Travel discomfort-time tradeoffs in Paris subway: an empirical analysis using interval regression models

Matthieu de Lapparent * Martin Koning †

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transp-or.epfl.ch

*Transp-OR, Ecole Polytechnique Fédérale de Lausanne, CH-1015 Lausanne, Switzerland, matthieu.delapparent@epfl.ch

†Université Paris-Est. Institut Français des Sciences et Technologies des Transports, de l'Aménagement et des Réseaux. 14-20 Boulevard Newton, Cité Descartes, Champs-sur-Marne, F-77447 Marne-la-Vallée Cedex 2, France. E-mail: martin.koning@ifsttar.fr

Abstract

We analyze individual travel discomfort-time tradeoffs in Paris subway using stated choice experiments. The survey design allows to set up in a willingness-to-pay space to estimate the distributions of elasticities of values of travel time savings to crowd density and time multipliers. Several formulations of a generalized travel cost function are tested. Accounting for heterogeneity in preferences, the econometric models all take the form of an ordered Probit with known bounds. We derive several estimates that could be used for fine-tuning of traffic simulation systems and more general transportation policy analysis.

Key words: travel discomfort-time tradeoff, stated choice survey, interval regression model

1 Introduction

Any transport policy that favors the use of public transportation (PT) has to account for related capacity constraints as they offset its expected benefits. Current overcrowding of PT systems in dense urbanized areas, i.e. lack of individual space in carriages[1], is downscaling attractiveness of such ways of traveling, especially during peak hours: long stand-up position, reluctance to close proximity with other people and agoraphobia, sanitary issues, unsafety and insecurity feelings, stress, etc. (Cox et al., 2006, Evans and Wener, 2007, Mohd Mahudin et al., 2012, Wener et al., 2005 or CRCFRI, 2012). All of these may restrain individual behavioral shifts that would support sustainable transport policies.

Also, as discussed by Parry and Small (2009) and estimated by Tirachini et al. (2010) in a different context, not accounting for existing capacity constraints introduces an upward bias in forecasting PT traffic, hence biasing optimal subsidies and pricing schemes. As a result (domino effect), road congestion is then underestimated and the bias propagates throughout the whole economic assessment of any considered transport policy.

Over the last decades, research on modeling travel demand considered budget, time, schedule, and more recently reliability, as the most prevailing determinants of individual choices. One typically observes that crowding costs in PT systems are often ignored when it comes to quantitative modeling of the different aspects of urban travel demand. It is currently changing. Li and Hensher (2011), Wardman and Whelan (2011), recently reviewed existing evidence on PT crowding costs. It is shown that such studies date back to the 80's. Most are reports produced for UK and Australian railways operators, thus difficult to access because not in the public domain. OECD-ITF (OECD-ITF, 2014) also coordinated a roundtable about valuation of

[1]Crowding in PT systems can be estimated according to different metrics. Load factors correspond to the ratio between the number of users in the trains and the number of seats proposed. Because this measure does not consider the varying in-vehicle design of the rolling-stock, passenger density is generally preferred. This will be our measure of crowding in this article. Note also that, in Japan, crowding is measured through the "*Japan Industrial Standard*" that merges together the seat and the standing capacities of the vehicles (see Kato, 2014).

"convenience" in mass transit. Crowding was a central theme.

From an academic point of view, Kraus (1991) initiated the analysis of discomfort externalities in PT. He introduced a dummy for standing vs. seated positions, assuming relative dislike for standing position as compared to seated position Haywood and Koning (2013), Kroes et al. (2013), recently proposed empirical estimates of crowding costs for Île-de-France (Paris region). They defined crowding as a discrete class variable, also distinguishing seated or standing positions (see also Hensher et al., 2011). Jara-Diaz and Gschwender (2003), Tirachini et al. (2010), de Palma et al. (2011), extended the framework to continuous variations of crowd density, be they monotonic or not. The latter developed a strictly theoretical framework of analysis whereas the others were more interested in using their approaches for empirical analyses. Parry and Small (2009) laid in between: they theoretically considered crowding costs when assessing the optimal level of PT subsidies but they did not incorporate them in their empirical application. Whelan and Crockett (2009) highlighted how sensitive could be the results along with the way crowding costs are modeled.

These formulations have behavioral implications. It is typically assumed that discomfort and travel time interact. Precisely, discomfort affects the value of travel time savings (VTTS). It is defined as a VTTS "multiplier": the more crowd, the larger the VTTS (see Wardman and Whelan, 2011). In the present article, as we are definitely oriented on empirical valuation of PT crowding costs, we keep in line with earlier studies in that we adapt, and test, some of the existing generalized traveling cost functions. We also propose a simple variant of the generalized traveling cost function where discomfort enters additively and independently from travel time: crowding is evaluated *per se* and does not affect the VTTS.

Methods that are used for empirical estimation of such crowding effects mostly rely on a combination of stated preference (SP) surveys (Hensher et al., 2005) and random utility maximization (RUM) discrete choice models (Ben-Akiva and Lerman, 1985, Train, 2009). We differ from the existing crowding valuation studies by proposing an interval regression approach (Maddala, 1986, Long, 1997) in "willingness-to-pay" space.

We use data on stated choices of 667 travelers that were collected in late

2010 on platforms of the Paris subway using face-to-face interviews. The survey design is based on a double bounded contingent valuation method with follow up question (Hanemann et al., 1991). We take advantage of the underlying bracketing procedure to estimate distributions of elasticities of the VTTS with respect to crowd density, and travel time multipliers. Whichever the formulation of the generalized traveling cost function that we use, the resulting econometric specification is an ordered Probit model with known bounds. Whereas our approach is fairly standard in experimental economics, it differs from what is usually done in transportation economics. In addition of testing several specifications of a generalized cost function, we believe it is important to show that experimental procedures could be used to assess various dimensions of travel activities. We also are convinced that such an approach is relevant to structurally model heterogeneity of preferences.

The rest of the article is organized as follows. Section 2 develops our framework of analysis and the specific functional forms we use. Section 3 describes the survey design, how data were collected, and some descriptive statistics. Section 4 develops our econometric methodology. Section 4.2 discusses the estimation results. Conclusion is drawn in a last section.

2 Model

2.1 Framework

We assume that a traveler i associates a real-valued generalized cost function to a trip alternative m:

$$C_i \left(p_m, t_m, d_m\right), \tag{1}$$

where $p_m > 0$ models the trip cost, $t_m > 0$ models travel time, and $d_m \geq 0$ models crowd density. $C_i : \mathbb{R}^3 \to \mathbb{R}$ is continuously increasing with p_m, t_m, and d_m. For the sake of simplicity, we here focus on a public mode of transport and we consider that traveler i is captive: there is no change in destination, mode, route, and time of the day. Price p_m does not change: $\forall m, p_m \equiv p$. Only t_m and d_m may vary. We also assume that there is no other attribute affecting the generalized cost function (such as scheduling costs, reliability, etc.) and that there is no distinction between different dimensions of travel time (in-vehicle time, waiting time, connection time, etc.). We also do not distinguish the path links used by travelers within a full journey, as done for instance in Kato et al. (2010). We actually consider a situation where it is asked the traveller how much he is willing to spend additional total travel time for less crowd density on the path link starting from the node he was surveyed.

Two alternatives are proposed. One of these is the current one. We agree that this "anchor point" might be problematic (see Tversky and Kahneman, 1991 for an analysis in riskless choice situations). The second alternative systematically proposes less crowd density in carriage, $d \geq 0, \Delta d \geq 0, d - \Delta d \geq 0$, but a larger travel time $t + \Delta t, t > 0, \Delta t > 0$. This is an important point in that we only consider a decrease in crowd density compensated by an increase in travel time with respect to an actual travel condition. As a consequence, our approach is designed to infer "willingness-to-pay" for lesser crowd density but not "willingness-to-accept" a larger one. We are aware that Tversky and Kahneman (1991) highlighted existence of asymmetry between willingness-to-pay and willingness-to-accept. Given our data, we cannot deal with such an issue.

Traveler i prefers her current alternative if and only if the associated generalized travel cost is strictly lesser than the generalized travel cost of the proposed alternative. The proposed (stated) alternative is preferred if and only if the associated generalized cost is strictly lower than the generalized cost of the current alternative. There is indifference between both if and only if the generalized travel costs are equal:

$$C_i(p, t, d) = C_i(p, t + dt, d - dd). \tag{2}$$

It is straightforward that there exists an unique balancing point under our assumptions, independently of the exact structure of the generalized cost function:

$$\frac{\frac{\partial C_i(p,t,d)}{\partial t}}{\frac{\partial C_i(p,t,d)}{\partial d}} = -\frac{dd}{dt}. \tag{3}$$

The left-hand side of the equation defines the MRS between travel time and crowd density. The right-hand side of the equation defines the ratio of the variations of crowd density and travel time. If this MRS is larger then the traveler i prefers the current travel alternative. If it is strictly lower then the proposed one is preferred. Because of a presumed retentive behavior, there is no reason why traveler i would change if it was strictly equal although there is indifference.

The explicit formulation of C_i leads to particular characterization of the problem as, structurally, one specific functional form models one specific interpretation. We now turn to some of those and their implications.

2.2 Functional forms

We consider a menagerie made of 5 formulations of the generalized cost function. These are built up on earlier work of Whelan and Crockett (2009), Jara-Diaz and Gschwender (2003):

$$C_{i,m} = p_m + \alpha_i \left(1 + \phi_i d_m\right) t_m, \tag{4}$$

$$C_{i,m} = p_m + \alpha_i \exp\left(\phi_i d_m\right) t_m, \tag{5}$$

$$C_{i,m} = p_m + \alpha_i \left(1 + d_m\right)^{\phi_i} t_m, \tag{6}$$

$$C_{i,m} = p_m + \alpha_i \exp\left(-\phi_i \left(\exp\left(-d_m\right) - 1\right)\right) t_m, \tag{7}$$

and

$$C_{i,m} = p_m + \gamma_i t_m, + \delta_i d_m. \tag{8}$$

As already stated, these functions strictly increase with price, travel time, and crowd density: $\alpha_i > 0$, $\phi_i > 0$, $\gamma_i > 0$, $\delta_i > 0$. We agree that, under some circumstances, it would be acceptable that individuals prefer crowd to nobody while traveling by PT, for instance in the late evening on some specific routes in order to feel more secure. We here consider it is not the case since the survey was carried out during peak hours.

The functional forms are of two types. The first assumes that crowd density affects the generalized cost of traveling through the VTTS (specifications in equations 4 to 7). $\alpha_i > 0$ models the VTTS when crowd density is equal to 0. When crowd density is strictly positive, $d_m > 0$, the VTTS is multiplied by a strictly positive factor. The 4 formulations are driven by a parameter $\phi_i > 0$. They model different sensitivity of the VTTS to crowd density.

The second assumes that crowd density affects the generalized cost of traveling independently of the VTTS (specification in equation 8). As contrary to the other specifications, travel time and crowd density do not interact. No matter crowd density in the carriage, the shadow price of travel time is unique. It is always equal to $\gamma_i > 0$. But crowd density still appears as a determinant of the generalized cost of traveling. Its weight is defined as $\gamma_i > 0$.

Table 1 reports some key properties of the functional forms.

Table 1 here

Specifications 4 to 7 interact crowd density with travel time in different ways. Elasticity of the VTTS with respect to crowd density differs along with them. Specifications 4 and 6 assume that elasticity of the VTTS with respect to crowd density is increasing and concave. The slopes of their response functions are different. Specification 5 assumes that it is linearly increasing with crowd density. Specification 7 assumes that it has a S-shape. The inflexion point is defined at $d_m = 1$. Increase is convex when $d \leq 1$ and concave when $d > 1$. Specification 8 is the additive extension of the standard linear generalized cost function in which crowd density independently just adds to the other determinants. As a result, the VTTS is not sensitive to it.

3 Survey design and data collection

3.1 Experimental procedure

Our stated choice survey is designed to quantify "willingness to spend travel time to save for discomfort". "discomfort" is here defined as crowd density in carriage. The design of the survey is based on a double bounded contingent valuation method with follow up question (Hanemann et al., 1991,Haab and McConnel, 2003).

For a traveler i, it relies on a series of two nested questions. They are generated from an actual traveling situation. As compared to the latter, it is first proposed a decrease in crowd density, say $\Delta d \leq 0$. To compensate for this presumed gain, it is proposed an increase in travel time, say $\Delta_1 t > 0$. If traveler i accepts the alternative, it is proposed a second trade-off with an even larger variation of travel time $\Delta_2 t > \Delta_1 t$. If traveler i sticks to her actual travel condition, it is rather proposed a second trade-off with a lesser variation of travel time $0 < \Delta_3 t < \Delta_1 t$.

We use time bids to reduce propensity of travelers to free-ride on choices of other travelers (strategic bias) and to reduce existence of a hypothetical bias (as pricing in Paris subway is flat, it is easier for travelers to express their preferences for comfort in time units). PT users also let sometimes pass a train or change route because of overcrowding (Kato et al., 2010), thereby showing relevance of trade-off between time and crowd density.

It was deliberately chosen to propose only two trade-offs. Whereas "first bid biases" may pollute individuals' answers (Flachaire and Hollard, 2007), lengthening sequences of choices might magnify these problems. Sort of "fatigue" phenomenon may appear, making answers less reliable (see also Bradley and Daly, 1994). We also wanted the survey to be short to minimize sample selection bias, assuming that people would easily accept to participate and quickly answer to it.

Given our formulations of the generalized travel cost functions, observing outcomes of such series of nested questions allows to directly bracket ϕ_i or δ_i/γ_i. To make things clear, let us consider specification 8 of the generalized travel cost function. If traveler i prefers $t + \Delta_1 t$, then:

$$p_m + \gamma_i t_m + \delta_i d_m > p_m + \gamma_i \left(t_m + \Delta_1 t\right) + \delta_i \left(d_m - \Delta d\right). \tag{9}$$

A simple manipulation of the equation just states that:

$$\frac{\delta_i}{\gamma_i} > \frac{\Delta_1 t}{\Delta d}. \tag{10}$$

By construction, the second alternative then proposes a larger $(\Delta_2 t)$ increase in travel time for the same decrease in crowd density (Δd). If traveler

i rejects this new alternative, then:

$$\frac{\Delta_2 t}{\Delta d} > \frac{\delta_i}{\gamma_i} > \frac{\Delta_1 t}{\Delta d}. \quad (11)$$

Table 2 summarizes the relation between observed outcomes and intervals to which may belong ϕ_i or δ_i/γ_i under a cost minimization assumption. These thresholds will serve in econometric estimation.

Table 2 here

The SP experiments were built up on an actual situation. Travelers had initially to estimate their current travelling conditions in terms of travel time and crowd density they were expecting to face using subway lines 1 or 4. They were first proposed to visualize and to tick 1 out of 7 possible crowd density situations: 0, 1, 2, 2.5, 3, 4 or 6 passengers per square meter, see figure 1. We assume that these revealed expected crowd density levels are these that travelers think to usually face. We build up on these to propose variations.

As contrary to Kroes et al. (2013) and Whelan and Crockett (2009) who proposed a "from the top" representation of carriages, we used "quasi-perspective" showcards to better describe the physical pressure characterizing crowding. Because in-vehicle design may differ across subway services, it was chosen to retain the simplest representation[2]. Door-to-door travel times were self-reported by subway users. In-vehicle travel times were drawn from both timetables and empirical measures.

Figure 1 here

For each traveler, starting from the "reference" point, a decrease in crowd density ($\Delta d < 0$) at the cost of an increase in travel time ($\Delta t > 0$) was proposed. The decrease in crowd density was randomly drawn from all the possible alleviating situations conditional on the revealed point. The

[2]We here recognize there is an important shortfall in the survey design. Because the showcards only represents the central part of the carriages where the doors are located, we are not able to study the value of seat-crowding, as done by Kroes et al. (2013) or Whelan and Crockett (2009) who present the whole vehicle to users.

following question was asked: "*In order to travel with this hypothetical level of comfort, instead of your current one, would you agree to use a subway which takes X additional minutes to reach your destination?*" The increase in travel time was "quasi-randomly" drawn from 6 possible values: 3, 6, 9, 12, 15, and 18 minutes. We "forced" large variations of travel time for only about 1 out of 20 travelers. It was otherwise variations below 12 minutes. It is not reported but data show consistent answers in that the larger increase of travel time (wrt current one), the larger rate of rejection of such a travel alternative independently of crowding. Depending on the answer to the first stated choice situation, the second question considered the same diminution of crowd density but either increased or decreased travel time by 25%. We assumed that travelers understood that they had to trade increased in-vehicle travel time against decreased in-vehicle crowding, i.e. slower subways rather than a lower service frequency.

3.2 Data collection

On-site data were collected in late 2010 on platforms of 11 subway stations, some being transportation hubs, all directly connected to lines 1 and 4 of Paris subway. Lines 1 and 4 are diagrammatically going from West to East and North to South. They cross at the center of Paris. They potentially offer important differences in crowd density and socioeconomic characteristics of travelers.

About 800 travelers were surveyed during peak morning and peak evening periods (07:30 - 10:00 AM and 05:00 - 07:30 PM) while they were waiting for their trains[3]. As already stated, the face-to-face questionnaire was purposely short to characterize the best possible individual time-discomfort trade-offs without introducing excessive sample selection, yet at the cost of lesser collected information. It was designed in two small parts to quickly focus on our problem. The first part was about collecting few information on individual characteristics of travelers. The second part proposed them stated choice experiments.

[3]Of course, we would have preferred a larger sample. As compared to the few existing studies, it however seems that the sample size is not that small (Li and Hensher, 2011)

3.3 Descriptive statistics

Once data are cleaned, the final sample contains observations of 667 subway users. Table 3 reports descriptive statistics. They pertain to some characteristics of the observed respondents and their choices about the stated travel scenarios.

Table 3 here

Gender is equally distributed. The average net monthly income is 2,444 €[4]. 57% of individuals live in Paris, 25% in its inner suburbs, and 18% in its outer suburbs and outside of the "*Île-de-France*" region. About 70% of trips are carried out for home to work purpose. Also, 64% of travelers use subway lines 1 and 4 on a daily basis.

The average door-to-door travel time is about 46 minutes and the average trip duration using the subway line on which travelers were surveyed is about 9.6 minutes.

The average "expected crowd density", i.e. estimated by travelers prior to train arrival, is 3.1 passengers per square meter. The full distribution is described in Table 4.

Table 4 here

A discussion point is whether expected crowd density (*ex ante*) matches observed one (*ex post*). Actual crowd in carriages was estimated on sites during the survey. We also had count data from the PT operator (for whole trains). Correlation between *ex ante* and *ex post* crowding is about 0.40. Expected crowding is what traveller was anticipating whereas actual crowding is what was really experienced after the interview. The latter is one outcome of an actual distribution whereas the former is an anticipated outcome of a perceived distribution. Low correlation between both shows that there is big difference between anticipated and actual crowding. Haywood and Koning (2013) analyzed such difference. They showed that expected crowding is positively driven by monthly net incomes of individuals, by the subway service as measured by frequency of trains (higher for line 1) and by the time of the day (higher during evening peaks). We however think that using an *ex ante* measure of crowd density as a "reference point" is

[4]We used color cards to incite travelers to report their net monthly incomes.

not that much a problem. What really matter here are the variations of crowd densities between declared and hypothetical states of nature.

The hypothetical crowd density proposed to travelers was on average 1.3 passengers per square meter (an average decrease of 58%, see the distribution of proposed crowd densities in Table 4). To compensate, it was proposed to increase travel time by 8.7 minutes on average. We observe that 25% of the travelers accepted both increases in travel time to benefit from lesser crowd density. 41% of them rejected both offers. 17% accepted the first increase in travel time but not the second and larger one. 17% rejected the first increase but accepted the second and lesser one.

4 Empirical modeling

4.1 Econometric specification

What is modeled is a sequence of decisions y_i:

$$y_i = \begin{cases} 1 \text{ iif traveler } i \text{ answers No to all stated alternatives} \\ 2 \text{ iif traveler } i \text{ answers No-Yes to these} \\ 3 \text{ iif traveler } i \text{ answers Yes-No to these} \\ 4 \text{ iif traveler } i \text{ answers Yes-Yes to these} \end{cases} . \quad (12)$$

Given the structure of the stated choice experiments and the presumed theoretical framework of decision (minimizing a generalized cost function), it means that either ϕ_i or δ_i/γ_i lies in between some values $\mathbf{b}_i$ that are determined by the levels of attributes of both the actual travel situation and the proposed (stated) ones. These values are computable and bound some parameters of the generalized cost functions, as reported in Table 2.

For the sake of clarity, let $\theta_i \equiv \phi_i$ or $\theta_i \equiv \delta_i/\gamma_i$. Given one case s out of the 5 presented in subsection 2.2, we assume that:

$$\ln(\theta_{i,s}) = \mathbf{x}_i'\beta_s + \epsilon_{i,s} \quad (13)$$

where $\mathbf{x}_i$ is a (column) vector of independent (exogenous) variables, β_s is a (column) vector of unknown parameters we want to estimate, and $\epsilon_{i,s}$ is an additive random term. The error terms are, conditional on the case s, the known thresholds $\mathbf{b}_i$, the observed variables $\mathbf{x}_i$, and the parameters β_s, independently and identically distributed with distribution F_{ϵ_s} with a scale parameter σ_s. Because of data, we here limit to distributions that are fully characterized by their location and scale parameters:

$$\forall s, \epsilon_{i,s} \overset{iid}{\to} F_{\epsilon_s}\left(a_{i,s}|\mathbf{b}_{i,s}, \mathbf{x}_i; \beta_s, \sigma_s\right), a_{i,s} \in \mathbb{R}. \tag{14}$$

The parameters β_s weigh the (observable) independent variables. They affect the (conditional) expectation of $\ln(\theta_{i,s})$. The individual contribution to the likelihood function may therefore be written as:

$$\begin{aligned}&\Pr\left(y_i|\mathbf{x}_i, \mathbf{b}_{i,s}; \beta_s, \sigma_s\right) = \\ &\Pr\left(b_{i,k-1,s} \le \ln(\theta_{i,s}) \le b_{i,k,s}|\mathbf{x}_i, \mathbf{b}_{i,s}; \beta_s, \sigma_s\right) = \\ &\quad \prod_{k=1}^{4}\left(F\left(\frac{\ln(b_{i,k,s})-\mathbf{x}_i'\beta_s}{\sigma_s}\right) - F\left(\frac{\ln(b_{i,k-1,s})-\mathbf{x}_i'\beta_s}{\sigma_s}\right)\right)^{\mathbb{I}(y_i=k)}\end{aligned} \tag{15}$$

where, by convention, $\forall s, \ln(b_{i,0,s}) \equiv -\infty$ and $\ln(b_{i,4,s}) \equiv +\infty$, and where $\mathbb{I}(y_i = k)$ is equal to 1 if the observed outcome is $k \in \{1, 2, 3, 4\}$ and 0 otherwise.

In doing so, we actually stick to the "Interval Data Model" (IDM) as introduced by Hanemann et al. (1991). In specifying a model using contingent valuation data from "following-up dichotomous choices" questionnaires, Cameron and Quiggin (1994), Bradley and Daly (2000), however argued that the second offered threshold may not be independent of valuation information which the respondent has revealed in answering the first question. We actually use a restricted approach in exogenously constraining the mean to be identical across individual responses and assuming zero covariance to assure independence of the response equations. We obviously recognize that further work is needed to be sure that, given data, IDM is the right approach in WTP space. We here build up on this latter, comparing different functional forms.

The log-likelihood function of a sample of n individuals is defined as:

$$\sum_{i=1}^{n}\sum_{k=1}^{4}\mathbb{I}(y_i = k)\ln\left(\Pr\left(y_i = k|\mathbf{x}_i, \mathbf{b}_{i,s}; \beta_s, \sigma_s\right)\right). \tag{16}$$

It takes the form of a standard ordered discrete choice model with known thresholds (Maddala, 1986). The choice of F is up to the modeler. We here choose a Normal distribution, i.e. an ordered Probit model with known bounds. We may have chosen another probability distribution, such as the more conventional Logistic one in transportation analysis. We actually fitted the models also assuming a Logistic distribution[5]. We have just made the choice to present the results using a Normal distribution. Both are very similar despite asymmetry of the Logistic distribution. We acknowledge that choice of a distribution of the error terms characterizes what is not observed by the modeler and how the latter envision it. This is another issue on which there is further research to carry out in our context.

Note that the thresholds being known and variable across respondents, there is no further need to normalize the scale of the presumed distribution for identification purpose: all the parameters are identified.

4.2 Results

We estimated the parameters related to some variables that might play roles on distributions of ϕ (specifications 4 to 7) and δ/γ (specification 8). We remind that, given data, we are not able to isolate the distribution of the "baseline" VTTS (we should have proposed additional time vs. money tradeoffs). Tables 5 and 6 report estimation results. The latter gives estimates of the models using only significant variables.

Tables 5 and 6 here

It is found that the conditional mean of ϕ and δ/γ depend on a limited set of factors.

The role of income is robust to specification of the model. The results show that the larger income, the lesser sensitivity to crowd density. For specifications 4 to 7, VTTS increases with crowd density but less for high-income people as compared to low-income people. It is however known that the total effect of income on VTTS is positive: high-income people have larger VTTS than low-income people. We here only quantify the indirect effect of income on VTTS considering that it affects sensitivity to crowd density. Assuming that the α_i term, the "baseline VTTS" in our

[5] Results are available on request

approach, may also be function of income, the total sensitivity of VTTS to income would then be the sum of two partial effects: one that affects the baseline VTTS and one that affect sensitivity to crowd. As the sum of these two effects has to be positive to comply with earlier findings, it means that sensitivity of the "baseline VTTS" has to overcompensate the effect of income on crowd density. Such a conjecture should be tested with appropriate data that make it possible to simultaneously estimate the baseline VTTS and its crowd density related part.

Traveling during morning peak is significant but only for some of the specifications. When it is so, it is negative: there is lesser sensitivity to crowd during morning peak. It just means that PT travelers anticipates larger crowd density during morning peak hours because of work-related daily trips during these periods. They accept more discomfort.

The results also show that there is difference between the two surveyed subway lines. There is larger sensitivity to crowd when traveling on line 1 (West-East both ways) as compared to traveling on line 4 (North-South both ways). According to the PT operator, it is reported that there was more crowd density on line 1 as compared to line 4 in 2010. Line 1 carried about 207 millions passengers in 2010, with an average headway of 105 seconds in between two trains during peak hours during peak hours. Line 4 carried about 171 millions passengers in 2010, with the same average peak headway. Both subway lines have similar passenger capacities. It is also reported that the increase in traffic was by far the largest on line 1 since 1992. The results show that increase in crowd density is less accepted when the initial level is already large.

Dispersion of the distribution of parameters is larger for specifications 4 and 7. This is not surprising for specification 4 as sample size strongly matters in estimation efficiency: lesser observations were actually admissible for our analysis. Specification 4 actually involves a further constraint that directly affects the admissible values of Δt and Δd that should be used for generation of our SP scenarios in the present approach[6]. We did not initially account for them in generation of stated choice situations, preferring to keep less specific in our approach, i.e. we did not initially have

[6]This is why the sample size is different as compared to the other specifications

in mind testing this specific functional form. Actually, one of the author in Haywood and Koning (2013) had in mind specifying a random utility maximizing model with linear utility functions, interacting crowd density (defined as a class variable)) with travel time, to compute time multipliers. As it regards specification 7, the S-shape seems to be at stake.

One important point is about the "preferred" specification that we may use for policy implications. Specification 8 appears to statistically perform better. Specification 7 is the one where gains in adding explanatory variables are the best. Specification 4 is not directly comparable but, using a Schwartz criterion, it appears as a good competitor. Given our results, there should be no reason to interact the VTTS with crowding for pure statistical performance. We however keep in line with Wilkinson (1999): modelers must think about what the models mean, regardless of fit. One must not strictly stick to goodness of fit but also to the meaning of the model or one might promulgate nonsense: theory should also drive model selection, not only data. We have to account for this in search of an appropriate functional form. Despite our statistical results showing that crowd density does not affect travel time, we would prefer a model that accounts for such interaction in that it is "a priori" a "more intuitive" representation of choice behaviors. In addition, as stated by Kroes et al. (2013), "*crowding penalties that are proportional to travel time can easily be added to the models that are used for appraisal purposes, whereas constant penalties are much more difficult to apply in practice*". Based on this, specifications 4 and 5 thus may appear to be appropriate.

4.3 Elasticities and time multipliers

Given our specifications, it is virtually possible to compute any distribution quantiles of our estimates or any function of these. We here report some using median estimates of the (point) elasticities of the VTTS to crowd density and of the time multipliers for some predetermined values of the following independent variables: subway line, morning/evening peak periods, and crowd density. We refer the reader to table 1 as it regards the formulas that we used. Elasticities are reported in tables 7 and 8.

Tables 7, 8 here

For levels of crowd density in between 1 and 5, the values of elasticity spans from 0.02 to 1.93. For specifications 4 and 6, the results show that VTTS is somewhat inelastic (i.e. absolute value ≤ 1) to crowd density. We notice some exception as it pertains to low income travelers on line 1 during peak evening hours when crowd density is equal to 5 persons per square meters. Elasticities above 1 mostly come from specification 5 that considers a strictly convex relation between the VTTS and crowd density d. The results show that VTTS becomes elastic to crowd density for large levels of crowd density in this case. Elasticity values are rather low for case 4 (specification 7) due to the double exponential formulation and the fact that the relation between the VTTS and crowding is a decreasing function when crowd density is ≥ 1 person per square meter.

As Whelan and Crockett (2009) suggested, it is also interesting to evaluate by how much is varying the VTTS with crowd density by defining a multiplicative factor between a target situation and a reference one. These "time multipliers" are reported in tables 9, 10, 11, and 12. We here chose a reference situation of 1 person per square meter.

Tables 9, 10, 11, 12 here

Considering specification 4, the time multipliers go up to 2.5 when crowd density increase from 1 to 5 passengers per square meters. In case of very high congestion in carriage, the value of travel time is multiplied by 2.5 as compared to a very comfortable situation. Our results are in line with those of Haywood and Koning, 2013. They seem to overestimate a little time multipliers as compared to those found by Kroes et al. (2013). Note that we here have opportunity to distinguish thee time multipliers along with different types of travelers.

Another series of interesting results comes from specification 5. In our view, this is an intuitive specification as it allows for a convexly increasing relation between the VTTS and crowd density, i.e. cost of having more people in the carriage when it is already overcrowded is valued far more than having more people in the carriage when it is initially almost empty. The results show that there is an inflexion point around 3 persons per square meter. VTTS can be multiplied by up to 4.7 when crowd density increase from 1 to 5 passengers per square meters. We agree that it might exaggerate. We think that there may exist an upper bound on crowd density above which time multipliers are constant.

To make things easier to understand, we depict some time multipliers of specifications 4 and 5 them in figures 2 and 3.

Figures 2, 3 here

5 Conclusion

Studying crowding costs in Paris subway appears illustrative of modern urban challenges. Promoting the use of PT networks needs to be accompanied by guarantees about supply capacity. Even if the latter was improved, the corresponding modal shift and 20% growth of the PT patronage has led to a 10% increase of the passenger density in Paris subways (Observatoire des déplacements à Paris, 2008). Uncomfortable travel conditions are logically highlighted as disruptive factors (crowding and unreliability) that minimize the success of such sustainable policies.

Our results show that sensitivity to crowding mostly depends on income, time of the day, and the specific PT infrastructure that is used for traveling. Also, computing point estimates about elasticities of VTTS, MRS, and time multipliers show that PT users are significantly accounting for discomfort. Sensitivity appears to be varying in line with presumed behavior they may have but the results show that it never can be ignored.

We recognize that our analysis may be extended in several ways. First, data collection should be extended to disentangle the distributions of the different structural parameters of the generalized cost functions. The purpose is to simultaneously characterize both the VTTS, schedule delays, and crowding effects in a consistent framework of analysis. Ideally, to also account for recent work on risky travel choice models, data collection should be adapted. We think it should be rather easy to adapt our strategy to generate and to assign proper stated choice experiments.

Second, the generalized cost functions may also be extended in several ways. It may be accounted for nonlinearities in either travel costs and travel times. We here presented a simple menagerie of functional forms where the generalized travel cost function is linear with travel time and travel cost. There might also exist other functional forms to test, and these also should be implemented. There is still a gap to fill as search for an optimal formulation of the problem is not yet solved.

Finally, having a larger sample size and a greater spatial coverage may lead to an accurate characterization of how is affected PT demand by crowding.

We are convinced that individual travel demand modeling would clearly improve in systematically considering in-vehicle discomfort. Results of policy scenarios would of course change. Future research can not ignore crowding in public transport in economic evaluation of transport policies.

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Table 1: Summary of functional forms

Case ID	Generalized cost function	$MRS_{t/p}$ (VTTS)[a]	$\epsilon_{VTTS/d}$[b]	TM[c]
1	$C_{m,i} = p_m + \alpha_i (1 + \phi_i d_m) t_m$	$\alpha_i (1 + \phi_i d_m)$	$\frac{\phi_i d_m}{1+\phi_i d_m}$	$\frac{1+\phi_i d_m}{1+\phi_i d^\star}$
2	$C_{m,i} = p_m + \alpha_i \exp(\phi_i d_m) t_m$	$\alpha_i \exp(\phi_i d_m)$	$\phi_i d_m$	$\exp(\phi_i (d_m - d^\star))$
3	$C_{m,i} = p_m + \alpha_i (1 + d_m)^{\phi_i} t_m$	$\alpha_i (1 + d_m)^{\phi_i}$	$\phi_i \frac{d_m}{1+d_m}$	$\left(\frac{1+d_m}{1+d^\star}\right)^{\phi_i}$
4	$C_{m,i} = p_m + \alpha_i \exp(-\phi_i (\exp(-d_m) - 1)) t_m$	$\alpha_i \exp(-\phi_i (\exp(-d_m) - 1))$	$\phi_i \exp(-d_m) d_m$	$\exp(-\phi_i (\exp(-d_m) - \exp(-d^\star)))$
5	$C_{m,i} = p_m + \gamma_i t_m, + \delta_i d_m$	γ_i	0	0

[a] MRS: Marginal Rate of Substitution, VTTS: Value of Travel Time Savings
[b] Elasticity of VTTS with respect to crowd density d
[c] TM: Time Multiplier, w.r.t a reference level $d^\star$

Table 2: Observed outcomes and thresholds for the different cases

		Observed outcomes				
		Reject-Reject (1) LB	Reject-Reject (1) UB / Reject-Accept (2) LB	Reject-Accept (2) UB / Accept-Reject (3) LB	Accept-Reject (3) UB / Accept-Accept (4) LB	Accept-Accept (4) UB
Case	Bracketed parameter	$b_{i,0}$	$b_{i,1}$	$b_{i,2}$	$b_{i,3}$	$b_{i,4}$
1	ϕ_i	0	$\frac{\Delta_3 t}{t\Delta d - \Delta_3 t(d-\Delta d)}$	$\frac{\Delta_1 t}{t\Delta d - \Delta_1 t(d-\Delta d)}$	$\frac{\Delta_2 t}{t\Delta d - \Delta_2 t(d-\Delta d)}$	$+\infty$
2	ϕ_i	0	$\frac{1}{\Delta d}\ln\left(1+\frac{\Delta_3 t}{t}\right)$	$\frac{1}{\Delta d}\ln\left(1+\frac{\Delta_1 t}{t}\right)$	$\frac{1}{\Delta d}\ln\left(1+\frac{\Delta_2 t}{t}\right)$	$+\infty$
3	ϕ_i	0	$\frac{\ln\left(1+\frac{\Delta_3 t}{t}\right)}{\ln\left(1+\frac{\Delta d}{1+d-\Delta d}\right)}$	$\frac{\ln\left(1+\frac{\Delta_1 t}{t}\right)}{\ln\left(1+\frac{\Delta d}{1+d-\Delta d}\right)}$	$\frac{\ln\left(1+\frac{\Delta_2 t}{t}\right)}{\ln\left(1+\frac{\Delta d}{1+d-\Delta d}\right)}$	$+\infty$
4	ϕ_i	0	$\frac{\ln\left(1+\frac{\Delta_3 t}{t}\right)}{\exp(-d)(\exp(\Delta d)-1)}$	$\frac{\ln\left(1+\frac{\Delta_1 t}{t}\right)}{\exp(-d)(\exp(\Delta d)-1)}$	$\frac{\ln\left(1+\frac{\Delta_2 t}{t}\right)}{\exp(-d)(\exp(\Delta d)-1)}$	$+\infty$
5	δ_i/γ_i	0	$\frac{\Delta_3 t}{\Delta d}$	$\frac{\Delta_1 t}{\Delta d}$	$\frac{\Delta_2 t}{\Delta d}$	$+\infty$

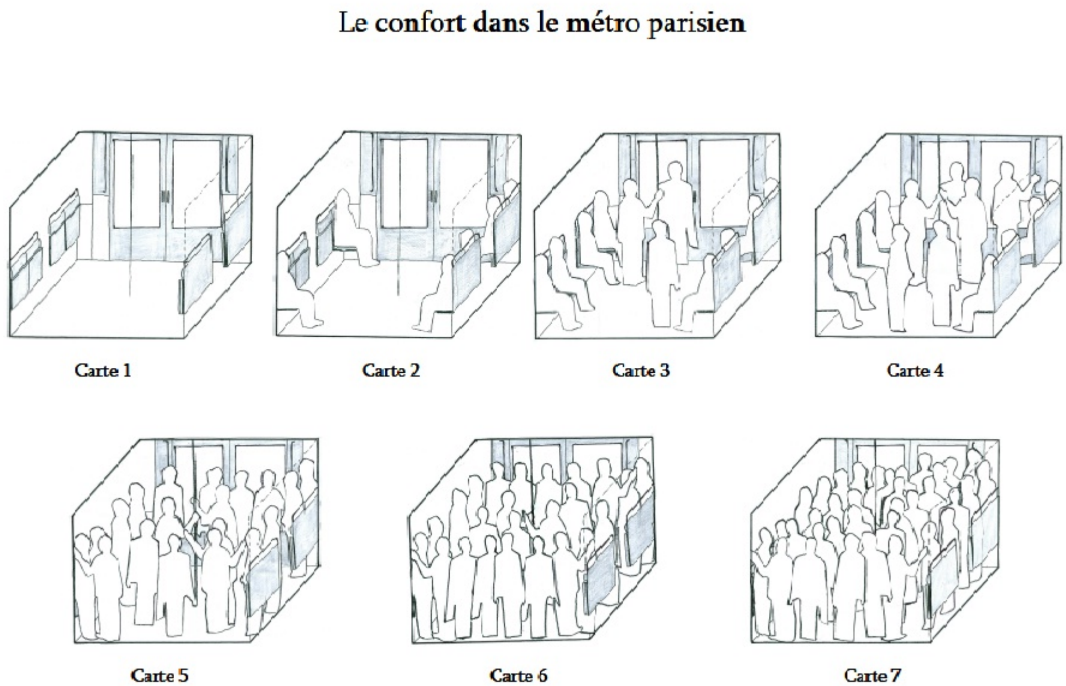

Figure 1: Cards shown during the survey

Table 3: Sample statistics

Label of variables	Frequency	Mean
Total sample size	667	
Current crowd density (in pass./m^2)		3.1
Hypothetical crowd density (in pass./m^2)		1.3
Current in-vehicle time (in min.)		9.6
Current "door-to-door" time (in min.)		46
First time bid (in min.)		8.7
Second time bid		8.0
Choice: (reject-reject)	275	
Choice: (reject-accept)	115	
Choice: (accept-reject)	115	
Choice: (accept-accept)	162	
Morning peak	337	
Traveler is a man	333	
Work purpose	467	
Daily use of subway line	426	
Monthly income (in 000's €)		2.44
Home located in Paris	417	
Home located in inner suburbs	166	
Home located in outer suburbs	84	
Traveler sample on line 1	329	
Traveler sample on line 4	338	

Table 4: Current and hypothetical levels of crowding

Expected crowding (pass/m^2)	0	1	2	2.5	3	4	6
Distribution (pct interviews)	0.0	2.3	16.6	27.8	23.9	20.5	8.8
Hypothetical crowding:							
0 pass/m^2 (pct interviewees)	n.a.	100.0	51.3	30.0	26.4	19.4	16.7
1 pass/m^2			48.7	31.4	21.6	20.9	8.3
2 pass/m^2				38.6	31.1	21.6	16.7
2.5 pass/m^2					21.0	20.1	18.3
3 pass/m^2						18.0	13.3
4 pass/m^2							26.7

Table 5: Maximum Likelihood estimates, full specifications

	Case 1		Case 2		Case 3		Case 4		Case 5	
Label	Est.	T-stat	Est.	T-stat	Est.	T-stat.	Est.	T-stat.	Est.	T-stat
Intercept	-0.84	-3.30	-1.08	-6.62	-0.10	-0.54	0.68	2.75	1.55	11.05
Morning peak	-0.07	-0.38	-0.11	-0.98	-0.26	-2.06	-0.59	-3.38	-0.20	-1.99
Income in 000's €	-0.20	-3.67	-0.10	-3.04	-0.11	-3.03	-0.15	-3.02	-0.09	-3.34
Traveler is a man	0.04	0.21	0.03	0.25	0.04	0.35	0.08	0.47	0.07	0.67
Work purpose	0.09	0.45	0.06	0.42	0.13	0.90	0.30	1.49	0.10	0.89
Line used every day	0.00	-0.01	-0.09	-0.72	-0.11	-0.83	-0.18	-0.96	-0.15	-1.48
Home located in inner suburbs	0.16	0.74	0.01	0.09	0.02	0.14	0.07	0.36	-0.09	-0.77
Home located in outer suburbs	-0.05	-0.17	0.18	0.99	0.13	0.68	0.06	0.22	-0.14	-0.91
Subway line 1	0.53	2.68	0.31	2.57	0.52	3.99	0.99	5.55	0.22	2.18
Variance	2.32	8.76	1.52	11.05	1.85	11.03	3.45	11.00	1.10	11.13
Goodness-of-fit statistics										
Log-likelihood at convergence	-542.12		-996.31		-1020.29		-1095.57		-874.57	
Log-likelihood. intercept only	-551.53		-1004.87		-1034.51		-1120.25		-884.48	
Sample size	401		667		667		667		667	

Table 6: Maximum Likelihood estimates, specifications with only significant variables

	Case 1		Case 2		Case 3		Case 4		Case 5	
Label	Est.	T-stat	Est.	T-stat	Est.	T-stat.	Est.	T-stat.	Est.	T-stat
Intercept	-0.77	-4.84	-1.12	-10.84	ns		0.77	4.47	1.49	14.99
Morning peak	ns		ns		-0.27	-2.39	-0.55	-3.18	-0.18	-1.87
Income in 000's €	-0.20	-3.75	-0.10	-3.16	-0.11	-3.84	-0.14	-2.87	-0.08	-3.05
Traveler is a man	ns		ns		ns		ns		ns	
Work purpose	ns		ns		ns		ns		ns	
Line used every day	ns		ns		ns		ns		ns	
Home located in inner suburbs	ns		ns		ns		ns		ns	
Home located in outer suburbs	ns		ns		ns		ns		ns	
Subway line 1	0.54	2.80	0.32	2.71	0.52	4.31	1.02	5.82	0.21	2.09
Variance	2.32	8.79	1.51	11.06	1.85	11.06	3.47	11.00	1.11	11.13
Goodness-of-fit statistics										
Log-likelihood at convergence	-542.63		-997.60		-1021.40		-1097.13		-876.51	
Log-likelihood. intercept only	-551.53		-1004.87		-1034.51		-1120.25		-884.48	
Sample size	401		667		667		667		667	

Table 7: Point estimates: elasticities of the VTTS to crowd density, line 1, computed at median values of parameters

Crowd density, persons / sqm	morning	line 1	income ('000s €)	Case 1	Case 2	Case 3	Case 4	Case 5
1	No	Yes	1.5	0.37	0.39	0.71	1.79	0
1	No	Yes	3	0.30	0.33	0.60	1.45	0
1	No	Yes	5	0.23	0.27	0.49	1.09	0
1	Yes	Yes	1.5	0.37	0.39	0.54	1.03	0
1	Yes	Yes	3	0.30	0.33	0.46	0.84	0
1	Yes	Yes	5	0.23	0.27	0.37	0.63	0
3	No	Yes	1.5	0.64	1.16	1.07	0.73	0
3	No	Yes	3	0.57	1.00	0.91	0.59	0
3	No	Yes	5	0.47	0.82	0.73	0.44	0
3	Yes	Yes	1.5	0.64	1.16	0.82	0.42	0
3	Yes	Yes	3	0.57	1.00	0.69	0.34	0
3	Yes	Yes	5	0.47	0.82	0.56	0.26	0
5	No	Yes	1.5	0.75	1.93	1.19	0.16	0
5	No	Yes	3	0.69	1.66	1.01	0.13	0
5	No	Yes	5	0.59	1.36	0.81	0.10	0
5	Yes	Yes	1.5	0.75	1.93	0.91	0.09	0
5	Yes	Yes	3	0.69	1.66	0.77	0.08	0
5	Yes	Yes	5	0.59	1.36	0.62	0.06	0

Table 8: Point estimates: elasticities of the VTTS to crowd density, line 4, computed at median values of parameters

Crowd density, persons / sqm	morning	line 1	income ('000s €)	Case 1	Case 2	Case 3	Case 4	Case 5
1	No	No	1.5	0.26	0.28	0.42	0.64	0
1	No	No	3	0.20	0.24	0.36	0.52	0
1	No	No	5	0.15	0.20	0.29	0.39	0
1	Yes	No	1.5	0.26	0.28	0.32	0.37	0
1	Yes	No	3	0.20	0.24	0.27	0.30	0
1	Yes	No	5	0.15	0.20	0.22	0.23	0
3	No	No	1.5	0.51	0.84	0.64	0.26	0
3	No	No	3	0.43	0.73	0.54	0.21	0
3	No	No	5	0.34	0.59	0.43	0.16	0
3	Yes	No	1.5	0.51	0.84	0.49	0.15	0
3	Yes	No	3	0.43	0.73	0.41	0.12	0
3	Yes	No	5	0.34	0.59	0.33	0.09	0
5	No	No	1.5	0.63	1.40	0.71	0.06	0
5	No	No	3	0.56	1.21	0.60	0.05	0
5	No	No	5	0.46	0.99	0.48	0.04	0
5	Yes	No	1.5	0.63	1.40	0.54	0.03	0
5	Yes	No	3	0.56	1.21	0.46	0.03	0
5	Yes	No	5	0.46	0.99	0.37	0.02	0

Table 9: Point estimates: time multipliers, morning peak, line 1, computed at median values of parameters and for reference density $d^{\star} = 1$

crowd density, persons / sqm	morning	line 1	income ('000 €)	Case 1	Case 2	Case 3	Case 4	Case 5
0	Yes	Yes	1.5	0.63	0.68	0.47	0.17	0
0	Yes	Yes	3	0.70	0.72	0.53	0.24	0
0	Yes	Yes	5	0.77	0.76	0.60	0.34	0
1	Yes	Yes	1.5	1.00	1.00	1.00	1.00	0
1	Yes	Yes	3	1.00	1.00	1.00	1.00	0
1	Yes	Yes	5	1.00	1.00	1.00	1.00	0
2	Yes	Yes	1.5	1.37	1.47	1.55	1.92	0
2	Yes	Yes	3	1.30	1.39	1.45	1.70	0
2	Yes	Yes	5	1.23	1.31	1.35	1.49	0
3	Yes	Yes	1.5	1.74	2.17	2.13	2.44	0
3	Yes	Yes	3	1.61	1.95	1.90	2.06	0
3	Yes	Yes	5	1.45	1.72	1.67	1.73	0
4	Yes	Yes	1.5	2.11	3.19	2.71	2.66	0
4	Yes	Yes	3	1.91	2.71	2.33	2.21	0
4	Yes	Yes	5	1.68	2.27	1.97	1.82	0
5	Yes	Yes	1.5	2.48	4.70	3.31	2.75	0
5	Yes	Yes	3	2.21	3.79	2.76	2.27	0
5	Yes	Yes	5	1.90	2.97	2.26	1.86	0

Table 10: Point estimates: time multipliers, evening peak, line 1, computed at median values of parameters and for reference density $d^\star = 1$

crowd density, persons / sqm	morning	line 1	income ('000 €)	Case 1	Case 2	Case 3	Case 4	Case 5
0	Yes	No	1.5	0.74	0.76	0.64	0.53	0
0	Yes	No	3	0.80	0.79	0.68	0.60	0
0	Yes	No	5	0.85	0.82	0.74	0.68	0
1	Yes	No	1.5	1.00	1.00	1.00	1.00	0
1	Yes	No	3	1.00	1.00	1.00	1.00	0
1	Yes	No	5	1.00	1.00	1.00	1.00	0
2	Yes	No	1.5	1.26	1.32	1.30	1.26	0
2	Yes	No	3	1.20	1.27	1.25	1.21	0
2	Yes	No	5	1.15	1.22	1.20	1.15	0
3	Yes	No	1.5	1.51	1.75	1.57	1.38	0
3	Yes	No	3	1.41	1.62	1.46	1.30	0
3	Yes	No	5	1.29	1.49	1.36	1.22	0
4	Yes	No	1.5	1.77	2.32	1.81	1.42	0
4	Yes	No	3	1.61	2.07	1.65	1.33	0
4	Yes	No	5	1.44	1.81	1.50	1.24	0
5	Yes	No	1.5	2.02	3.08	2.04	1.44	0
5	Yes	No	3	1.81	2.63	1.83	1.34	0
5	Yes	No	5	1.58	2.21	1.62	1.25	0

Table 11: Point estimates: time multipliers, morning peak, line 4, computed at median values of parameters and for reference density $d^{\star} = 1$

crowd density, persons / sqm	morning	line 1	income ('000 €)	Case 1	Case 2	Case 3	Case 4	Case 5
0	No	Yes	1.5	0.63	0.68	0.37	0.05	0
0	No	Yes	3	0.70	0.72	0.43	0.08	0
0	No	Yes	5	0.77	0.76	0.51	0.15	0
1	No	Yes	1.5	1.00	1.00	1.00	1.00	0
1	No	Yes	3	1.00	1.00	1.00	1.00	0
1	No	Yes	5	1.00	1.00	1.00	1.00	0
2	No	Yes	1.5	1.37	1.47	1.78	3.09	0
2	No	Yes	3	1.30	1.39	1.63	2.50	0
2	No	Yes	5	1.23	1.31	1.48	2.00	0
3	No	Yes	1.5	1.74	2.17	2.69	4.68	0
3	No	Yes	3	1.61	1.95	2.31	3.50	0
3	No	Yes	5	1.45	1.72	1.96	2.58	0
4	No	Yes	1.5	2.11	3.19	3.69	5.46	0
4	No	Yes	3	1.91	2.71	3.03	3.96	0
4	No	Yes	5	1.68	2.27	2.43	2.83	0
5	No	Yes	1.5	2.48	4.70	4.79	5.77	0
5	No	Yes	3	2.21	3.79	3.78	4.14	0
5	No	Yes	5	1.90	2.97	2.90	2.93	0

Table 12: Point estimates: time multipliers, evening peak, line 4, computed at median values of parameters and for reference density $d^\star = 1$

crowd density, persons / sqm	morning	line 1	income ('000 €)	Case 1	Case 2	Case 3	Case 4	Case 5
0	No	No	1.5	0.74	0.76	0.56	0.33	0
0	No	No	3	0.80	0.79	0.61	0.41	0
0	No	No	5	0.85	0.82	0.67	0.51	0
1	No	No	1.5	1.00	1.00	1.00	1.00	0
1	No	No	3	1.00	1.00	1.00	1.00	0
1	No	No	5	1.00	1.00	1.00	1.00	0
2	No	No	1.5	1.26	1.32	1.41	1.50	0
2	No	No	3	1.20	1.27	1.34	1.39	0
2	No	No	5	1.15	1.22	1.26	1.28	0
3	No	No	1.5	1.51	1.75	1.80	1.75	0
3	No	No	3	1.41	1.62	1.65	1.57	0
3	No	No	5	1.29	1.49	1.49	1.41	0
4	No	No	1.5	1.77	2.32	2.17	1.84	0
4	No	No	3	1.61	2.07	1.93	1.64	0
4	No	No	5	1.44	1.81	1.70	1.45	0
5	No	No	1.5	2.02	3.08	2.54	1.88	0
5	No	No	3	1.81	2.63	2.20	1.67	0
5	No	No	5	1.58	2.21	1.88	1.47	0

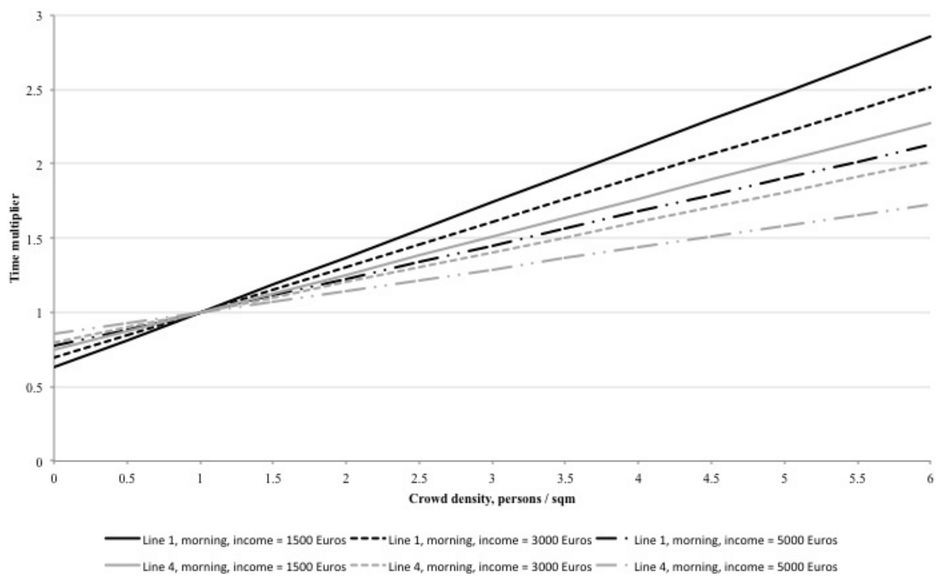

Figure 2: Time multipliers, morning peak, case 1

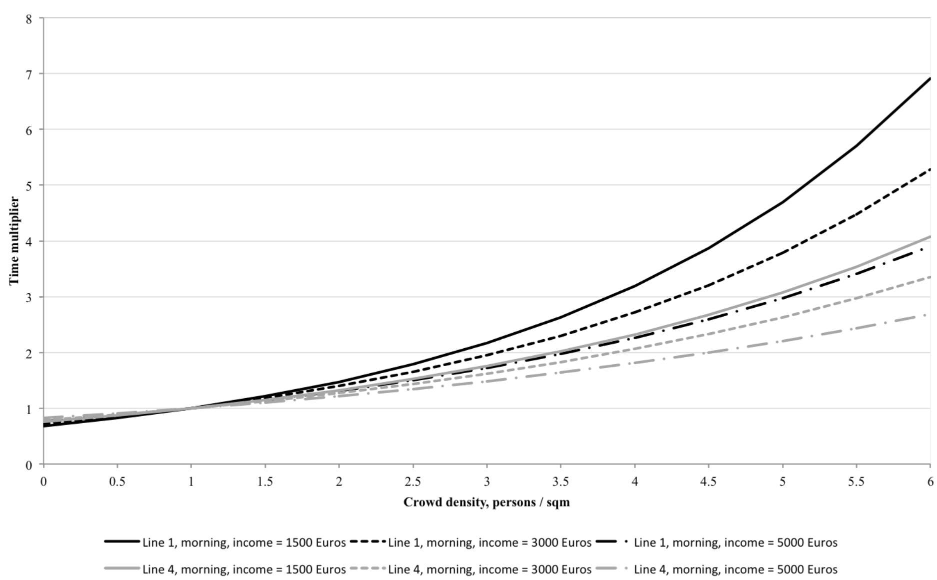

Figure 3: Time multipliers, morning peak, case 2