or seated.

We consider a specification where the utility derived for individual i of class c from making choice j in choice situation t is:

$$U^c_{itj} = TT_{itj}\beta^c_{i,1} + TC_{itj}\beta^c_{i,2} + (TT_{itj} \times OL_{itj})\alpha^c_1 + (TT_{itj} \times OL_{itj} \times STAND_{itj})\alpha^c_2 + \varepsilon_{itj} \quad (1)$$

5.3.1 Econometric models

One of the most flexible discrete choice models is the mixed mixed logit model or mixture-of-normals logit (MON-MNL) (Greene and Hensher, 2013; Keane and Wasi, 2013; Bujosa et al., 2010; Fosgerau and Hess, 2008). MON-MNL nests the whole family of the most common logit models, from the multinomial logit model (no preference heterogeneity), to the latent class logit (discrete distributions of preference heterogeneity) and mixed logit models (continuous distributions of preference heterogeneity).

MON-MNL is basically is logit model in which random parameters have a discrete-continuous heterogeneity distribution (the mixture of normals). MON-MNL is specified as follows. The population has C latent classes (i.e., components in the mixture), and utility derived for individual i of class c from making choice j in choice occasion t is:

$$U_{itj} \quad \boldsymbol{x}_{itj}^{\mathsf{T}}\boldsymbol{\alpha}_c + \boldsymbol{z}_{itj}^{\mathsf{T}}\boldsymbol{\beta}_i^c + \varepsilon_{itj}, \tag{2}$$

where $i \in \{1, \ldots, N\}$, $j \in \{1, \ldots, J\}$, $t \in \{1, \ldots, T\}$, and $c \in \{1, \ldots, C\}$. Suppose we distinguish between class-specific fixed parameters ($\boldsymbol{x}$) and random parameters ($\boldsymbol{z}$). The alternative-specific characteristics $\boldsymbol{x}_{itj}$ have a fixed marginal utility $\boldsymbol{\alpha}_c$, and $\boldsymbol{z}_{itj}$ has random marginal utility $\boldsymbol{\beta}_i^c$ (specific to class c). The error term ε_{itj} is independent and identically distributed Type-I Extreme Value.

If individual i of class c chooses alternative j in choice occasion t, one can define the choice indicator $d_{itj} \quad 1$. For the sequence of choices made by the individual, the conditional likelihood $\mathcal{L}_i(\boldsymbol{\alpha}_c, \boldsymbol{\beta}_i^c)$ is:

$$\mathcal{L}_i(\boldsymbol{\alpha}_c, \boldsymbol{\beta}_i^c) \quad \prod_{t=1}^{T}\prod_{j=1}^{J}[P_{itj}]^{d_{itj}} \quad \prod_{t=1}^{T}\prod_{j=1}^{J}\left[\left(\frac{\exp(\boldsymbol{x}_{itj}^{T}\boldsymbol{\alpha}_c + \boldsymbol{z}_{itj}^{T}\boldsymbol{\beta}_i^c)}{\sum_{k=1}^{J}\exp(\boldsymbol{x}_{itk}^{T}\boldsymbol{\alpha}_c + \boldsymbol{z}_{itk}^{T}\boldsymbol{\beta}_i^c)}\right]^{d_{itj}} \tag{3}$$

A latent class membership model $\boldsymbol{w} \quad (w_1, \ldots, w_N)$, such that : $P(w_i \quad c)$ $s_c \quad i \in \{1, \ldots, N\}$, where $0 \leq s_c \leq 1$ and $\sum_1^C s_c \quad 1$ completes specification of the MON-MNL model.

Conditional on class membership, the random parameter $\boldsymbol{\beta}_i^c$ is normally distributed with mean γ_c and variance-covariance matrix $\boldsymbol{\Delta}_c$.

The loglilkelihood $\ell(\boldsymbol{\psi})$ of the sample in terms of the unconditional likelihood $P_i(\boldsymbol{\psi})$ of individual i is:

$$\ell(\boldsymbol{\psi}) \quad \sum_{i=1}^{N}\ln\Big(P_i(\boldsymbol{\psi})\Big)\Bigg(\sum_{i=1}^{N}\ln\sum_{c=1}^{C} s_c\left[\int_{\boldsymbol{\beta}}\mathcal{L}_i(\boldsymbol{\alpha}_c, \boldsymbol{\beta})f(\boldsymbol{\beta}|\gamma_c, \boldsymbol{\Delta}_c)d\boldsymbol{\beta}\right]\Bigg), \tag{4}$$

where

$$\boldsymbol{\psi} \quad \{\boldsymbol{\alpha}_1, s_1, \gamma_1, \boldsymbol{\Delta}_1, \ldots, \boldsymbol{\alpha}_C, s_C, \gamma_C, \boldsymbol{\Delta}_C\}. \tag{5}$$

The loglikleihood above can be maximized by simulation to derive the maximum simulated likelihood estimator of the model.

5.3.2 Modeling Results

With the collected choice microdata we estimated MON-MNL with two and three classes, and also compared the estimates with the traditional logit (MNL), as well as with a mixed logit model (MMNL) with normal and lognormal heterogeneity distributions.

Table 1 presents the estimates of the MNL and latent class logit model, considering 3 classes.

Table 1: **MNL and Latent Class MNL Results (Preference Space)**

	MNL		Latent Class (LC) MNL					
			Class 1		Class 2		Class 3	
	Estimate	**z-value**	**Estimate**	**z-value**	**Estimate**	**z-value**	**Estimate**	**z-value**
ASC	0.12	3.64	-0.63	-2.87	0.52	5.40	6.81	1.01
Time:Density	-1.36	-32.65	-4.98	-6.02	-0.81	-9.66	-48.21	-0.85
Time:Density:Stand	-0.58	-13.47	-3.50	-4.46	-0.54	-4.22	34.17	0.95
Cost	-1.39	-38.39	-2.91	-7.39	-1.43	-18.66	-8.06	-0.95
Time	-0.66	-20.12	-0.49	-2.03	-0.55	-6.11	-21.78	-0.75
Class weight	-	-	0.50	-	0.43	-	0.07	-
Loglikelihood	-3018.5		-2927.2					

Note: Time is in minutes and density is in passenger per square meter, and both are normalized by 10.

All estimates have the expected signs (negative), indicating that all the considered attributes provoke a disutility to the subway users. Since the marginal utilities are hard to interpret, table 4 summarizes the willingness to pay for reducing travel time in one hour as a function of passenger density.

Table 2: **Willingness to Pay for Travel Time Saving ($/hour)**

	Density (Passenger per square meter)	MNL	Latent Class (LC) MNL		
			Class 1	Class 2	Class 3
Standing	1	3.7	2.8	2.9	17.3
	3	5.4	6.3	4.0	19.4
	6	7.9	11.5	5.7	22.5
Sitting	1	3.4	2.0	2.7	19.8
	3	4.6	4.1	3.3	27.0
	6	6.4	7.2	4.4	37.8

As expected, when passenger density is higher, individuals are willing to pay more to save one marginal unit of travel time. Although the value of time of class 3 of the latent class logit is really high, we note that the marginal utilities are not significant.

Table 3: **Mixture-of-Normal (MON) MNL in Willingness to Pay Space**

	Class 1		Class 2		Class 3	
	Estimate	**z-value**	**Estimate**	**z-value**	**Estimate**	**z-value**
Marginal Utility of cost/scale (mean)	-3.48	-6.57	-2.13	-9.55	-0.98	-7.63
Marginal Utility of cost/scale (std dev)	-	-	0.64	2.80	-	-
WTP						
time:dens:stand (mean)	0.089	2.00	1.12	5.10	-0.28	-1.03
time (mean)	0.42	9.00	0.29	4.84	0.92	4.20
time:dens (mean)	0.70	11.34	0.96	7.96	5.40	6.42
L11 (time,time)	-0.18	-2.77	-	-	-	-
L21 (time, time:dens)	-0.29	-4.12	-	-	-	-
L22 (time:dens,time:dens)	-	-	0.47	5.50	2.71	5.73
Class membership parameters						
I(Male)	-0.54	-2.44	-	-		
I(Own or lease a car)	-	-	-0.48	-1.71		
I(Single)	0.87	3.64	0.74	2.89		
I(Caucasian)	-	-	-0.48	-1.70		
I(Age 50+)	-	-	0.74	2.19		
I(Personal income >$100K)	-0.37	-1.53	-1.39	-2.87		
Loglikelihood	-2742.9					

Note: Time is in minutes and density is in passenger per square meter, and both are normalized by 10.

Figure 9: Discrete choice experiment sample

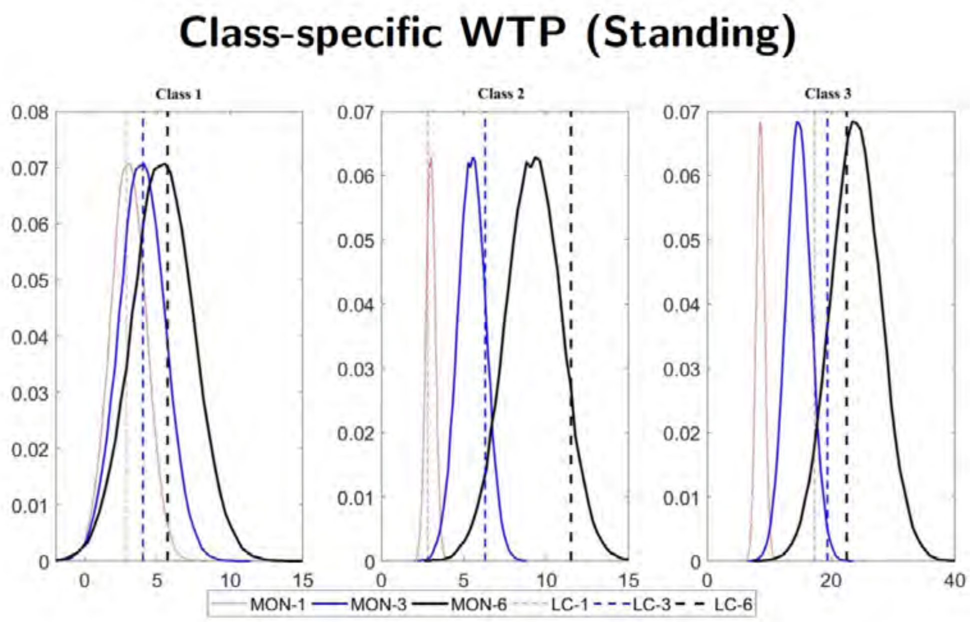
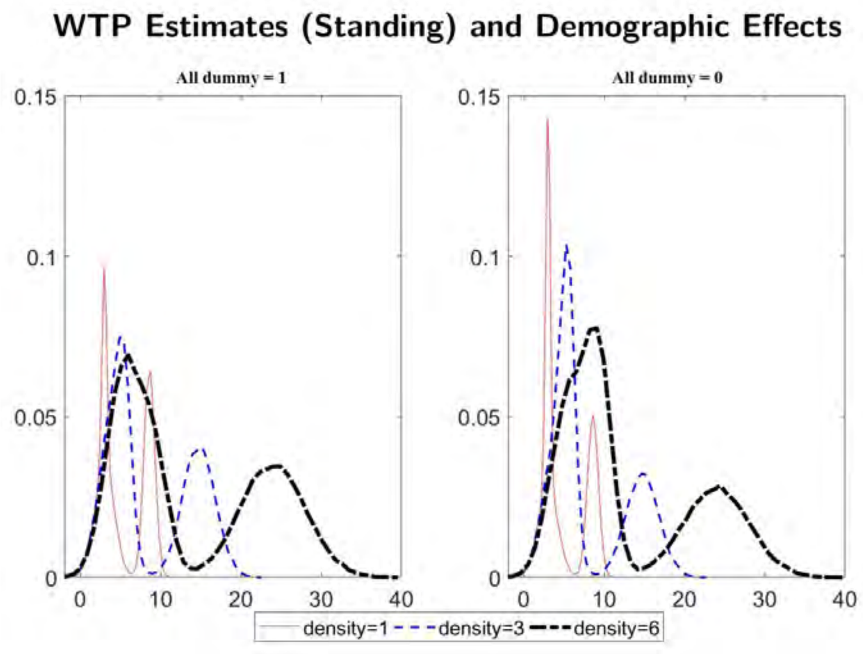


Figure 10: Discrete choice experiment sample



6 Conclusions and Recommendations

In this project two case studies were performed to analyze the tradeoff between travel time and crowding in two different subway systems. The valuation of traveling standing and sitting was also derived and examined.

In the pretest carried out in the subway system of Santiago of Chile, three treaments for passenger density visualization were tested, namely: text description (dominant tool in applied work analyzing comfort), 2D diagrams (bird?s-eye view), and actual (and yet controlled) photos. Using discrete choice models, it was determined that no evidence could be found of perception bias due to visualization of crowding conditions, meaning that in our sample crowding visualization has no impact on preferences.

Given the results of the Santiago case study, in the case of New York City only 2D visualization was used to represent passenger density conditions in the discrete choice experiments. Unlike Santiago, in New York City we also included travel cost as an experimental attribute to add the possibility of deriving estimates of the value of time. In fact, we estimated a flexible nonparametric choice model in the form of a mixture of normals logit (MON-MNL) model. MON-MNL models with two and three mixture components were estimated and also compared to the estimates with MNL and MMNL with normal and lognormal heterogeneity. Table 4 shows simulated means of value of time (VOT) estimates under different crowding conditions for these models. As expected, when passenger density is higher, individuals are willing to pay more to save one marginal unit of travel time.

Table 4: Estimates of the mean VOT ($/hr) under varying passenger density

	Density	MNL	MMNL (Normal)	MMNL (Lognormal)	MON-MNL (2 Classes)
		Standing			
Class 1	1	3.8	3.6	3.2	2.5
	3	5.5	5.2	4.8	5.4
	6	8.0	7.7	7.1	9.9
Class 2	1				3.4
	3				4.4
	6				6.0
		Sitting)			
Class 1	1	3.6	3.3	2.9	2.3
	3	4.7	4.4	4.0	4.8
	6	6.5	6.0	5.5	8.6
Class 2	1				3.1
	3				3.6
	6				4.4

Note: Density is in passengers per square meter.

Whereas the MON-MNL model with two classes resulted into statistically significant estimates of all parameters (ψ), the model with three classes yield statistically insignificant estimates for all parameters of one class, suggesting the possibility of only two classes in the data. VOT estimates indicate that subway route choice of class 1 is more sensitive to crowding than that of class 2.

From the VOT estimates, crowding multiplier estimates were derived (Table 5).

On the one hand, the MNL, mixed logit with normally distributed parameters and mixed logit with lognormally distributed parameters produce average crowding multipliers that are almost undistinguishable: for the average subway rider traveling seated in a subway car at technical capacity (6 passengers per square meter) travel time bothers twice as much as traveling on an empty subway car. If the passenger is standing, travel time bothers the passenger 15% more. On the other hand, from the mixture-of-normals logit specification it is very clear to see one class that is relatively less sensitive to crowding, with crowding multipliers that are around 80% of the value of the MNL and MMNL average results, and a class that is very sensitive to crowding. For the segments of subway riders that are very sensitive to crowding, travel time under extreme overcrowding (technical capacity) while standing is perceived as 4.4 times worse than under zero passenger density. Even if the passenger is seated the crowding multiplier at 6 passengers per square meter is 4.2. In fact, the crowding multipliers between standing and sitting conditions are not very different for this class of riders, which can be interpreted again as travelers that focus on comfort in terms of crowding much more than the possibility of traveling seated.

In terms of international comparisons, our estimates are closer to those reported for London than those from other cities such as paris and Hong Kong. For example, the London crowding multiplier when standing at technical capacity has been determined as 2.2, and 1.8 at 3 passengers per square meter (Whelan and Crockett, 2009). The London sitting crowding multipliers are lower than our estimates at 1.55 (6 passengers per square meter) and 1.28 (3 passengers per square meter). Our estimates are also close to the crowding multipliers that we derived for Santiago (Tirachini et al., 2017), which are summarized below in tables 6 and 7

Table 5: Crowding multipliers under varying passenger density in NYC

	Density	**MNL**	**MMNL (Normal)**	**MMNL (Lognormal)**	**MON-MNL (2 Classes)**
				Standing	
Class 1	1	1.11	1.08	1.05	1.11
	3	1.61	1.55	1.58	2.40
	6	2.34	2.30	2.34	4.40
Class 2	1				1.09
	3				1.41
	6				1.92
				Sitting	
Class 1	1	1.09	1.10	1.06	1.12
	3	1.42	1.47	1.47	2.34
	6	1.96	2.00	2.02	4.2
Class 2	1				1.09
	3				1.26
	6				1.54

Note: Density is in passengers per square meter.

Table 6: Santiago crowding multipliers: Sitting conditions

	MNL		ML				LC			
	Mean		Mean		Median		Class 1		Class 2	
pax/m2	Est.	St. Err	Est.	St. Err	Est.	St. Err	Est.	St. Err	Est.	St. Err
1	1.10	0.01	1.57	0.16	1.11	0.01	1.33	0.06	1.02	0.01
3	1.30	0.02	2.71	0.49	1.33	0.04	1.98	0.18	1.06	0.02
6	1.60	0.04	4.42	0.97	1.67	0.08	2.95	0.35	1.13	0.03

The subjective crowding valuation estimates that were be produced in this project –and the methodology proposed to produce those estimates– are relevant in assessing welfare improvements that come from a more efficient use of public space devoted to transportation. As we conclude in Tirachini et al. (2017), "Regarding policy implications, the estimated crowding multiplier should be tried in the evaluation of changes to the existing metro network and service in, for example, the number of seats per train or increasing/reducing the service frequency in peak and

Table 7: Santiago crowding multipliers: Standing conditions

	MNL		ML				LC			
	Mean		Mean		Median		Class 1		Class 2	
pax/m2	Est.	St. Err	Est.	St. Err	Est.	St. Err	Est.	St. Err	Est.	St. Err
1	1.17	0.01	2.02	0.29	1.16	0.02	1.56	0.09	1.07	0.01
3	1.50	0.03	4.05	0.88	1.49	0.06	2.67	0.27	1.20	0.02
6	2.00	0.05	7.10	1.76	1.98	0.11	4.33	0.54	1.39	0.04

off-peak periods (as analysed by Tirachini et al. (2014) for buses and de Palma et al. (2015) for trains). Without a crowding disutility, increasing train frequency only has a value on reducing waiting time. The approach presented here can be used to estimate the effect of that intervention on the comfort of travel time.

Finally, we cannot confirm that crowding multipliers obtained from stated preferences might be larger than those from revealed preferences, as suggested by Kroes et al. (2014) and Hörcher et al. (2017), because we found mixed results when comparing different cities and research methods. The advent of large AFC and AVL databases for the estimation of crowding and standing externalities (as recently advanced by Tirachini et al. (2016) and Hörcher et al. (2017), with the implementation of route choice methods) paves the way for the extended use of revealed preferences for the economic analysis of crowding discomfort and other quality-of-service attributes in the near future. It is expected that as more RP-based results arise, a clearer picture of potential stated preferences biases will be obtained."

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Estimation of crowding discomfort in public transport: results from Santiago de Chile

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Abstract

The relationship between train occupancy, comfort and perceived security is analysed, using data from a survey and stated choice (SC) study of users of Santiago's Metro (subway) system. Mode choice models where crowding is one of the main explanatory variables are estimated and crowding multipliers to measure its relevance on travel time disutility for sitting and standing are computed. An international comparison with previous studies from London, Paris, Singapore and Sweden is presented. The type of estimated models include Multinomial Logit, Mixed Logit, and Latent Class models. Results show that there is significant heterogeneity in crowding perception across the population. Users classes with low and high crowding multipliers are identified, in which gender, age and income play a role. In the SC survey,

occupancy levels were shown with three alternative forms of representation (text, 2D diagram or photo), however we did not find relevant influences of the different forms of representation on crowding perception.

A Introduction

In public transport, crowding refers to a subjective perception of the physical phenomenon represented by a high density of passengers in vehicles and at stations, stops and access-ways. In-vehicle crowding is, after price and travel time, one of the most important explanatory variables of mode choice. This is particularly true for public transport modes where high levels of crowding can result in physical discomfort, psychological burden and perceived risk and insecurity (Cox et al., 2006; Cheng, 2010; Mahudin et al., 2012). Moreover, crowding externalities (e.g. slower boarding and alighting from vehicles, increasing waiting times) have an important effect on the overall level of service and optimal fare of public transport systems (Tirachini et al., 2014).

Crowding in public transport is a common phenomenon in Santiago, Chile. Its city-wide integrated public transport system launched in February 2007, also known as the Transantiago system (Muñoz et al., 2014; Munizaga and Palma, 2012), deploys full fare integration between buses and Metro through the use of a single (smartcard) payment method. The implementation of Transantiago heavily loaded the metro network, making it the main artery of the system (Gómez-Lobo, 2012; Muñoz et al., 2014). The total number of daily passengers served by metro duplicated overnight and crowding conditions in the trains became extreme, reaching 6 passengers per square meter or more during peak hours[1]. This triggered many behavioural responses from the users ranging from selecting different modes of transport (there has been an increase in car and bicycle use) to route choices that, in regular crowding conditions, would be classified as being counter-intuitive or irrational (Raveau et al., 2014). For example, it may happen that users opt for longer routes in order to increase the chance of obtaining a seat in the train, or prefer not to board a train or bus because it is considered *too full* (although not reaching yet its full capacity). These behavioural responses reveal the extent to which users dislike crowding in public transport. A further case in point is provided by a user survey revealing that the attribute *comfort*, related to overcrowding, was the worst evaluated attribute of Transantiago (Yï¿œï¿œez et al., 2010), a critical issue if we consider that comfort has been reported as a factor that reduce stress of public transport commuters (Legrain et al., 2015).

[1]There are three reasons for this sudden increase in Metro usage: an integrated fare system in which users pay a very low fee for a bus-metro transfer; the redesign of parts of the bus network to serve as feeders of the metro network; and the noticeable reduction of bus service quality in terms of longer waiting and in-vehicle times, especially at the beginning of Transantiago

Despite the large impact of crowding on quality-of-service, the optimization model to design the Transantiago network (Fernï¿œndez et al., 2008) did not consider quality-of-service factors such as passenger density and service reliability valuation by users in the design of routes, optimal frequencies and vehicle sizes[2]. Instead the optimization model minimized the summation of users and operator costs. In other words, one minute travelling with five passengers per square meter was assumed to have the same weight in the users' cost function as one minute travelling with one passenger per square meter, thereby ignoring the discomfort of crowding on users.

Understanding and measuring the willingness to trade an increase in travel time for improved travel conditions in terms of reduced crowding levels, and vice-versa, is not only relevant for the planning of new public transport services, but also for the management of currently operating routes and services and cost-benefit analysis of policy interventions aimed at reducing crowding levels, either as a primary or secondary goal. Crowding multipliers (Wardman and Whelan, 2011; Tirachini et al., 2013) can be used for this objective. Crowding multipliers can be interpreted as a measure of how the disutility of travel time under different crowding levels relate to each other. Subsequently, they can be used to amplify the (monetary) value of in-vehicle time savings in order to account for the fact that reductions of travel time in crowded conditions are worth more than reducing travel time on a similar but less crowded trip.

The literature on crowding valuation has progressed quickly during the past ten years, and today we are aware of studies estimating the sensitivity of the value of travel time savings (VTTS) to different vehicle or station crowding conditions in Great Britain (Whelan and Crockett, 2009; Wardman and Whelan, 2011), the Paris region (Kroes et al., 2014; Haywood and Koning, 2015), Sydney (Hensher et al., 2011), Mumbai (Basu and Hunt, 2012), Los Angeles (Vovsha et al., 2013), Singapore (Tirachini et al., 2016), Hong Kong (Lam et al., 1999; Hörcher et al., 2017) and Santiago (Batarce et al., 2015), amongst other cities. Even in cycling research it was recently found that crowding (with other bicyclists) significantly influence route choice for bicyclists in Copenhagen (Vedel et al., 2017).

This paper makes a number of contributions to the crowding valuation literature. First, we test the impact of the crowding representation format on the perceived level of crowding, resulting travel behaviour and corresponding crowding valuation measures. To this end a stated choice survey is designed in which occupancy levels are presented to respondents either in the form of text, 2D diagrams or photos. Other studies have also used images (2D diagrams and photos) to describe crowding levels. Use of images has shown to influence the perception of attributes of the

[2]In the design model, high occupancy of vehicles does not influence the perception of time but may increase the extension of waiting time through limited capacity considerations (Fernï¿œndez et al., 2008)

alternatives on stated preferences surveys (Rizzi et al., 2012) and facilitates the description of complex choice scenarios, where an exhaustive text-based description of the attributes would over-complicate the choice task (Motoaki and Daziano, 2015; Hurtubia et al., 2015). However, some evidence indicates that the form of representation used to describe single attributes has no effect on the perception of the respondent (Arentze et al., 2003).

Second, in this study the usual way to determine crowding externalities by means of a stated choice model is complemented by questions on the relationship between train occupancy and perceived levels of comfort and security, providing a link between subjective user perceptions and observable train occupancies.

Third, this paper follows the recommendations of Basu and Hunt (2012) who argue that significant care is required when establishing crowding multipliers based on Mixed Multinomial Logit (ML) models. In previous crowding valuation studies, user preferences have been estimated using Multinomial Logit (MNL) and ML models. In the realm of MNL models, Wardman and Whelan (2011) develops a meta-analysis of crowding multipliers using MNL values from 17 studies in Great Britain. Ease of application in optimal public transport supply models is one argument that has been used to support the use of MNL models in crowding valuation (Tirachini et al., 2014). Most studies, however, highlight that (unobserved) heterogeneity in crowding and time sensitivities is important to take into account.

Whelan and Crockett (2009)'s ML model assumes a normal distribution to introduce unobserved heterogeneity in user preferences towards crowding levels in trains, and find that around 25% of respondents have 'wrong signed' taste parameters. The authors, however, discard the use of the lognormal distribution as a solution, given that it may shift the mean of the (crowding sensitive) VTTS parameter. The referred study of Basu and Hunt (2012) for crowding valuation in Mumbai, compares MNL and ML models using a triangular distribution for travel time parameters for different crowding levels, as a way to avoid the issue of large spreads in unconstrained distributions. In this study, we acknowledge the limitations of the lognormal density, but prefer its use as the resulting densities for the crowding multipliers are analytically tractable and much better behaved when looking at the median values. Additionally, we contrast the MNL and ML models to a Latent Class (LC) specification. Results show that significant heterogeneity in crowding perception exist across the population, as exposed by estimated ML and LC models. Gender, income and age are significant variables in explaining heterogeneity in crowding disutility. MNL, mean LC and median ML models produce similar sitting and standing crowding multipliers for a given occupancy level, unlike mean ML values which produce crowding multipliers that are unreasonably high.

Finally, an international comparison of crowding multipliers with values found in other cities is performed. We find that the Santiago Metro crowding multipliers are close to those previously found in the Paris Metro system (Kroes et al., 2014) and in Hong Kong's Mass Transit Railway (MTR) network (Hörcher et al., 2017) On a more local level, this is the first article in which the value of sitting and standing are separately estimated in Santiago.

The paper is organized as follows: Section B describes the survey and its main results, while Section C focuses on the analysis of the relationship between crowding, comfort and perceived security. Section D describes the methodology for the estimation of the proposed models. Section E shows and discusses results while Section F compares Sanatiago's crowding multipliers with those from other cities and countries. Finally, Section G concludes the paper.

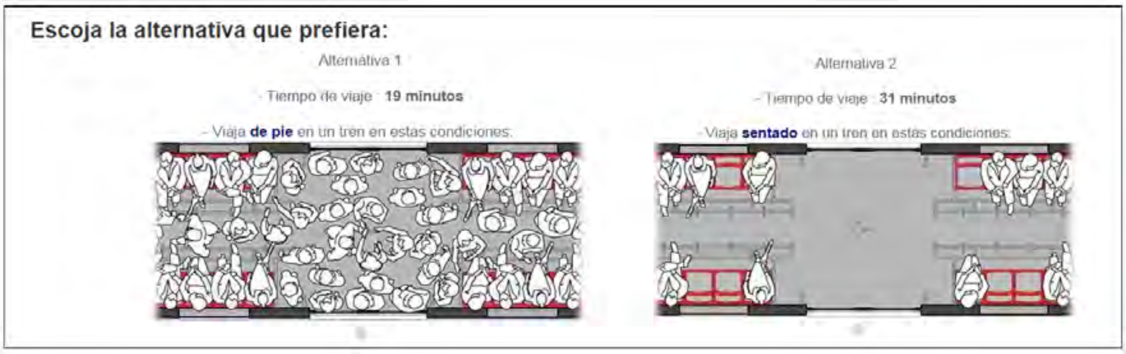
B Data Collection

A survey to measure the relevance of crowding in route choice was designed and executed. In order to simplify the choice task, only metro-based alternatives were considered and fare was excluded as an attribute (because in Santiago, within a time period, the metro fare is fixed regardless of trip distance).

The main survey included seven sections:

1. Background and socio-economic characteristics: e.g. gender, age, income, occupation and access to car.
2. Metro usage: average numer of times the respondent travels by metro each week and characteristics of latest trip (origin, destination, travel time, crowding level).
3. Smartphone availability and use: if the respondent has a smartphone, and if so, what (s)he uses it for while traveling by metro, and how frequently the smartphone is used.
4. Stated choice (SC) component: six binary choice tasks in which the respondent needs to choose between two alternatives for metro trips (see details below).
5. Crowding perception: the respondent is asked about how secure and how comfortable (s)he feels for three different crowding levels (low, medium and high).
6. Crowding description: the respondent is asked which phrase most accurately describes a specific crowding level shown on either a 2D diagram or a photo.
7. Trip perception and time use: the respondent is asked how (s)he feels about particular situations like having to share a reduced space with strangers, if

Figure 11: Example of stated choice task



(s)he likes to use a smartphone, read, listen to music, talk to people, etc., while travelling by metro.

In the SC component three attributes were used to characterize an alternative: i) travel time, ii) occupancy level, and iii) whether the passenger has to stand or can sit down during the trip. Travel time is pivoted around the travel time of the respondent's latest metro trip (question set 2). Five attribute levels are specified around this base travel time (-25%, -12.5%, 0, +12.5% and +25%). The crowding attribute was presented by means of six levels. The levels go from 1 (almost empty train) to 6 (completely full train). The way in which the crowding attribute was presented to respondents varied across versions of the survey. We used three alternative representation formats: i) text, ii) 2D diagrams (bird's-eye view), and iii) photos taken inside a metro car (edited with a photo edition software, if necessary, to match with the exact number of persons required for a particular passenger density level). In Figure 11 we show an example of a choice task, as shown to respondents, in which train occupancy level is depicted by means of a 2D diagram. The representation of all six occupancy levels and representation formats are shown in Figures 17 and 18 and Table 15 the Appendix. In total, a design of 12 choice tasks was constructed, grouped in two blocks of 6 tasks. Each respondent was presented with a single block of choice tasks and a single representation format.

The survey was programmed on the online survey platform Qualtrics. After a pilot carried out in September 2014, the final survey was conducted in October 2014 by a private consultant. In the pilot, the SC survey was designed using an orthogonal design; whereas for the final survey a D-efficient design was constructed using the SC experimental design software NGene (Rose et al., 2008). Priors for the parameters were obtained from the pilot study.

Two survey application methods were used: (a) online, in which the survey is distributed by email to a panel of respondents from the consultant, (b) face-to-face, in which surveyors with tablets interview metro users outside selected

Table 8: Income profile network versus survey

Total Metro			Survey		
Household income (Euro/month)	Percent.	Accum.	Personal income (Euro/month)	Percent.	Accum.
0 - 448	18%	18%	0 - 299	15%	15%
448 - 1,194	46%	65%	299 - 597	20%	35%
1,194 - 2,090	22%	86%	597 - 896	19%	54%
2,090 – 2,836	8%	94%	896 – 1,493	16%	70%
2,836 – 3,731	3%	97%	1,493 – 2,239	11%	81%
3,731 or higher	3%	100%	2,239 or higher	19%	100%

stations. The total number of correct complete surveys is 413 (210 online surveys, 203 face-to-face surveys). The sampling strategy attempted to resemble the income profile of Santiago´s metro users, as described by a network-wide origin-destination survey performed by the Metro company in 2013. Accordingly, Metro stations with different user income profile were chosen. The percentage of users by income range in both the total network survey and our survey is shown in Table 8.

From Table 8, likely there is a slight over-representation of higher-income users in our sample, as 70% and 81% of our respondents have personal incomes lower than 1,493 and 2,239 Euros, whilst on the network 86% of users report a household income lower than 2,090 Euros. However, there is no indication of large differences in income between the two samples. Regarding gender and age representation, 55% of metro users in Santiago are women (47% female respondents in our survey) and 48% of metro users are 29 years old or younger (30% of respondents in our survey are in that age range). The fact that our survey was applied only to adults partially explains the under-representation of young users in our sample.

C The relationship between occupancy level, perceived comfort and security

In this section we focus on the relationship between occupancy levels in Metro trains, as shown to survey respondents in section five of the survey, and their perceived level of comfort and security. Out of the six levels for the crowding attribute (see Appendix) three were shown to the respondents [3]. This was done after the SP part of the survey in order to not influence response patterns. For each of the three levels the following questions were asked:

- How secure do you feel to travel in these conditions? (security with respect

[3]the three levels were randomly chosen between crowding levels 1 and 2, 3 and 4, and 5 and 6

to theft, or physical and psychological threat)

- How comfortable do you feel to travel in these conditions?

Respondents had to rate each level of occupancy on a 1 to 7 Likert scale, where 1 meant very insecure (very uncomfortable), and 7 meant very secure (very comfortable). The 1 to 7 scale has the advantage of been highly intuitive in Chile since it is the scale of marks in the Chilean education system (where 7 is the maximum possible mark, 1 is the lowest mark and 4 is the minimum mark to pass). Results of the average score for the six occupancy levels are shown in Fig. 12 where, to ease understanding, all six levels are shown with their respective 2D representation.

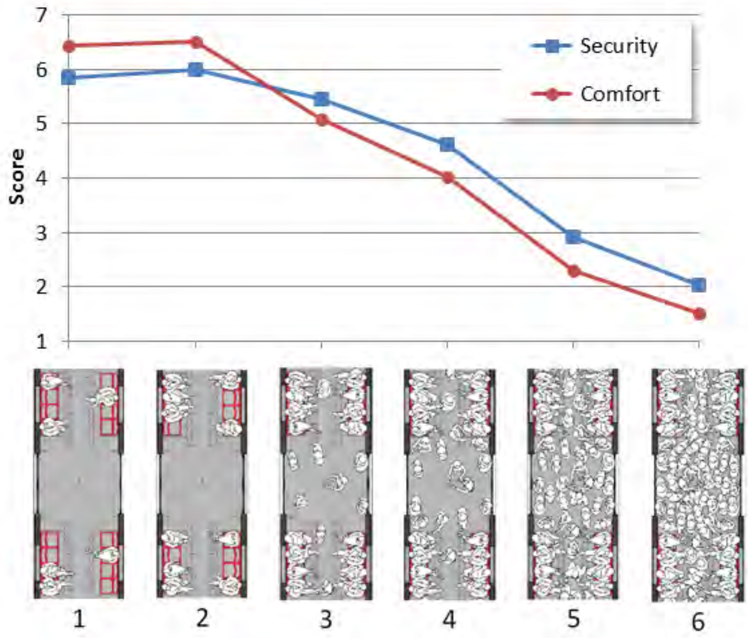


Figure 12: Average security and comfort levels for different occupancy levels

On average, users do not perceive a difference in comfort or security between levels 1 and 2 or occupancy, in which all passengers are sitting, and therefore it can be suggested that the main variable affecting both security and comfort is the presence of standees (in fact, both scores are 0.1 points higher in level 2, but the difference is not statistically significant at the 5% level). Due to the presence of standees the level of comfort drops quicker than the level of safety between levels 2 and 3. From level 3 and above, the perceived security has a higher average mark than perceived comfort. Notably, between levels 4 to 6 perceived comfort and security are dropping at a similar pace.

A more detailed analysis can be presented by moving beyond average scores. To ease understanding, we only present histograms of answers for occupancy levels 1 (the lowest), 3 (medium) and 6 (the highest), for all forms of crowding representation shown to respondents (see Fig. 13). It is interesting to note that there is more variation in the answers to the security question than in the answers to perceived comfort. For instance, respondents clearly relate an almost empty train with a high level of comfort (Fig. 13b), however less than 50% of respondents feel that situation as "very secure" (Score 7 in Fig. 13a). This finding is in line with the hypothesis of Cox et al. (2006), who state that the relationship between security and train occupancy varies by crime type, as muggings are more likely to happen in crowded trains but assaults are more likely to happen in empty trains. A similar outcome is observed with the histograms of occupancy level 6 (Fig. 13e and 13f), which 68-70% of respondent perceive as "very uncomfortable", but less than 50% of respondents perceive it as "very insecure". Therefore, there exists a more straightforward relationship between occupancy and the perception of comfort, than between occupancy and the perception of (in)security. Regarding gender differences, it is observed than men tend to feel more secure but less comfortable in an almost empty train than women (Fig. 13a and 13b), however, when comparing mean scores there are no significant differences for gender.

With respect to differences in perception of security and comfort among the forms of representation for occupancy, Fig. 14 shows average scores for all occupancy levels. No discernible tendency is observed in the perception of security. In the case of comfort perception, it is found that for low and medium occupancy levels the text representation has a lower average score than 2D and Photo, which may point towards a misrepresentation of the actual comfort conditions of a text explanation compared against graphical forms.

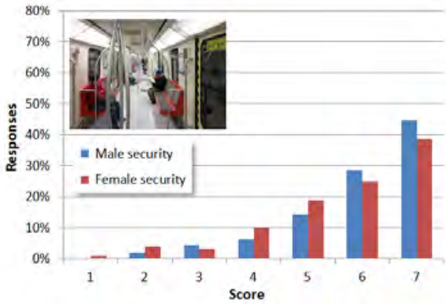
Overall, we find that feelings of insecurity and discomfort increase with density and number of passengers standing in a metro carriage.

D Choice modelling: methodology

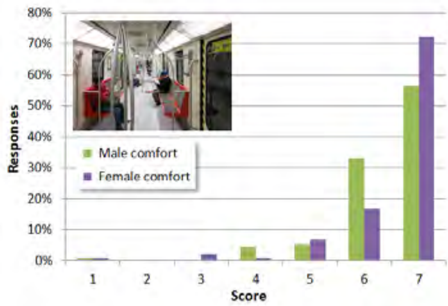
In this section we introduce the discrete choice models used to estimate crowding multipliers for Santiago's Metro system. Our survey included a binary stated choice (SC) component, in which each choice task presented two alternative metro routes to the respondent, as previously depicted by Fig. 11. The choice between scenarios 1 and 2 in choice task situation $t \quad 1, \ldots, T$ for individual $n \quad 1, \ldots, N$ is modelled using the following random utility maximization (RUM) specification:

$$
\begin{aligned}
U_{1nt} &= \beta_{TT} TT_{1nt} + \beta_{TTdens}[TT_{1nt} \times dens_{1nt}] + \beta_{TTdensST}[TT_{1nt} \times dens_{1nt} \times 1_{stdg_{1nt}}] + \varepsilon_{1nt} \\
U_{2nt} &= \beta_{TT} TT_{2nt} + \beta_{TTdens}[TT_{2nt} \times dens] + \beta_{TTdensST}[TT_{2nt} \times dens_{2nt} \times 1_{stdg_{2nt}}] + \beta_0 + \varepsilon_{2nt}
\end{aligned} \tag{6}
$$

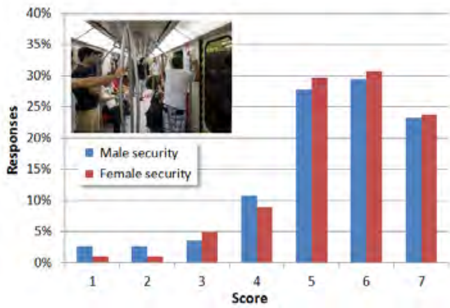
where TT_{int} is travel time in alternative i (min), $density_{int}$ is passenger density (pax/m^2) and $1_{stdg_{int}}$ is a binary variable indicating whether the passenger is



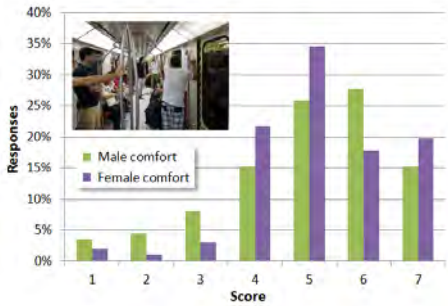
(a) Occupancy level 1, security



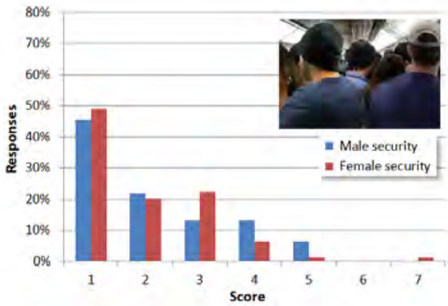
(b) Occupancy level 1, comfort



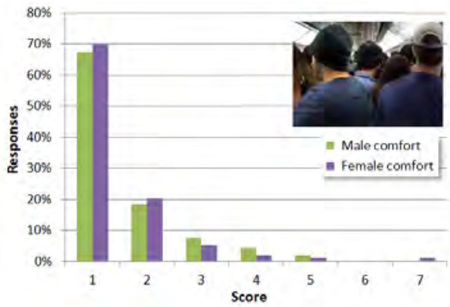
(c) Occupancy level 3, security



(d) Occupancy level 3, comfort

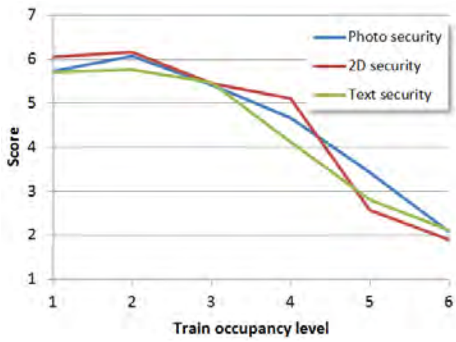


(e) Occupancy level 6, security

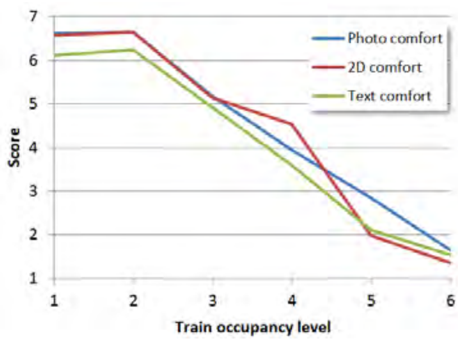


(f) Occupancy level 6, comfort

Figure 13: Perceptions of security and comfort, share of responses per score level for three ocupancy levels



(a) Security



(b) Comfort

Figure 14: Average scores security and comfort per form of representation

standing or not. $\boldsymbol{\beta} \quad (\beta_0, \beta_{TT}, \beta_{TTdens}, \beta_{TTdensST})$ then represents a vector of corresponding preference parameters, and ε_{int} denotes the error term. The latter is assumed to follow a Type-I extreme value distribution such that logit type models can be estimated (Train, 2009) using the well-known MNL choice probabilities:

$$P_n^{MNL} \quad \prod_{t=1}^{T} \left[\left(\frac{\exp(\mathbf{x}_{1nt}'\boldsymbol{\beta})}{\exp(\mathbf{x}_{1nt}'\boldsymbol{\beta}) + \exp(\mathbf{x}_{2nt}'\boldsymbol{\beta})} \right]^{y_{1nt}} \left[\left(\frac{\exp(\mathbf{x}_{2nt}'\boldsymbol{\beta})}{\exp(\mathbf{x}_{1nt}'\boldsymbol{\beta}) + \exp(\mathbf{x}_{2nt}'\boldsymbol{\beta})} \right]^{y_{2nt}} \tag{7}$$

where $\mathbf{x}_{1nt} \quad (0, TT_{1nt}, TT_{1nt} \times dens_{1nt}, TT_{1nt} \times dens_{1nt} \times 1_{standing_{1nt}})$, $\mathbf{x}_{2nt} \quad (1, TT_{2nt}, TT_{2nt} \times dens_{2nt}, TT_{2nt} \times dens_{2nt} \times 1_{standing_{2nt}})$, and where $y_{int} \quad 1$ if alternative i was chosen in choice situation t.

The above model specification is motivated by previous model specifications used to derive crowding multipliers (e.g. Whelan and Crockett, 2009; Wardman and Whelan, 2011; Tirachini et al., 2013). Passenger load (i.e. density measures) are interacted with travel time to represent a higher dis-utility of crowding for longer trips; and if the passenger is standing then there is empirical evidence that crowding is even more bothersome (Wardman and Whelan, 2011). These hypotheses are in line with our results in Section C. The crowding multipliers can accordingly be derived as the marginal utility of travel time under crowding conditions over marginal utility of travel time under non-crowded conditions:

$$\begin{aligned} CM^{sitting} \quad & \frac{\beta_{TT} + \beta_{TTdens} dens}{\beta_{TT}} \quad 1 + \lambda_1 \cdot dens \\ CM^{standing} \quad & \frac{\beta_{TT} + \beta_{TTdens} dens + \beta_{TTdensST} dens}{\beta_{TT}} \quad 1 + (\lambda_1 + \lambda_2) \cdot dens \end{aligned} \tag{8}$$

β_{TT} is the travel time parameter, whereas β_{TTdens} and $\beta_{TTdensST}$ are the parameters associated with the product between travel time and density for sitting and standing, respectively. Moreover $\lambda_1 \quad \frac{\beta_{TTdens}}{\beta_{TT}}$ and $\lambda_2 \quad \frac{\beta_{TTdensST}}{\beta_{TT}}$. Therefore, $CM^{sitting}$ represents the crowding multiplier for a passenger who is seated, and $CM^{standing}$ is the respective multiplier for a standing passenger. Standard errors for the crowding multipliers will be calculated using the Delta method (Daly et al., 2012). We will specifically test for differences in the crowding multipliers across the alternative representation formats of the crowding attribute.

The second specification is the mixed logit model where we assume there is unobserved heterogeneity in β_n across respondents. The heterogeneity is captured by a mixing density of the form $f(\beta_n|\theta)$, where θ represents the hyper parameters characterising the mixing density, such as the mean and standard deviation. As a result the expected choice probability for observing the sequence of choices by individual n is now given by:

$$P_n^{ML} \quad \int_{\beta_n} \prod_{t=1}^{T} \left[\frac{\exp(\mathbf{x}_{1nt}' \boldsymbol{\beta}_{\mathbf{n}})}{\exp(\mathbf{x}_{1nt}' \boldsymbol{\beta}_{\mathbf{n}}) + \exp(\mathbf{x}_{2nt}' \boldsymbol{\beta}_{\mathbf{n}})} \right]^{y_{1nt}} \left[\frac{\exp(\mathbf{x}_{2nt}' \boldsymbol{\beta}_{\mathbf{n}})}{\exp(\mathbf{x}_{1nt}' \boldsymbol{\beta}_{\mathbf{n}}) + \exp(\mathbf{x}_{2nt}' \boldsymbol{\beta}_{\mathbf{n}})} \right]^{y_{2nt}} f(\beta_n|\theta) d\beta_n \tag{9}$$

We explicitly account for the fact that β_n^{TT}, β_n^{TTdens} and $\beta_n^{TTdensST}$ are expected to be negative by specifying a lognormal mixing density. The benefit of using a lognormal density is that the λ parameters in Eq. 8 have finite moments (and therefore also the crowding multipliers) (e.g. Daly et al., 2011) and are analytically tractable. Hence, there is no need for simulation exercises after estimation.

The third specification is derived according to the Latent Class model (Greene and Hensher, 2003). If we assume that the parameters β_n are random with a discrete instead of a continuous heterogeneity distribution, then for class q utility becomes:

$$\begin{aligned} U_{1nt}^{(q)} &= \beta_{TT}^{(q)} TT_{1nt} + \beta_{TTdens}^{(q)} [TT_{1nt} \times dens_{1nt}] + \beta_{TTdensST}^{(q)} [TT_{1nt} \times dens_{1nt} \times 1_{stdg_{1nt}}] + \varepsilon_{1nt}^{(q)} \\ U_{2nt}^{(q)} &= \beta_{TT}^{(q)} TT_{2nt} + \beta_{TTdens}^{(q)} [TT_{2nt} \times dens_{2nt}] + \beta_{TTdensST}^{(q)} [TT_{2nt} \times dens_{2nt} \times 1_{stdg_{2nt}}] + \beta_0^{(q)} + \varepsilon_{2nt}^{(q)} \end{aligned} \tag{10}$$

where $\boldsymbol{\beta} \quad \boldsymbol{\beta}^{(q)}$ with probability $w_n^{(q)} \quad \exp(\mathbf{z}_n' \boldsymbol{\gamma}^{(q)}) / \sum_{q=1}^{Q} \exp(\mathbf{z}_n' \boldsymbol{\gamma}^{(q)})$, with $\mathbf{z}_n$ denoting sociodemographic characteristics of the individual and where the class-specific constant $\gamma^{(1)} \quad \mathbf{0}$ is normalised. We assume assignment to class is influenced by gender, age and income.

$$\begin{aligned} w_n^1 &\quad \frac{1}{1 + \exp(\gamma^{(2)} + \gamma_{\text{male}} 1_{\text{male}_n} + \gamma_{\text{age}} \text{age}_n + \gamma_{\text{inc}} \text{inc}_n)} \\ w_n^2 &\quad \frac{\exp(\gamma^{(2)} + \gamma_{\text{male}} 1_{\text{male}_n} + \gamma_{\text{age}} \text{age}_n + \gamma_{\text{inc}} \text{inc}_n)}{1 + \exp(\gamma^{(2)} + \gamma_{\text{male}} 1_{\text{male}_n} + \gamma_{\text{age}} \text{age}_n + \gamma_{\text{inc}} \text{inc}_n)} \end{aligned} \tag{11}$$

where age_n, inc_n and 1_{male_n} stand for age in years, personal income range and whether individual n is a male, respectively.

In this latent class model, the probability of the observed sequence of choices for an individual is given by:

$$P_n^{LC} = \sum_{q=1}^{2} \left\{ w_n^{(q)} \prod_{t=1}^{T} \left[\frac{\exp(\mathbf{x}_{1nt}' \boldsymbol{\beta}^{(q)})}{\exp(\mathbf{x}_{1nt}' \boldsymbol{\beta}^{(q)}) + \exp(\mathbf{x}_{2nt}' \boldsymbol{\beta}^{(q)})} \right]^{y_{1nt}} \left[\frac{\exp(\mathbf{x}_{2nt}' \boldsymbol{\beta}^{(q)})}{\exp(\mathbf{x}_{1nt}' \boldsymbol{\beta}^{(q)}) + \exp(\mathbf{x}_{2nt}' \boldsymbol{\beta}^{(q)})} \right]^{y_{2nt}} \right\}. \tag{12}$$

The maximum likelihood estimator of the full vector of parameters θ can be derived by plugging the correct P_n into $\arg\max_{\boldsymbol{\theta}} \ell(\mathbf{y}|\mathbf{X}; \boldsymbol{\theta}) \quad \sum_{n=1}^{N} \ln(P_n(\boldsymbol{\theta}))$. In the

Table 9: Basic MNL

Coefficients	Estimate	Std. Error	t-value	Pr(>|t|)	
intercept (i 2)	0.130	0.042	3.136	0.002	**
TT	-0.101	0.010	-10.306	< 2.2e-16	***
TTdens	-0.010	0.001	-10.086	< 2.2e-16	***
TTdensST	-0.007	0.001	-6.950	0.000	***
Log-Likelihood:	-1628.8				
McFadden R^2:	0.043777				

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

case of the Mixed Logit model, the likelihood needs to be simulated by considering a Monte Carlo approximation of P_n for which we use 1,500 halton draws.

E Choice modelling: results

E.1 Estimation results

Results for the basic multinomial logit model (MNL) are presented in Table 9.[4] All parameter estimates are significant and have the expected sign. The intercept for alternative 2 is significant and indicating a potential bias towards choosing the alternative presented on the right hand side. Left-right bias is not uncommon in the stated choice literature. Such effects, however, often become less pronounced when moving towards more sophisticated model structures. Note that we also tested whether there was a penalty for standing during the length of the trip irrespective of the occupancy level, but this parameter turned out to be insignificant and was therefore not presented.

The second MNL model (Table 10) examines the impact of the crowding representation format on occupancy perceptions and, accordingly, behavioural responses. During the analysis, the 2D diagrams were considered as the referential crowding representation format. Table 10 reveals that perception bias is not present in our dataset. On the one hand, this is reassuring as the alternative representation formats were carefully developed. On the other hand, this is a remarkable result considering the amount of cognitive effort required from the respondent when being presented with a text description of crowding levels (see Table 15 in the Appendix). Since the representation format has no impact on the model results, the respective control variables are excluded in the remaining analyses.

Results for the ML and LC model are presented in Tables 11 and 12. Both models reveal a significant improvement in model fit over the MNL base model, highlighting there is substantial heterogeneity in sensitivities to travel time and crowding

[4]All models are estimated using the R package *gmnl* (Sarrias and Daziano, 2015)

Table 10: Basic MNL accounting for type of crowding representation

Coefficients	Estimate	Std. Error	t-value	Pr(>|t|)	
2:(intercept)	0.131	0.042	3.137	0.002	**
TT	-0.101	0.010	-10.303	< 2.2e-16	***
TTdens	-0.011	0.001	-8.107	0.000	***
TTdensST	-0.006	0.002	-4.013	0.000	***
TTdens (photo)	0.002	0.001	1.124	0.261	
TTdens (text)	0.000	0.002	0.240	0.810	
TTdensST (photo)	-0.001	0.002	-0.350	0.727	
TTdensST (text)	-0.002	0.002	-0.835	0.404	
Log-Likelihood:	-1627.6				

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

levels across respondents. In the ML model there is still a tendency to prefer the right alternative, but this effect is no longer significant in the LC model. After transformation of the lognormal parameters, the median (and mean) travel time and crowding level sensitivities are all higher compared to the basic MNL model, but these values are surrounded by significant heterogeneity. We provide a more detailed discussion when looking at the crowding multipliers, which are the model outcomes of interest. The LC model indicates that an individual is more likely to belong to Class 2 if (s)he is male, young and has higher income.[5] Travellers belonging to Class 2 are very sensitive to travel time, but much less sensitive to crowding levels than members of Class 1. This is a reasonable result regarding the role of age and gender in the class membership equation, but not necessarily regarding income as wealthier passengers might be more negatively affected by a large passenger density than lower income travellers, as found by Haywood et al. (2017) in Paris. We explain the observed effect as a result of higher income people being more adverse to long travel times, i.e. having higher values of time. This is, however, an inconclusive interpretation given that in our survey the trade-off between travel time, level of train occupancy and trip fare was not present, as fare was not an attribute in the SP experiment. We now turn to the crowding multipliers derived from the above models.

E.2 Crowding Multipliers

Table 13 presents the crowding multipliers when metro users are able to sit whilst travelling. When there are no other passengers standing, i.e. $pax/m2 \quad 0$, the

[5]We experimented with models having more than two classes and allowing for unobserved preference heterogeneity within classes. However, this respectively resulted in counter-intuitive parameter estimates and signs of model over-specification. Also ML and LC models in 'time space', i.e. directly estimating the crowding multipliers, were estimated. These did not offer additional insights

Table 11: ML model using lognormal mixing densities

Coefficients	Estimate	t-stat	p-value	Sign.
Intercept (i 2)	0.175	2.963	0.003	**
TT - μ	-1.596	-12.753	0.000	***
TTdens - μ	-3.791	-27.105	0.000	***
TTdensST - μ	-4.561	-18.583	0.000	***
TT - σ	1.012	7.931	0.000	***
TTdens - σ	1.498	11.078	0.000	***
TTdensST - σ	1.813	10.415	0.000	***
Log-Likelihood:	-1404.9			
obs	2467			
n	413			
draws	1500			

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table 12: Latent Class Model

Coefficients	Estimate	t-stat	p-value	Sign.
Class 1: Intercept (i 2)	0.115	1.472	0.141	
Class 1: TT	-0.090	-4.127	0.000	***
Class 1: TTdens	-0.029	-11.563	0.000	***
Class 1: TTdensST	-0.021	-6.511	0.000	***
Class 2: Intercept (i 2)	0.173	1.898	0.058	.
Class 2: TT	-0.223	-13.258	0.000	***
Class 2: TTdens	-0.005	-3.539	0.000	***
Class 2: TTdensST	-0.010	-6.964	0.000	***
Class Membership (class 2)				
Intercept	0.268	1.868	0.062	.
Gender	0.394	3.877	0.000	***
Age	-0.022	-6.555	0.000	***
Income	0.446	4.192	0.000	***
Log-Likelihood:	-1456.8			
obs	2467			
n	413			

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 ‘regular’ value of travel time savings applies, irrespective of the preferred model specification. As expected, the crowding multipliers are increasing with passenger density, showing that increased crowding levels increase the disutility of travel time. Metro users are therefore willing to accept longer travel times in return for less crowded conditions. Subsequently assuming metro users are also willing to pay for reductions in travel time, allows us to infer they are willing to pay more for reductions in travel time under crowded conditions. This willingness-to-pay increases with crowding density.

The multiplicative relation between λ and density in equation (8), however, also causes the standard error of the crowding multiplier to go up with density ($pax/m2$). This is consistent across the three model specifications. Standard errors increase further when moving from the MNL model to the more complex ML and LC models. The latter increase in the standard error is caused by introducing a more flexible model specification. Standard errors are notably higher for the mean crowding multipliers of the ML model and for Class 1 of the LC model than for the Median ML model and Class 2 of the LC model. In the ML model, the fat upper tail of the lognormal distribution causes both the mean and the standard error of the crowding multipliers to go up. People with a high crowding sensitivity have less of an impact on the median crowding multiplier. In ML models it is not uncommon to find that the median of the mixing density, or its WTP-like transformation, is most comparable to the MNL estimates. This is a direct result of the density’s tails having a smaller impact on the median than on the mean (e.g. Borjesson et al., 2012). The tail of the distribution also has an impact on the Class 1 crowding multipliers of the LC model, but this effect is less pronounced due to the estimation of only a discrete number of classes rather than a continuous distribution as done by the ML model.

For the ML model, the median crowding multipliers closely correspond to those for the MNL model. As discussed above, the fat-tail of the lognormal density spurs the mean of the ML crowding multipliers up to an unreasonably high level relative to the values usually found in the extant literature (sitting multipliers not larger than 2, and standing standing usually not larger than 3, even under very crowded conditions). On the other hand, median estimations (up to 1.7 for sitting and 2.0 for standing) are very similar to those of the MNL model and within the range of values found in e.g., Great Britain (Wardman and Whelan, 2011). Regarding our mean ML values, it is often not recommended to use such high values for policy evaluations and in many national value of time savings studies (e.g. Borjesson et al., 2012) censoring approaches are applied accordingly. The LC model, however, provides a more reasonable alternative where part of the sample has a high crowding multiplier, which is somewhat tempered by a second latent class of travellers experiencing only a limited disutility of crowding.

A very similar story emerges from Table 14. The crowding multipliers of MNL

Table 13: Crowding multipliers: Sitting conditions

	MNL		ML				LC			
	Mean		Mean		Median		Class 1		Class 2	
pax/m2	Est.	St. Err	Est.	St. Err	Est.	St. Err	Est.	St. Err	Est.	St.
0	1.00	-	1.00	-	1.00	-	1.00	-	1.00	
1	1.10	0.01	1.57	0.16	1.11	0.01	1.33	0.06	1.02	0
2	1.20	0.01	2.14	0.32	1.22	0.03	1.65	0.12	1.04	0
3	1.30	0.02	2.71	0.49	1.33	0.04	1.98	0.18	1.06	0
4	1.40	0.03	3.28	0.65	1.45	0.06	2.30	0.24	1.08	0
5	1.50	0.03	3.85	0.81	1.56	0.07	2.63	0.29	1.10	0
6	1.60	0.04	4.42	0.97	1.67	0.08	2.95	0.35	1.13	0

model are highly comparable to median ML value. The mean ML crowding multipliers and associated standard errors are again unreasonably high for which the LC model provides a more acceptable alternative.

In the Latent Class model we observe quite different crowding multipliers when comparing Classes 1 and 2, as shown in Tables 13 and 14: Class 1 (more likely higher income younger males) has very large crowding multipliers with mean values 2.95 for sitting and 4.33 for standing with 6 pax/m2, whilst Class 2 have lower multipliers of 1.13 and 1.39 for the same density of standees. When computing average multipliers for both classes combined, taking into account the probability of class membership for all respondent in the sample, we obtain an average multiplier that go up to 2.1 for sitting and 3.0 for standing. These values are larger than the crowding multipliers implied by the MNL and (median) ML values, as shown in Fig. 15, and also seem to be too large when compared to most of the existent international literature. We conclude that even though there is quite a substantial amount of heterogeneity in users aversion to crowding, a good indication of crowding multipliers for the population would be values up to 1.5-1.6 for sitting, and up to 2.0-2.3 for standing, for a density of standees of 6 pax/m2.

The actual levels of the crowding multipliers will be contrasted against other national and international measures in Section F.

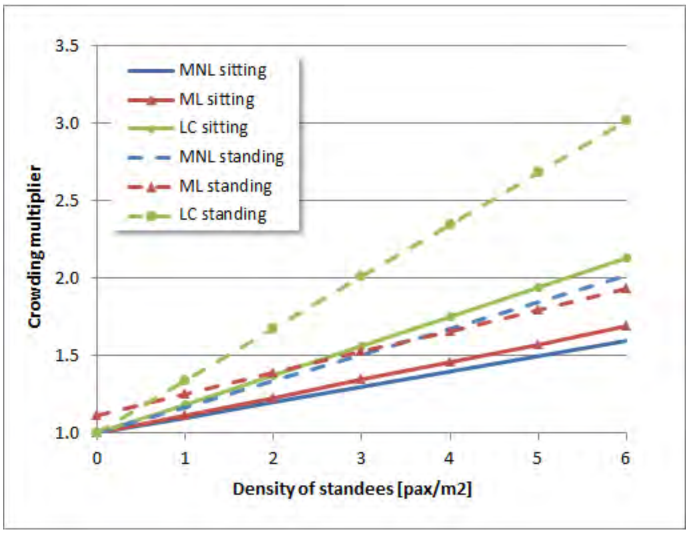
F International Comparisons

We compare our median ML multipliers with those of London and South East (SE) England (Whelan and Crockett, 2009), the Paris region (Kroes et al., 2014), Singapore (Tirachini et al., 2016), Hong Kong (Hörcher et al., 2017) and Swedish cities (Bj'orklund and Sw'ardh, 2015). Crowding multipliers for sitting and standing are shown in Fig. 16a. Sitting multipliers in Santiago are almost equal to those recently estimated in Hong Kong and not far from those in Paris and London SE,

Table 14: Crowding multipliers: Standing conditions

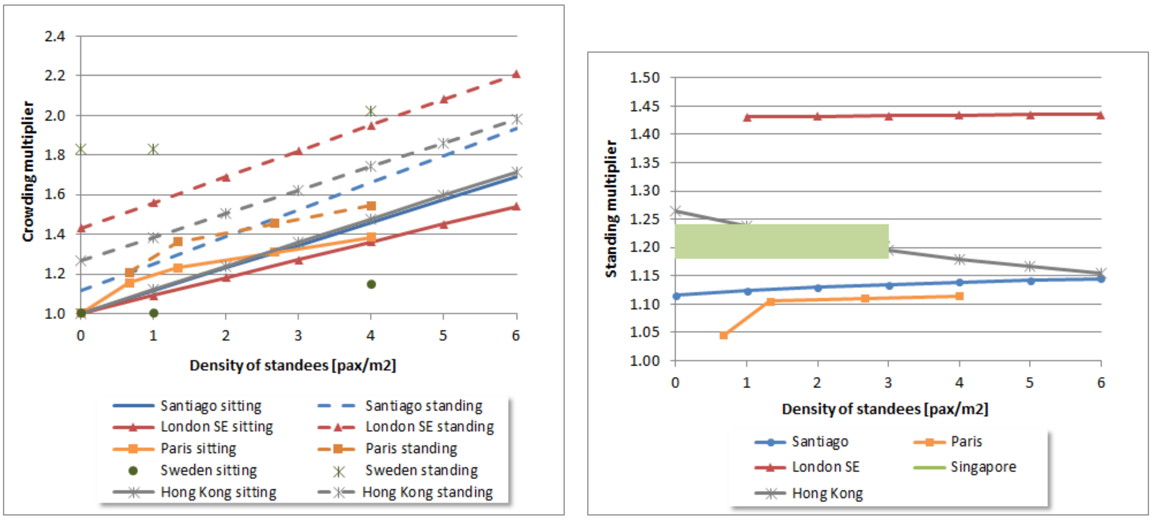
	MNL		ML				LC			
	Mean		Mean		Median		Class 1		Class 2	
pax/m2	Est.	St. Err	Est.	St. Err	Est.	St. Err	Est.	St. Err	Est.	St. E
0	1.00	NA	1.00	NA	1.00	NA	1.00	NA	1.00	N
1	1.17	0.01	2.02	0.29	1.16	0.02	1.56	0.09	1.07	0
2	1.33	0.02	3.03	0.59	1.33	0.04	2.11	0.18	1.13	0
3	1.50	0.03	4.05	0.88	1.49	0.06	2.67	0.27	1.20	0
4	1.67	0.03	5.06	1.17	1.65	0.08	3.22	0.36	1.26	0
5	1.84	0.04	6.08	1.47	1.81	0.10	3.78	0.45	1.33	0
6	2.00	0.05	7.10	1.76	1.98	0.11	4.33	0.54	1.39	0

Figure 15: Comparison of implied crowding multipliers: MNL, ML, LC models



whereas Sweden has lower sitting multipliers (up to 1.15 for 4 pax/m2). For standing, the estimated multipliers in Santiago are similar to those in Paris, slightly lower to those in Hong Kong and clearly lower to those estimated in Sweden and London SE.

On the other hand, Fig. 16b depicts the value of having a seat, that is the ratio between the standing and sitting multipliers. We find the Santiago values closer to those of the Paris Metro system for sitting and standing. The value of having a seat in Santiago and Paris are for the most part between 1.10 and 1.15, which means that travel time is valued between 10 and 15 percent more when standing than when sitting. The value of having a seat in Hong Kong is estimated between 1.15 and 1.27, and is a decreasing function of the density by construction of the model (Hörcher et al., 2017). The London SE value of a seat is much higher at 1.44, which is possibly explained by a longer trip distance in the British study (it includes interurban travel) and having trains with more seats. As shown in the diagrams, in Santiago metro trains have very few seats and the probability of getting a seat is close to zero in peak hours (except for users that board trains at the first station of a line), and therefore people may not give a great value to having a seat since they are used to stand. The value of having a seat in Singapore's MRT was estimated between 1.18 and 1.24, a value that lies between those in Santiago and London. Therefore, we conclude that with evidence from four urban heavy rail systems, value of travel time savings when travelling standing should be around 1.10-1.26 larger than the value of travel time savings when sitting, a value that likely increases for suburban or interurban longer trips.



(a) Crowding multipliers

(b) Standing multipliers

Figure 16: International comparison for crowding and standing multipliers. Own elaboration based on Whelan and Crockett (2009), Kroes et al. (2014), Tirachini et al. (2016) and Bj'orklund and Sw'ardh (2015)

G Conclusions

Mode choice models where crowding is one of the main explanatory variables were estimated. A basic Multinomial Logit (MNL) model, a Latent Class (LC) model and a Mixed Logit (ML) model were estimated and crowding multipliers were computed for each of them. Additionally, the relevance of the type of representation of the crowding level was tested, showing it has no significant effect.

Results show that crowding is relevant to explain user behaviour in Santiago, and that different travel time multipliers for sitting and standing could be estimated. The quantification of the crowding effect and the value of having a seat has the potential to influence project appraisal, allowing to consider different benefits for users under different crowding conditions. This would have been of use, for example, in the public transport design model for Santiago, where it was assumed that, while travelling, one minute is worth the same regardless of crowding conditions in trains or buses. Our results can be used to estimate the value of increasing service frequency, increasing train size or increasing the number of seats as measures to improve the service quality. We found that the sitting multiplier is up to 1.5-1.6 for a density of standees of 6 pax/m2, whereas the standing multiplier goes up to a value between 1.9 and 2.2 for the same density. The MNL and the median ML were not far from each other, which in the case of Santiago allows us to infer that for policy evaluation the use of crowding multipliers from a simple MNL model is enough to model the crowding sensitivity of the population as a whole. However, significant heterogeneity is present in our sample, which could be picked up by both ML and LC models. We used a latent class model to differentiate between groups of users that have different preferences. The group with low crowding sensitivity is more likely to be populated by younger people, males and users with higher income, whereas the group that is more sensitive to crowding is more likely to have females, older people and lower income travellers.

Regarding policy implications, the estimated crowding multiplier should be tried in the evaluation of changes to the existing metro network and service in, for example, the number of seats per train or increasing/reducing the service frequency in peak and off-peak periods (as analysed by Tirachini et al. (2014) for buses and de Palma et al. (2015) for trains). Without a crowding disutility, increasing train frecuency only has a value on reducing waiting time. The approach presented here can be used to estimate the effect of that intervention on the comfort of travel time, for a real metro line in Santiago.

Finally, when comparing the results obtained in this article with the extant literature, it is interesting to analyse the similarities of the Santiago results in particular to those of Paris and Hong Kong, taking into account the fact that the research methods used by the authors and the contexts are different: in Santiago and Paris, stated preferences have been used while in Hong Kong revealed preferences have been inferred using large automatic fare collection (AFC) and automatic vehicle location (AVL) databases. Importantly, we cannot confirm that crowding multipliers obtained from stated preferences might be larger than those from revealed preferences, as suggested by Kroes et al. (2014) and Hörcher et al. (2017), because we found mixed results when comparing different cities and research methods. The advent of large AFC and AVL databases for the estimation of crowding and standing externalities (as recently advanced by Tirachini et al. (2016) and Hörcher et al. (2017), with the implementation of route choice methods) paves the way for the extended use of revealed preferences for the economic analysis of crowding discomfort and other quality-of-service attributes in the near future. It is expected that as more RP-based results arise, a clearer picture of potential stated preferences biases will be obtained.

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Appendix: Crowding representations in the SC experiments

Three different types of representation of the crowding level were used in the SC experiments: 2d diagrams, photos and text descriptions. Because it offers the possibility of depicting standing passenger density in a very accurate way, the 2D diagram was built as the referential way to represent crowding. Figure 17 shows the 6 crowding levels and their corresponding representation with 2D diagrams while Figure 18 shows the corresponding photos used for each level. Table 15 shows the text used to represent each of level.

Figure 17: Crowding levels using 2D diagrams

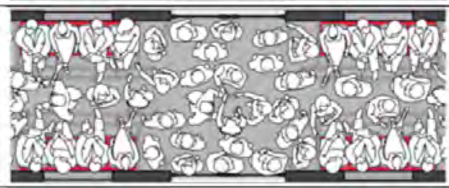
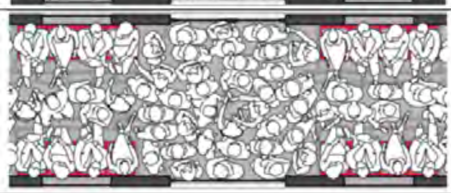
Crowding level	Diagram (shown to respondents)	Description (not shown to respondents)
1		35% seats occupied, 0 standees
2		69% seats occupied, 0 standees
3		100% seats occupied, 1 pax/m2 standing
4		100% seats occupied, 2 pax/m2 standing
5		100% seats occupied, 4 pax/m2 standing
6		100% seats occupied, 6 pax/m2 standing

Figure 18: Crowding levels using photos

level	Diagram and photo representation	level	Diagram and photo representation
1		2	
3		4	
5		6	

Table 15: Crowding levels using text

level	Description
1	Less than half of seats are occupied. No one is standing.
2	More than half of seats are occupied. No one is standing.
3	All seats are occupied. Few people standing, there is no difficulty moving.
4	All seats are occupied. People standing, minor difficulty moving.
5	All seats are occupied. Many people standing, it is difficult to move.
6	All seats are occupied. Maximum number of people standing, maximum difficulty to move.

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