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Crowding valuation in urban tram and bus transportation based on smart card data

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ABSTRACT

Crowding in public transport can be of major influence on passengers' travel experience and therefore affect route and mode choice. In this study, crowding valuation for urban tram and bus travelling is determined fully based on revealed preference data. Urban tram and bus crowding valuation is estimated in a European context based on a Dutch case study network. Based on the estimated discrete choice model, we conclude that crowding plays a significant role in passengers' route choice in public transport. The average crowding multiplier of in-vehicle time equals 1.16 when all seats are occupied. For frequent travellers, this value is equal to 1.31. Our study results suggest that infrequent travellers do not incorporate expected crowding in their route choice. The insights gained from our study can support the decision-making process of policy-makers, by quantifying the benefits of measures aiming to reduce crowding levels for example in a cost–benefit analysis framework.

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1. Introduction

Crowding in public transport can be of major influence on passengers' travel experience and therefore affect route and mode choice. Because of the expected increasing concentration of activities within urban agglomerations in many countries worldwide, crowding is expected to become an even more dominant factor in urban public transportation in the future. Therefore, it is important to understand and quantify how crowding in urban public transport is perceived by passengers. This can contribute to the quantification of societal benefits of measures aiming to alleviate passenger congestion, and thus potentially support policy-makers in the decision-making process regarding the implementation of such measures (see e.g. Prud'homme et al. 2012; Haywood and Koning 2015; Cats, West, and Eliasson 2016).

Congestion and crowding are not always incorporated in public transport modelling, contrary to highway modelling. In highway modelling, link travel times are a direct function of (amongst other) the link congestion level. In public transport modelling, congestion and crowding levels influence passengers' perceived in-vehicle times. Public transport crowding only affects the nominal travel times if dwell times would increase or in more extreme

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cases of denied boarding, what can result in costs for passengers and operators. Thus, in public transport there is a behavioural relation instead of a traffic flow relation between crowding and (perceived) travel times.

The majority of studies which do incorporate public transport crowding use stated preference (SP) experiments for crowding valuation. For example, MVA Consultancy (2008), Whelan and Crockett (2009), Batarce, Munoz, and Ortuzar (2016) and Tirachini et al. (2017) use SP surveys where crowding is represented by pictures of crowding levels in public transport carriages, and crowding valuation is expressed using the average number of standing passengers per square metre. Lu, Fowkes, and Wardman (2008) express crowding as the probability on occurrence (e.g. 2 out of 5 times) in a SP experiment, whereas Li, Gao, and Tu (2017) describe and show different crowding levels using colours. Douglas and Karpouzis (2005) use pictures of crowding in their SP experiment, and estimate crowding in-vehicle time multipliers for different levels of crowding (e.g. seated no crowding, seated crowding, standing, crush standing) for different durations (e.g. during 10 or 20 minutes). In some studies where crowding valuation is estimated based on SP experiments, results are validated against revealed preference (RP) data, for example by using surveys, passenger observations or cameras. For example, Kroes et al. (2014) validate SP based crowding estimates for Ile-de-France based on observed behaviour of passengers on platforms skipping a very crowded service and waiting for a next less crowded service. Batarce et al. (2015) estimate a mixed SP/RP model for the case of Santiago, Chile, combining a SP survey with pictured crowding levels and revealed passenger route choice based on smart card data. These mainly SP based results are applied in public transport models aiming to improve passenger assignment and predictions, see for example Hamdouch et al. (2011), Schmöcker et al. (2011), Nuzzolo, Crisalli, and Rosati (2012), Pel, Bel, and Pieters (2014), Cats, West, and Eliasson (2016) and Van Oort et al. (2016). Extensive literature reviews regarding crowding valuation studies can be found in Wardman and Whelan (2011) and in Li and Hensher (2011).

We conclude that most crowding valuation studies are based on SP experiments. Studies which use RP data generally only use a relatively small RP dataset to validate SP estimates. It is, however, known that there can be a discrepancy between stated choices of respondents in SP experiments, compared to revealed choice behaviour in reality. This is a systematic discrepancy in which SP experiments tend to overestimate values compared to observed valuation in reality. This discrepancy can occur if respondents have difficulties imagining the stated, hypothetical choice situation, or if respondents lack sufficient experience with similar circumstances in reality to fully understand the trade-offs between the attributes in the choice set. The shortage of RP data usage in studies concerned with passenger perception of on-board crowding arguably stems from the sparsity and difficulty to obtain passenger-related data in many public transport systems. However, the increasing availability of automatic fare collection (AFC), automatic vehicle location (AVL) and automatic passenger count (APC) systems in public transport enables the estimation of crowding valuation fully based on large-scale RP data. In particular, the availability of individual smart card transactions allows gaining insights into revealed trade-offs between travel time, transfers, waiting time and crowding in public transport route choice. Only a limited number of studies exploited smart card data for this purpose, namely the works by Hörcher, Graham, and Anderson (2017) and Tirachini et al. (2016). Hörcher, Graham, and Anderson (2017) estimated discrete choice models incorporating crowding valuation in metro systems by fusion of AFC and AVL data. In their study, 32 origin-destination (OD) pairs of the MTR

metro network of Hong Kong are used to estimate the valuation of the standing probability and crowding density (expressed as the number of standing passengers per square metre). Since the AFC system in Hong Kong is a closed, station-based system where passengers have to tap-in and tap-out at the metro station, the exact route and trip choice had to be inferred using a passenger-to-train assignment method. Tirachini et al. (2016) estimated the passenger valuation of crowding for metro travelling on the Singapore network, fully based on observed behaviour of passengers willing to travel in the opposite direction first to secure a seat in the trip in their preferred direction.

The contribution of our study is that we estimate crowding valuation associated with urban tram and bus journeys, in a European context, entirely based on revealed route choice behaviour obtained from AFC and AVL data of the urban public transport network of The Hague, the Netherlands. We show additional evidence for the existing discrepancy between using RP and SP data for crowding valuation. Since passengers are required to tap-in and tap-out on-board each tram or bus vehicle, no inference of the exact route or the exact vehicle choice is required. By fusing AFC and AVL data, we directly determine the exact route and vehicle each passenger used, and deduce the stop-to-stop vehicle occupancy for each individual vehicle trip. This means we can eliminate one inference step of the methodology applied by Hörcher, Graham, and Anderson (2017), thereby reducing potential uncertainty. We apply our methodology to a high-density public transport case study network, in which there is a large number of OD pairs between which different route choices can be observed.

This paper is structured as follows. Section 2 describes the methodology, including data processing (Section 2.1), transfer inference (Section 2.2), selection of OD pairs (Section 2.3), determination of attributes and attribute levels (Section 2.4) and choice model formulation (Section 2.5). Section 3 provides the estimation results and discusses their implications. In section 4, conclusions and recommendations for further research are formulated.

2. Methodology

2.1. Raw data semantics and processing

When travelling by light rail, tram or bus in the Netherlands, passengers are required to tap-in and tap-out at devices located within each vehicle. This means that there is a closed, entry-exit, distance-based fare system applied in The Hague. This is different from most urban public transport systems in the world, in which especially for buses often an open, entry-only system with flat fare structure is applied. This can, for example, be seen in London (Gordon et al. 2013) or in Santiago, Chile (Munizaga and Palma 2012). The fare system as applied in the Netherlands means that for each journey leg made by each individual travelling by the abovementioned modes the boarding time and boarding location, as well as the alighting time and location, are directly available from the raw data set. Besides, for each smart card transaction the line number, vehicle number, trip number and smart card number are known. This means that each journey leg with its corresponding transaction information is registered as a separate row in the AFC dataset. In the Netherlands, the AFC data is closed data owned by the public transport operator. The AVL data, on the other hand, is open data and publicly available. The AVL dataset contains the scheduled and realised

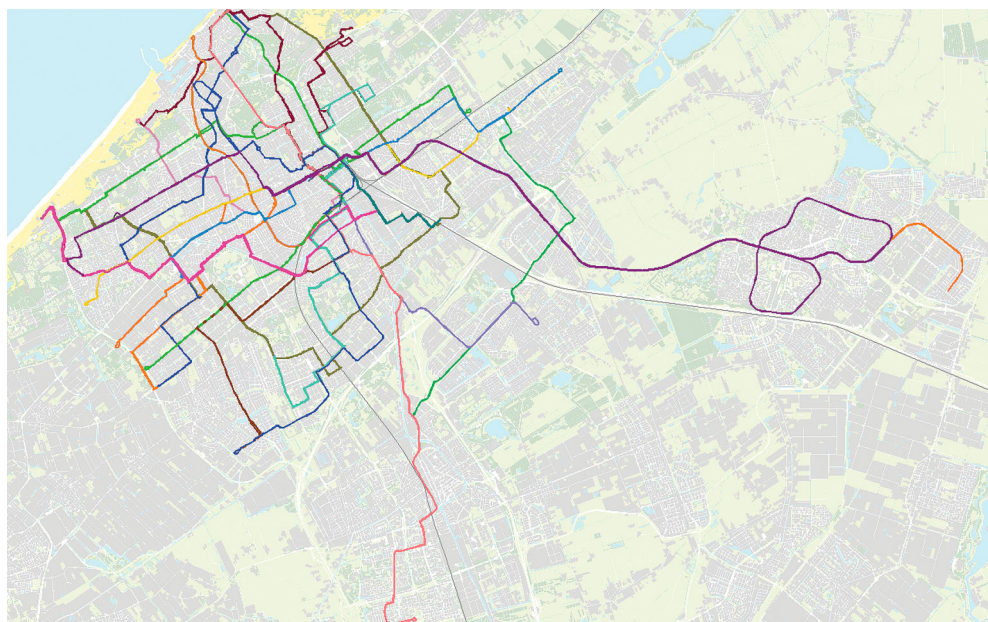


Figure 1. Overview of urban tram and bus lines of case study network The Hague, the Netherlands.

arrival time and departure time of each vehicle trip at each stop. In case spatiotemporal passenger information would not be directly available from the AFC system, boarding time and location, alighting time and location, and transfer times can be inferred. For example, Tu et al. (2018) propose a methodology to infer the boarding location for bus travels by fusion of smart card data and GPS trajectories, whereas Zhang et al. (2016) developed an approach to extract passengers' spatiotemporal information by inference of boarding times and transfer times.

We use the urban public transport network of The Hague, the Netherlands, to estimate public transport crowding valuation. This network consists of 12 tram lines and 8 bus lines, operated by the urban public transport operator HTM (Figure 1). Two of these 12 tram lines function as light rail service at the urban agglomeration network level, connecting The Hague with the satellite city of Zoetermeer. The other 10 tram lines and all bus lines function as urban lines within The Hague and neighbouring towns. During an average working day, more than 300.000 AFC transactions are made in the urban public transport network in The Hague.

AFC and AVL data of 28 days from 2–29 November 2015 was made available by the incumbent operator for this study. This amounts to a dataset that consists of approximately 7.4 million AFC transactions and about 3.1 million AVL registrations. In the data processing phase, we apply the following steps:

- Selection of morning peak data (07:00–09:00);
- Removal of morning peaks with disruptions;
- Removal of incomplete AFC transactions ;
- Inference and increase of occupancy data.

Since the aim of our study is to explore how passengers incorporate crowding in their route choice, it is essential that we select a time period in which crowding occurs. Compared to crowding levels reached in metro systems in cities like London, Santiago, Beijing or Tokyo, the level of crowding in The Hague can be considered quite moderate. Outside peak periods, in general no crowding occurs. In peak periods, crowding however does occur on several lines. Since public transport demand in the morning peak in the Netherlands is more concentrated within a relatively small period, compared to a more uniformly distributed demand in the evening peak, we only focus on AFC transactions during the morning peak. This means that only journeys of which the tap-in record time is between 07:00 and 09:00 on working days (Monday–Friday) are considered.

In our study, we focus on explaining route choice based on expected attribute values for travel time, waiting time and crowding. Therefore, it is important that only regular, undisturbed periods are incorporated in the dataset. Since disruptions can force passengers to adjust their route choice, this might cause bias in the analysis. Based on the operator log file, containing all registered disruptions with corresponding time, duration and location, we removed the AFC data from morning peaks of days where a disruption occurred. Given the possibility of second-order effects, in which a disruption on a certain public transport line might increase occupancies on other parallel lines, crowding levels on directly and indirectly affected lines can then deviate from expected crowding levels passengers have for undisturbed days (Malandri, Fonzone, and Cats 2018). Therefore, we adopted this conservative approach of excluding working day data if any disruption occurred anywhere on the considered case study network. From the 20 working days remaining in the dataset, data from 6 working days have been removed.

For the AFC data of the remaining 14-morning peaks, we removed incomplete transactions. Transactions can be incomplete due to a system error or due to a human cause (human error by forgetting to tap-out, or deliberately not tapping out), in both cases leading to a missing tap-out time and/or location. Although there exist many destination inference algorithms in scientific literature (e.g. the well-known trip chaining algorithm as applied by Trépanier, Tranchant, and Chapleau 2007; Zhao, Rahbee, and Wilson 2007 and Wang, Attanucci, and Wilson 2011), we removed all incomplete transactions, since the percentage of incomplete AFC transactions in The Hague is with 1.9% rather low due to the entry-exit AFC fare system. From studies validating destination inference algorithms (e.g. Munizaga et al. 2014; Yap et al. 2017), we know that between 65% and 85% of the destinations for urban tram or bus journeys are correctly inferred. By removing incomplete transactions, we avoid introducing inaccuracies resulting from possibly incorrect destination inference. Besides, given the entry-exit AFC system, the percentage of incomplete AFC transactions in The Hague is with 1.9% rather low and not expected to systematically influence results. Since in the Dutch public transport system a deposit is written off from each smart card when tapping in as incentive for passengers to tap-out due to its distance-based fare system, which is transferred back to the card when tapping out again, we expect no correlation between (higher) crowding levels and (lower willingness of) passenger tap-out behaviour.

Vehicle occupancies are derived by fusion of AFC and AVL data. Since both the AFC and AVL data contain the trip number, both data sources can be coupled. This results in the occupancy of each vehicle trip between each pair of stops. These smart card data-based occupancies are corrected for the percentage of travellers not using a smart card, and the

percentage of incomplete AFC transactions. In the Netherlands, most passengers travel using their smart card. Only passengers who buy a ticket in the vehicle at the driver or vending machine, and passengers who (un)deliberately do not tap in during their trips are not captured. Since our study focuses on experienced crowding levels, these passenger groups are however relevant. Based on passenger counts performed by the urban operator, for each public transport line a correction factor is determined which can be used to increase the smart card based occupancies. This factor varies between 5% and 14% for different lines. This correction factor is applied uniformly on a line-level, which implicitly assumes that the destination choice behaviour of non-smart card users is indistinguishable from the one characterising smart card users. Since our dataset contains transactions of morning peak periods in November, the share of very infrequent passengers (e.g. tourists) for whom the abovementioned assumption might not apply is arguably very low.

2.2. *Transfer inference*

For the individual AFC transactions for each trip, it is determined whether an alighting is a transfer or a final destination. To this end, we applied the transfer inference algorithm as described by Yap et al. (2017). This algorithm is an extension on the algorithm described by Gordon et al. (2013), and uses AFC, AVL and inferred occupancy data. Below, this algorithm is shortly discussed. For a more detailed explanation, the reader is referred to Yap et al. (2017). The algorithm consists of temporal, spatial and line-based criteria whether to classify an alighting activity as a transfer:

- Temporal criterion: an alighting activity is considered a transfer if the passenger boarded the first feasible vehicle of the next tap-in line passing by the next boarding location. A feasible vehicle is defined as the first vehicle passing by the next boarding location – given the alighting time of the previous journey leg and required walking time – of which the occupancy does not exceed the norm capacity;
- Spatial criterion: an alighting is considered a transfer if the distance between the alighting location and the next boarding location does not exceed a maximum transfer walking distance of 400 Euclidean metre. An exception to this threshold is made in case passengers use an intermediate public transport service offered by another operator, for which no AFC data is available;
- Line-based criterion: an alighting is not considered a transfer if the next boarding is on the same line as the previous journey stage, since this suggests that an activity was performed in between. An exception is made in case of boarding the first passing vehicle of the same line directly following the alighted vehicle, since this can indicate (for example) a transfer from a short-service to the long-service vehicle of the same line or a transfer to the same line in case of loops. Given the relatively high frequencies of urban public transport lines, it is highly unlikely that such alighting and boarding of the next vehicle will be an activity.

In total, the dataset contains 628,839 journeys resulting from 14 working days. Figure 2 (left) shows the resulting distribution of the number of transfers, whereas Figure 2 (right) shows the distribution of journeys over each half-hour period of the morning peak (using the journey tap-in time for aggregation). As can be seen, almost all journeys consist of 0 or 1

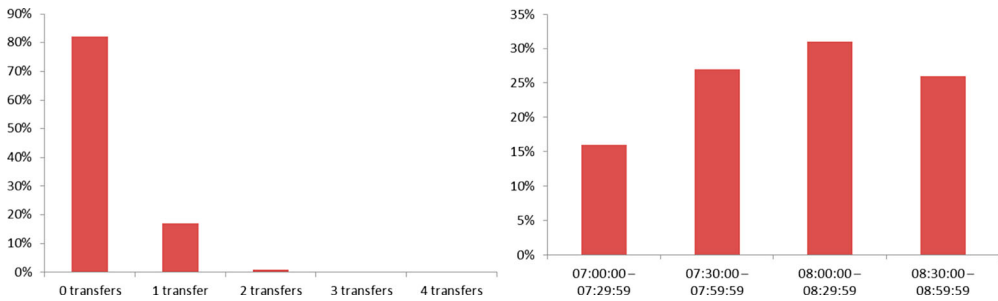


Figure 2. Journey distribution by number of transfers (left) and distribution per half-hour of the morning peak (right).

transfer. The busiest part of the morning peak on a network wide level is between 08:00 and 08:30, containing 31% of all morning peak journeys.

The boarding stop, alighting stop, and the travelled route and line of each passenger journey leg are directly observed from the AFC data, because of the entry-exit smart card regime with on-board devices for tap-in and tap-out. Applying our study to The Hague case study network has therefore the advantage that no inference is required in determining passenger route choice, so that our study fully relies on directly observed route choice. Vehicle occupancies are also the direct result of fusing empirical AFC and AVL transactions, without relying on any further inference. The transfer inference algorithm, which is the only inference algorithm applied to the dataset, only relates to the interpretation whether an alighting is considered a transfer or final destination, but is not consequential in determining route choice or occupancies.

2.3. Selection of origin-destination pairs

In total, the database consists of 49,231 different chosen routes. This value can be considered as the sum-product of the number of chosen OD pairs and the number of chosen route alternatives for each OD pair. Different routes are considered to belong to one and the same OD pair, if the boarding stops are located in each other's vicinity, as well as the alighting stops. The following criteria are used to select OD pairs to be included in the estimation of the discrete choice model with crowding effects:

- Minimum choice set size of 2 for each OD pair;
- Minimum number of 100 observed choices for each OD pair;
- Minimum observed choice probability of 0.1 for each route alternative in the choice set;
- Minimum expected seat occupancy of 50% on minimal one link of one route alternative;
- Attribute variation over all OD pairs

In our study, we only consider the observed route choice set. This prevents making assumptions regarding the incorporation of non-observed, possibly feasible route alternatives in the choice set and allows us to infer attribute levels for all alternatives entirely based on observed AFC and AVL data. The first criterion thus means that there should be an observed choice between at least two route alternatives for a given OD pair. A route is defined as

a unique sequence of boarding locations, alighting locations and intermediate (combination of) lines. In case of routes with the same origin stop and the same destination stop, the routes should physically differ from each other, to be considered as separate route alternative in the choice set. In case of a bundle of different lines sharing the same infrastructure (e.g. for journeys within the city centre), passengers might take the first arriving vehicle suitable for their destination. Given our aim to explain route choice, we consider route alternatives as different from each other, only if these do not share the exact same geographical path (i.e. 100% overlap).

A minimum number of 100 observed choices for each OD pair is deemed necessary to incorporate sufficient choices of individual passengers to infer generic coefficients from. By setting a minimum value for the observed choice probability of 10% per chosen route alternative, we ignore route alternatives which are chosen only in a very limited number of cases. Such route alternatives might be chosen in case of (non-registered) delays, disruptions or atypical passenger behaviour (e.g. passengers travelling for fun). Another requirement is that there should be at least a certain amount of crowding expected on (at least) one of the route alternatives of an OD pair. Since we want to estimate crowding valuation, we did not want to put a crowding constraint *a priori*. However, if no crowding occurs on all route alternatives at all, it is not possible to examine the influence of crowding on route choice. Therefore, we opted for a light requirement here. If the expected seat occupancy exceeds 50% during some period of the morning peak on some part of one of the observed route alternatives, this requirement is fulfilled. A seat occupancy threshold of 50% is used, since passengers start having to sit next to each other from a seat occupancy of 50% or higher. It is expected that negative crowding experiences might arise from this value onwards. The robustness of estimation results towards the latter assumption has been investigated in a sensitivity analysis. Reducing this threshold value by 20% (to 40%) showed not to influence the number of OD pairs and observations in the dataset. An increase of this threshold by 20% (to 60%) resulted in only one OD pair not satisfying this criterion anymore, thereby reducing the number of observations in the dataset by 2%. Since the total number of observations in the dataset is hardly influenced by this parameter value, this sensitivity test attests to the robustness of the estimation results to different values of this threshold. At last, we checked over all remaining OD pairs together whether they contain all attributes of the discrete choice model to be estimated. This means that at least some OD pairs should consist of a transfer, tram or bus, in order to be able to estimate the valuation of a transfer or to estimate the in-vehicle time perception in a tram compared to a bus.

Applying the abovementioned criteria results in 58 remaining OD pairs, with a total of 17,994 journeys (= 17,994 observed choices). The route set of 16% of these OD pairs consists of at least one route that involves a transfer. These 17,994 journeys are made by 7083 different smart card numbers. Under the assumption that each passenger uses one, unique smart card, this means that there are on average ≈ 2.5 observations per passenger in the total dataset.

2.4. Attributes and attribute levels of route choice alternatives

In this section, we discuss the different attributes and attribute levels for the estimated models.

2.4.1. In-vehicle time

The expected in-vehicle time t^{ivt} is determined for each journey leg of each route alternative separately. Based on the AVL data, we calculate the expected in-vehicle time by taking the average realised in-vehicle time over all observations using this route alternative for this OD pair. This means we use the expected in-vehicle time rather than the scheduled in-vehicle time as value for t^{ivt} . Since the scheduled travel times are fixed during the whole morning peak, t^{ivt} is calculated for the whole morning peak as well. For each journey leg, index m indicates whether the journey leg is made by tram or bus.

2.4.2. Waiting time

The expected waiting time t^{wait} expresses the initial waiting time before boarding the first journey leg. Since the AFC system in urban public transport in the Netherlands only has tap-in/tap-out devices on-board the vehicle, it is not possible to empirically derive the passenger arrival time at the initial boarding stop from the smart card data. In order to quantify the initial waiting time, we assume a random passenger arrival pattern. Given the high frequency of the urban public transport services in the considered case study network, this assumption is considered to be reasonable. Therefore, we set t^{wait} as equal to half of the scheduled headway of the boarding line in the corresponding time period.

2.4.3. Transfer time

The expected transfer time t^{trans} expresses the time between the alighting time from the first journey leg and the boarding time of the next journey leg of a certain route alternative. This means that t^{trans} equals the sum of the transfer walking time and transfer waiting time, and equals zero for a route alternative without transfers. The expected value t^{trans} for a certain route alternative is calculated by taking the average realised transfer time over all observed morning peak journeys using this route alternative.

2.4.4. Number of transfers

n^{trans} is an integer variable which reflects the number of transfers of a certain route alternative, and equals 0 in case of a route alternative without a transfer. This variable is used to determine the perceived transfer penalty, which expresses the additional penalty associated with the inconvenience of performing a transfer beyond the additional (perceived) travel time it induces.

2.4.5. Path size

We calculate the path size factor to determine and correct for overlap between route alternatives of a certain OD pair. The natural logarithm of the path size factor, denoted by r , is used and incorporated into a standard MNL model. We quantify this commonality factor using the distance-based amount of overlap between route alternatives, as shown in formula (1). We consider route alternative i from all route alternatives j of the observed choice set for a certain OD pair. Each route i consists of a sequence of links $a_i \in A_i$ with length l_{a_i} . The number of route alternatives of the choice set using link a is indicated by $|j|_a$. In case of two route alternatives without any overlap, r_i equals $\ln(1)$, whereas r_i equals $\ln(0.5)$ is case

of two fully overlapping route alternatives.

$$r_i = \ln \left(\sum_{a_i \in A_i} \left(\left(\frac{l_a}{\sum_{a_i \in A_i} l_a} \right) * \left(\frac{1}{|j|_a} \right) \right) \right) \quad (1)$$

2.4.6. Crowding: seat occupancy and standing density

To quantify the valuation of public transport crowding, we use two different attributes: the seat occupancy q and standing density d . Given the non-uniformly distributed demand pattern over the morning peak (Figure 2 right), it is not sufficient to calculate the average values for q and d over the whole morning peak. The attribute values for both attributes are therefore calculated per line, per link (stop-to-stop line segment), per 30 minutes time period. Since crowding levels vary across trips, using a too large time period can result in the use of average crowding levels which do not match with the expected and experienced crowding levels as they evolve during the morning peak. Notwithstanding, passengers will usually not have knowledge of the expected crowding levels for each individual trip departure. By dividing the morning peak into four periods of 30 minutes, we aim to balance between excluding non-uniformly distributed demand on the one hand, and applying a time period for which passengers can have realistic crowding expectations on the other hand.

The seat occupancy q is calculated using formula (2), and expresses the ratio between the expected passenger load l and the vehicle seat capacity κ . If the expected load exceeds the seat capacity, q remains equal to 1. The expected passenger load is calculated based on the average realised occupancy for each link $a_i \in A_i$ (stop-to-stop line segment) for each 30-minutes time period $t \in T$. κ is determined using data provided by the operator, based on the vehicle type used for each line. To calculate q_{it} for each journey leg for alternative i in the time period t , the weighted average value is calculated based on the expected seat occupancy and expected travel time $t_{a_i}^{ivt}$ per link $a_i \in A_i$ of the journey leg.

$$q_{it} = \min \left(\frac{\sum_{a_i \in A_i} \frac{l_{at}}{\kappa_{at}} \cdot t_{a_i}^{ivt}}{\sum_{a_i \in A_i} t_{a_i}^{ivt}}, 1 \right) \quad (2)$$

The standing density d is calculated using formula (3), and reflects the expected number of standing passengers per m^2 . In line with Wardman and Whelan (2011), we use the standing density per m^2 instead of the occupancy rate if $l > \kappa$, in order to account for different vehicle layouts. If the expected passenger load l does not exceed κ , this value equals zero. This expresses the assumption that passengers will stand only when all seats are occupied. When $l > \kappa$, is calculated by dividing the number of standing passengers by the total surface available in each vehicle type for standing θ , thus assuming an equal distribution of standing passengers over the available standing surface. The expected value of d_{it} for alternative i in the time period t is calculated for each link $a_i \in A_i$ (stop-to-stop line segment) for each 30 minutes time period $t \in T$ over all observed choices for route alternative i for a certain OD pair. The expected value per journey leg is computed by using the (by expected travel time $t_{a_i}^{ivt}$) weighted average over all links.

$$d_{it} = \max \left(\frac{\sum_{a_i \in A_i} \frac{l_{at} - \kappa_{at}}{\theta_{at}} \cdot t_{a_i}^{ivt}}{\sum_{a_i \in A_i} t_{a_i}^{ivt}}, 0 \right) \quad (3)$$

Table 1. Seat capacity and standing surface per vehicle type (HTM data).

Vehicle type	Mode	Lines	Seat capacity	Standing surface (m ²)
GTL-8	Tram	1,6,9,11,12,15,16,17	73	25.1
Citadis	Light rail	3,4,19	86	32.0
Avenio	Tram	2	70	33.8
MAN	Bus	18,21,22,23,24,25,26,28	31	8.9

Table 2. Min/max seat occupancy and standing density in dataset.

Time period	Seat occupancy		Standing density	
	Min	Max	Min	Max
07:00–07:30	0.10	1.0	0	0.81
07:30–08:00	0.08	1.0	0	2.48
08:00–08:30	0.13	1.0	0	2.04
08:30–09:00	0.11	1.0	0	2.31

Table 1 depicts the seat capacity κ and surface available for standing passengers θ per vehicle type for our case study network. Table 2 shows the minimum and maximum values observed for q_t and d_t per half-hour time period when calculated over the total dataset.

2.5. Model formulation

In this study, we estimate four discrete choice models in total. Model 1 reflects a model without crowding, whereas model 2 is an extension of model 1 in which the two crowding attributes are incorporated. Model 1 and 2 estimate coefficients averaged over all passenger segments. Since our study focuses on incorporating expected crowding levels in the route choice, it can be hypothesised that a segmentation between frequent and infrequent travellers is relevant. Passengers travelling frequently over a certain OD have a better expectation of crowding levels on the route choice alternatives based on their prior experiences, whereas infrequent passengers are expected to have limited or no prior crowding expectations on the specific route. Since the smart card number is known for all AFC transactions, it is possible to explicitly distinguish between frequent and infrequent travellers for each OD pair. We apply a binary classification, in which passengers who travel on average at least once per week on a certain route (in our case study: a minimum of 4 observations for a certain OD pair) are considered frequent travellers. Model 3 is a segment model without crowding, whereas model 4 is a segment model which incorporates crowding. We use a traditional utility maximisation framework, in which it is assumed that each respondent chooses the route alternative with the largest utility (smallest disutility). The expected utility of a certain route choice alternative $U(V, \vartheta, \varepsilon)$ consists of the structural utility component V , which is a vector of observable attributes with their corresponding weights, and a random utility component ε . The logarithm of the path size factor r is incorporated into all four models to account for overlapping between route alternatives. This allows us to estimate standard MNL models as basis. Since there are multiple route choice observations in our dataset made by the same smart card number (= the same individual), we extend the standard MNL model to a mixed logit model with panel effects to correct for possible

correlations between choices made by the same respondent. Therefore, U also consists of an individual specific utility component ϑ .

We use Biogeme as software package for performing the maximum likelihood estimations (Bierlaire 2003). In order to reduce the number of draws, we perform Halton draws from a normal distribution to incorporate the panel structure of the model. In order to determine the number of required Halton draws, we started with an initial number of 5 Halton draws and then doubled the number of draws and checked whether the model outcome can be considered stable. All four model showed to be very stable directly after doubling the number of Halton draws to 10.

2.5.1. Model 1: no crowding, no segmentation

Formula (4) shows the calculation of V , the structural deterministic part of the utility function, for model 1. The attributes corresponding to the first journey leg are denoted by index 1; attributes corresponding to the second journey leg are denoted by index 2. We experienced with all combinations between estimating only generic coefficients for t^{wait} , t^{ivt} , t^{trans} , n^{trans} and estimating all mode-specific coefficients. A model with mode-specific in-vehicle time coefficients, and generic waiting + transfer time and transfer penalty coefficients showed to give most reasonable results and the highest value for McFadden's adjusted R^2 . Hence, as can be seen in Equation (4), generic coefficients are estimated for the initial waiting time and transfer time simultaneously, and for the transfer penalty. Mode-specific coefficients are estimated for in-vehicle time. A 'tram bonus' indicating a lower perceived in-vehicle time for tram/rail travelling compared to bus travelled has been previously reported in the literature (Bunschoten, Molin, and Van Nes 2013). The selected model specification allows us to quantify this 'tram bonus' based on RP data as well. The estimated coefficients for all attributes are denoted by β .

$$V = \beta^{wait} \cdot t^{wait} + \beta_m^{ivt} \cdot t_{m,1}^{ivt} + \beta^{wait} \cdot t^{trans} + \beta^{trans} \cdot n^{trans} + \beta_m^{ivt} \cdot t_{m,2}^{ivt} + \beta_r \cdot r \quad (4)$$

2.5.2. Model 2: crowding, no segmentation

Model 2, being an extension of model 1, estimates the same mode-specific in-vehicle time coefficients and generic waiting + transfer time and transfer penalty coefficients. Formula (5) shows the structural part of the utility function when the seat occupancy q_t and standing density d_t for each 30 minutes time period t with their corresponding coefficients β^q and β^d are incorporated. As can be seen, the total in-vehicle time coefficient is now equal to the original in-vehicle time coefficient β^{ivt} , multiplied by a crowding multiplier which is equal to $(1 + (\beta^q \cdot q_t) + (\beta^d \cdot d_t))$

$$V = \beta^{wait} \cdot t^{wait} + (\beta_m^{ivt} \cdot t_{m,1}^{ivt} \cdot (1 + (\beta^q \cdot q_{t1}) + (\beta^d \cdot d_{t1}))) + \beta^{wait} \cdot t^{trans} + \beta^{trans} \cdot n^{trans} \\ + (\beta_m^{ivt} \cdot t_{m,2}^{ivt} \cdot (1 + (\beta^q \cdot q_{t2}) + (\beta^d \cdot d_{t2}))) + \beta_r \cdot r \quad (5)$$

2.5.3. Model 3: segmentation, no crowding

Model 3 can be considered an extension of model 1, to which initially an interaction-term is added for each estimated generic coefficient. The interaction-term is the product of an estimated interaction-coefficient and a dummy-coded indicator-variable indicating whether an observed choice made by a certain respondent is classified as a frequent or infrequent traveller. The indicator-variable equals 1 in case of a frequent traveller, and equals 0 in

case of an infrequent traveller. This means that each total estimated coefficient is equal to the estimated generic coefficient which applies to both segments, plus the estimated interaction-coefficient multiplied by the indicator-variable which only applies to the frequent traveller segment. Initially, interaction-coefficients are estimated for all coefficients. Presented results in the next section show the estimation results for the final estimated model in which only significant interaction-coefficients are incorporated in the model specification. The interaction-coefficient β^{int} is denoted by superscript *int*.

2.5.4. Model 4: segmentation, crowding

Model 4 can be considered an extension of model 2, where also interaction-terms are added to the estimated crowding model. We adopt a similar approach here as described for model 3. In the final model, only significant interaction-coefficients are incorporated in the model specification.

3. Results and discussion

This section first shows the estimation results of the four models in section 3.1. In section 3.2, implications of these results are discussed.

3.1. Results

Table 3 shows the values of the estimated coefficients with corresponding *t*-values for all four models, the number of estimated coefficients, the final log-likelihood and McFadden's adjusted Rho-square. From Table 3 we can conclude that all estimated coefficients are significant. We can also see that the direction of all estimations of time- and transfer related coefficients are negative, which is plausible. When extending model 1 with crowding (model 2), the adjusted Rho-square increases by 2.4%. Although the explanatory power of model 2 is only slightly higher than model 1, the LRS-test indicates that the improvement in goodness-of-fit is significant. The LRS-value of 40.6 is larger than the critical χ^2 value of 5.99 (with $8-6 = 2$ degrees of freedom for $\alpha = 0.05$). Extending segment model 3 with crowding (model 4) results in 3.5% increase in the adjusted Rho-square. Also in this case the improvement in explanatory power is significant, since the LRS-value of 84.0 is larger than the critical χ^2 value of 3.84 (with $8-7 = 1$ degree of freedom for $\alpha = 0.05$).

In order to expose the trade-offs, utility function coefficients are expressed in relation to travel time on-board a bus. Table 4 shows the estimation results for in-vehicle time, waiting + transfer time, transfer penalty and crowding, scaled in which the in-vehicle time coefficient for bus t_{bus}^{ivt} is set equal to 1. The trade-offs presented in Table 4 based on the estimation results for model 2 and model 4 (with crowding) exhibit plausible relations. A clear 'tram bonus' can be observed, since 1-minute in-vehicle time by bus is perceived as 0.6-minute in-vehicle time by tram. Earlier research based on SP experiments indicated values ranging between 0.67 and 0.80 (Bunschoten, Molin, and Van Nes 2013), which means that our research suggests an even more substantial 'tram bonus'. One minute waiting time is perceived 1.5 to 1.6 times more negatively, compared to one minute in-vehicle time. This is in line with values found in other studies (e.g. Balcombe et al. 2004), and also shows evidence that this multiplier has a lower value than assumed in earlier studies based on SP

Table 3. Estimation results.

	Model 1 (no crowding, no segments)	Model 2 (crowding, no segments)	Model 3 (segments, no crowding)	Model 4 (segments, crowding)
β_{tram}^{tvt} (in-vehicle time tram)	-0.158** (-20.6)	-0.151** (-13.7)	-0.156** (-16.9)	-0.154** (-16.8)
β_{bus}^{tvt} (in-vehicle time bus)	-0.262** (-15.4)	-0.250** (-18.0)	-0.261** (-22.3)	-0.255** (-21.5)
β^{wait} (waiting + transfer time)	-0.398** (-24.9)	-0.395** (-24.7)	-0.397** (-24.9)	-0.387** (-24.4)
β^{trans} (transfer penalty)	-0.994** (-9.06)	-1.20** (-10.3)	-1.42** (-9.49)	-1.33** (-11.6)
$\beta^{trans,int}$ (transfer penalty interaction)	—	—	0.681** (3.95)	—
β^r (log-path size factor)	2.65** (3.01)	2.37* (2.65)	—	—
$\beta^{r,int}$ (log-path size factor interaction)	—	—	4.02** (3.89)	3.44** (3.54)
β^a (seat occupancy)	—	0.158** (4.97)	—	—
$\beta^{a,int}$ (seat occupancy interaction)	—	—	—	0.305** (7.94)
β^d (standing density)	—	0.0611* (2.15)	—	—
$\beta^{d,int}$ (standing density interaction)	—	—	—	0.149** (3.98)
Number of observations	17,994	17,994	17,994	17,994
Number of individuals	7083	7083	7083	7083
Number of Halton draws	10	10	10	10
Number of estimated coefficients	6	8	7	8
Final log-likelihood	-11,404	-11,384	-11,398	-11,356
Adjusted Rho-square	0.085	0.087	0.086	0.089

Note: *t*-values in parentheses.**p* < .05.***p* < .01.**Table 4.** Scaled estimation results.

	Model 1 (no crowding, no segments)	Model 2 (crowding, no segments)	Model 3 (segments, no crowding)		Model 4 (segments, crowding)	
			Frequent	Infrequent	Frequent	Infrequent
In-vehicle time tram	0.6	0.6	0.6	0.6	0.6	0.6
In-vehicle time bus	1.0	1.0	1.0	1.0	1.0	1.0
Waiting + transfer time	1.5	1.6	1.5	1.5	1.5	1.5
Transfer penalty	3.8	4.8	2.8	5.4	5.2	5.2
Seat occupancy	—	1.16	—	—	1.31	1.00
Standing density	—	1.06	—	—	1.15	1.00

Table 5. Crowding multiplier as function of seat occupancy and standing density.

Seat occupancy <i>q</i> (% seats occupied)	Standing density <i>d</i> (standing pass/m ²)	Crowding multiplier model 2	Crowding multiplier model 4	
			Frequent	Infrequent
0	0	1.00	1.00	1.00
1	0	1.16	1.31	1.00
1	1	1.22	1.45	1.00
1	2	1.28	1.60	1.00
1	3	1.34	1.75	1.00

experiments. Also the transfer penalty of 5 minutes for each (urban) transfer is plausible. In general, we see that RP estimates for the transfer penalty are somewhat lower than values reported in SP studies (e.g. Schakenbos et al. 2016).

Next, we analyse the crowding effects on route choice. Table 5 and Figure 3 show the estimated crowding multiplier as function of the seat occupancy and standing density. As

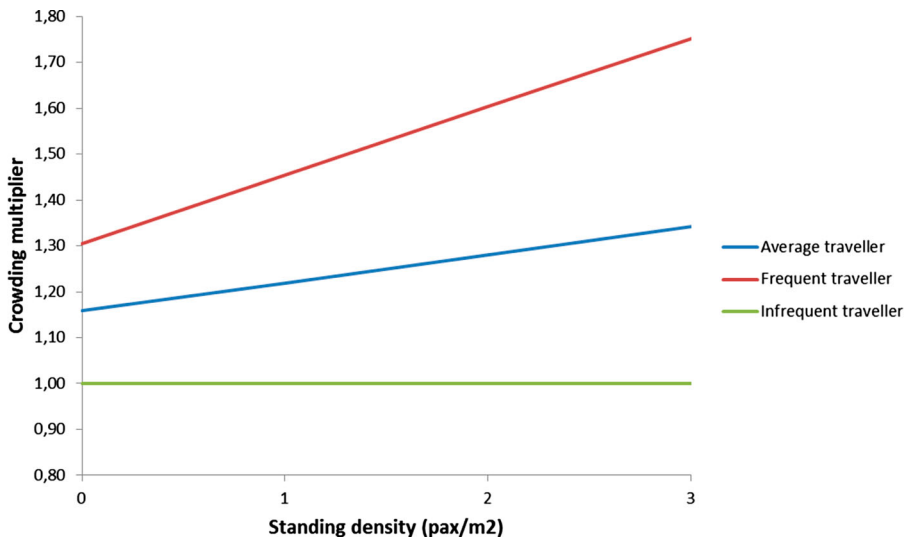


Figure 3. Crowding multiplier as function of the standing density for different traveller segments.

can be seen, in the generic model (model 2) the crowding multiplier equals 1.16 when all seats are occupied. In case the occupancy level increases further, the crowding multiplier increases with 0.06 for each increase in the integer number of standing passengers per m^2 , additional to the crowding multiplier of 1.16 at seat capacity. For instance, in case of on average 3 passengers per m^2 , the crowding multiplier thus equals $1.16 + (3 * 0.06) = 1.34$. When segmentation is applied, a clear distinction can be observed between frequent and infrequent travellers. For frequent travellers, the crowding multiplier equals 1.31 when all seats are occupied. The multiplier further increases with 0.15 for each increase in passengers per square metre, additional to this value of 1.31. In case of 3 standing passengers per square metre on average, this results in a crowding multiplier of 1.75. This shows that frequent travellers incorporate crowding significantly more in their route choice than the average passenger, as estimated in model 2 without segmentation. On the other hand, the insignificant generic seat occupancy and standing density coefficients clearly indicate that infrequent travellers do not incorporate anticipated crowding levels in their route choice. This is plausible, given their lack of prior knowledge and experience regarding expected crowding levels. From Table 4 it can be seen that the sum of coefficients estimated for the seat occupancy and standing density (generic coefficient plus interaction-term) remain equal to 1, the nominal in-vehicle time, for infrequent travellers.

We also tested the estimation of a non-linear crowding function both related to the seat occupancy and the standing density. No plausible and significant results could, however, be found, thereby indicating a linear relationship between crowding and perceived in-vehicle time. Testing the estimation of a model with mode-specific crowding coefficients, next to the already incorporated mode-specific in-vehicle time coefficient, also resulted in implausible results.

Figure 4 shows the estimated crowding multiplier as function of the load factor, which equals the passenger load divided by the seat capacity. As can be seen, there are different

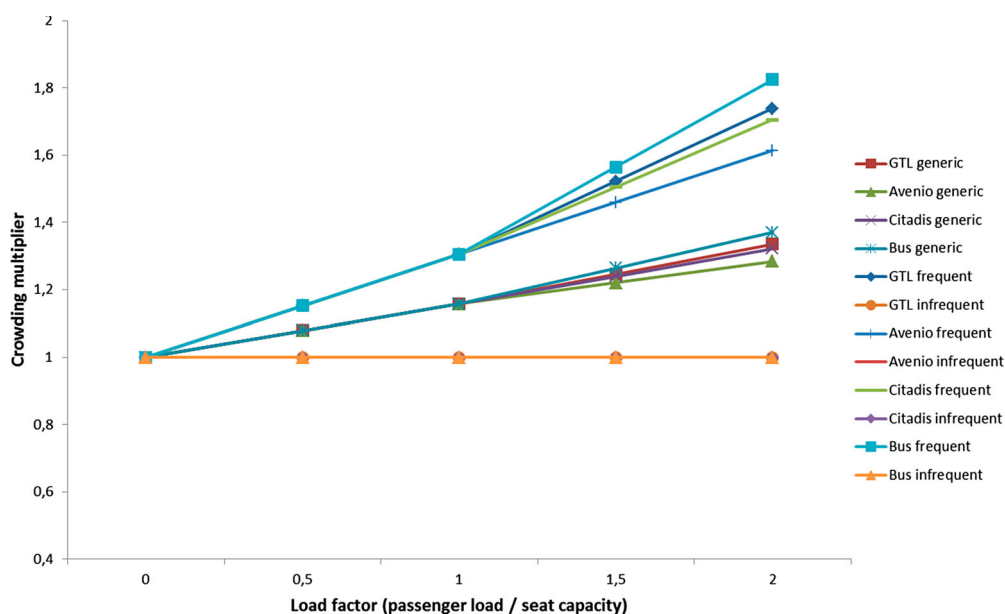


Figure 4. Crowding multiplier as function of the load factor per vehicle type.

crowding functions for the different vehicle types operated on the considered case study network. This shows the relevance of using the standing density instead of the load factor, when estimating crowding if passenger loads exceed seat capacity. It can be seen that the crowding multiplier increases steeper for vehicle types which have a relatively high number of seats, compared to the total capacity (e.g. vehicle type 'GTL' and 'bus' in Figure 4). For vehicle types with relatively few seats compared to the total capacity, the crowding function increases at a slower pace (e.g. the light rail vehicle types 'Citadis' and 'Avenio' in Figure 4). Besides, clear differences in crowding multiplier can be seen between frequent and infrequent travellers, where the crowding multiplier for infrequent travellers remains equal to the one for all vehicle types.

3.2. Discussion

The estimated coefficients exhibit plausible relations which are in line with directions found in earlier studies. When comparing model 3 (no crowding, segmentation) to model 1 (no crowding, no segmentation), a significant interaction coefficient is found for the transfer penalty and path size factor. These results suggest that frequent travellers have a less negative perceived transfer penalty compared to infrequent travellers. This might be explained by the higher level of knowledge about the network, transfer location and likelihood of reliability of the connecting service, compared to infrequent travellers. However, it can be seen that when crowding is incorporated in the segmented model (Model 4), the suggested difference in perceived transfer penalty between frequent and infrequent passengers in the segment model without crowding (Model 3) disappears. Besides, frequent travellers have a preference for non-overlapping route alternatives, whereas for infrequent travellers this

does not significantly add explanatory power to their route choice. A possible explanation here is again the higher knowledge level of frequent travellers of other, non-overlapping route alternatives available in the network.

Regarding crowding we see that estimated crowding multipliers are lower than values found in SP experiments. For example, MVA Consultancy reports crowding multipliers up to 1.6–1.9 when seat capacity has been reached, compared to the highest value of 1.3 found in our study for frequent travellers. This gives evidence for the tendency of SP experiments to overestimate values of coefficients, compared to RP based studies. In the context of choice experiments in a survey, respondents are arguably more inclined to attach greater importance to crowding in their stated route choice, compared to their decision-making in real-world settings. When we compare the results of this study with the RP results found for the Hong Kong MTR metro by Hörcher, Graham, and Anderson (2017), we note that for the Hong Kong case the estimated crowding multiplier equals 1.98 at a density of 6 passengers per square metre. This is the sum of a standing multiplier of 1.265 and an increase of the crowding multiplier by 0.119 for each additional standing passenger per square metre. If we would linearly interpolate these results, the crowding multiplier for 3 standing passengers per m^2 is estimated to be 1.49. In the RP-based study by Tirachini et al. (2016) the estimated crowding multiplier is 1.55 in case of a standing density of 3 passengers per m^2 . Our results suggest that the crowding multiplier equals 1.34 and 1.75 for average and frequent travellers, respectively, for a standing density of 3 passengers per m^2 . Our estimation for the average crowding coefficient thus yields somewhat lower values than those found for the Hong Kong and Singapore metro case studies. However, for frequent travellers the estimated crowding multiplier of 1.75 is slightly higher than the average values found for Hong Kong and Singapore.

From Table 4, it can be observed that 1 minute waiting time is perceived as 1.5 minutes in-vehicle time in a non-crowded vehicle by both frequent and non-frequent travellers. For frequent travellers, 1 minute travelling in a PT service with an average of 1.33 standing passengers per square metre is also perceived as equivalent to 1.5 minutes travelling in a non-crowded vehicle. This shows the trade-offs passengers perceive between waiting time and crowding, and can contribute to ridership forecasts for different types of measures. For example, increasing the frequency of a non-crowded service from 6 to 8 services per hour will reduce the perceived travel time by passengers by 1.88 minutes under the assumption of a random arrival pattern at stops. Alternatively, reducing the crowding level for a 10-minute trip from an average of 2.0 to 1.0 standing passengers per square metre, reduces the perceived in-vehicle time by 1.5 minutes for frequent travellers. Since infrequent travellers do not have knowledge about the expected crowding levels, measures purely aimed at reducing crowding without increasing the service frequency (e.g. use of longer vehicles) are not expected to increase the ridership of infrequent travellers, contrary to measures which target service headway.

We note that we only estimated coefficients for expected crowding levels, which can be different from *a posteriori* experienced crowding levels. Our study results also show the potential of crowding information provision to infrequent or less frequent travellers. Given the estimated values for frequent travellers, we might expect that infrequent travellers will incorporate crowding in a similar way in their route choice as frequent travellers if information is provided to them. This can affect route choice and occupancy levels on routes.

4. Conclusions

Crowding in public transport can be of major influence on passengers' travel experience and therefore affect route and mode choice. Due to the increasing concentration of activities within urban agglomerations in many countries worldwide, crowding is expected to become an even more dominant factor in urban public transportation in the future. Besides, it is important to incorporate valuation of crowding in a correct way within a cost–benefit analysis. Therefore, it is important to understand how crowding in urban public transport is perceived by passengers. In this study, the availability of individual smart card transactions was used to gain insights into revealed trade-offs between travel time, transfers, waiting time and crowding in public transport route choice entirely based on revealed preference data.

Model estimations confirm that crowding plays a significant role in passengers' route choice in public transport. The average crowding multiplier of in-vehicle time equals 1.16 when all seats are occupied. For frequent passengers, this value further increases to 1.31 when all seats are occupied. In case of standing passengers, the average crowding multiplier further increases with 0.06 for each increase in the integer number of standing passengers per m^2 . For frequent travellers, this increase per square metre is estimated to be equal to 0.15. Our results show that infrequent travellers do not incorporate expected crowding in their route choice, probably due to the lack of prior experience. Our results suggest that crowding valuation studies using stated preference experiments can have a tendency to overestimate crowding values.

Our study is the first in which crowding valuation is determined fully based on revealed preference data particularly for urban tram and bus services, in a European context, thereby adding to the knowledge gained from crowding valuation studies for metro networks. The insights gained from our study can support the decision-making process by quantifying the benefits of measures aiming to reduce crowding levels. For further research, it is recommended to consider how passengers are distributed throughout the vehicle. In case of unequal distributions, the experienced crowding can deviate from expected crowding levels based on equal passenger distributions. At last, an important limitation for this study is that no information is available regarding the realised passenger arrival time at the stop. Our study assumes that passenger route choice is fully based on expected crowding levels. Due to the lack of this information, we cannot determine whether a passenger boarded the first vehicle passing the stop, or deliberately skipped a crowding vehicle for a less crowded alternative. Information about this would enable us to investigate to which extent the real-time crowding level of the arriving vehicles affects route choice, compared to expected crowding levels based on prior experiences.

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References

- Balcombe, R., R. Mackett, N. Paulley, J. Preston, J. Shires, H. Titheridge, M. Wardman, and P. White. 2004. *The Demand for Public Transport: A Practical Guide*, TRL Report TRL 593. Crowthorne.
- Batarce, M., J. C. Munoz, and J. Ortuzar. 2016. "Valuing Crowding in Public Transport: Implications for Cost-benefit Analysis." *Transportation Research Part A* 91: 358–378.
- Batarce, M., J. C. Munoz, J. Ortuzar, S. Raveau, C. Mojica, and R. A. Rios. 2015. "Valuing Crowding in Public Transport Systems Using Mixed Stated/Revealed Preference Data: The Case of Santiago." *Transportation Research Record* 2535: 73–78.
- Bierlaire, M. 2003. "BIOGEME: A Free Package for the Estimation of Discrete Choice Models." Proceedings of the 3rd Swiss Transportation Research Conference, Ascona.
- Bunschoten, T., E. J. E. Molin, and R. Van Nes. 2013. "Tram or Bus: Does the Tram Bonus Exist?" Proceedings of the European Transport Conference, Frankfurt, AET.
- Cats, O., J. West, and J. Eliasson. 2016. "A Dynamic Stochastic Model for Evaluating Congestion and Crowding Effects in Transit Systems." *Transportation Research Part B* 89: 43–57.
- Douglas, N., and G. Karpouzis. 2005. "Estimating the Cost to Passengers of Station Crowding." Presented at the 28th Australasian Transport Research Forum, Sydney, September.
- Gordon, J. B., H. N. Koutsopoulos, N. H. M. Wilson, and J. P. Attanucci. 2013. "Automated Inference of Linked Transit Journeys in London Using Fare-transaction and Vehicle Location Data." *Transportation Research Record: Journal of the Transportation Research Board* 2343: 17–24.
- Hamdouch, Y., H. W. Ho, A. Sumalee, and G. Wang. 2011. "Schedule-based Transit Assignment Model with Vehicle Capacity and Seat Availability." *Transportation Research Part B* 45: 1805–1830.
- Haywood, L., and M. Koning. 2015. "The Distribution of Crowding Costs in Public Transport: New Evidence From Paris." *Transportation Research Part A* 77: 182–201.
- Hörcher, D., D. J. Graham, and R. J. Anderson. 2017. "Crowding Cost Estimation with Large Scale Smart Card and Vehicle Location Data." *Transportation Research Part B* 95: 105–125.
- Kroes, E., M. Kouwenhoven, L. Debrincat, and N. Pauget. 2014. "On the Value of Crowding in Public Transport for Ile-de-France." Transport Research Arena, Paris.
- Li, H., K. Gao, and H. Tu. 2017. "Variations in Mode-specific Valuations of Travel Time Reliability and In-vehicle Crowding: Implications for Demand Estimation." *Transportation Research Part A* 103: 250–263.
- Li, Z., and D. Hensher. 2011. "Crowding and Public Transport: A Review of Willingness to Pay Evidence and its Relevance in Project Appraisal." *Transport Policy* 18: 880–887.
- Lu, H., A. S. Fowkes, and M. Wardman. 2008. "Amending the Incentive for Strategic Bias in Stated Preference Studies: A Case Study in Users' Valuation of Rolling Stock." *Transportation Research Record* 2049: 128–135.
- Malandri, C., A. Fonzone, and O. Cats. 2018. "Recovery Time and Propagation Effects of Passenger Transport Disruptions." *Physica A: Statistical Mechanics and its Applications* 505: 7–17.
- Munizaga, M. A., F. Devillaine, C. Navarrete, and D. Silva. 2014. "Validating Travel Behaviour Estimated From Smart Card Data." *Transportation Research Part C* 44: 70–79.
- Munizaga, M. A., and C. Palma. 2012. "Estimation of a Disaggregate Multimodal Public Transport Origin-destination Matrix from Passive Smart Card Data from Santiago." *Chile. Transportation Research Part C* 24: 9–18.
- MVA Consultancy. 2008. *Valuation of Overcrowding on Rail Services*. Report prepared for the UK Department of Transport.
- Nuzzolo, A., U. Crisalli, and L. Rosati. 2012. "A Schedule-based Assignment Model with Explicit Capacity Constraints for Congested Transit Networks." *Transportation Research Part C* 20: 16–33.

- Pel, A., N. Bel, and M. Pieters. 2014. "Including Passengers' Response to Crowding in the Dutch National Train Passenger Assignment Model." *Transportation Research Part A* 66: 111–126.
- Prud'homme, R., M. Koning, L. Lenormand, and A. Fehr. 2012. "Public Transport Congestion Costs: The Case of the Paris Subway." *Transport Policy* 21: 101–109.
- Schakenbos, R., L. La Paix, S. Nijenstein, and K. Geurs. 2016. "Valuation of a Transfer in a Multimodal Public Transport Trip." *Transport Policy* 46: 72–81.
- Schmöcker, J.-D., A. Fonzone, H. Shimamoto, F. Kurauchi, and M. G. H. Bell. 2011. "Frequency-based Transit Assignment Considering Seat Capacities." *Transportation Research Part B* 45: 392–408.
- Tirachini, A., R. Hurtubia, T. Dekker, and R. A. Daziano. 2017. "Estimation of Crowding Discomfort in Public Transport: Results from Santiago de Chile." *Transportation Research Part A* 103: 311–326.
- Tirachini, A., L. Sun, A. Erath, and A. Chakirov. 2016. "Valuation of Sitting and Standing in Metro Trains Using Revealed Preferences." *Transport Policy* 47: 94–104.
- Trépanier, M., N. Tranchant, and R. Chapleau. 2007. "Individual Trip Destination Estimation in a Transit Smart Card Automated Fare Collection System." *Journal of Intelligent Transportation Systems* 11: 1–14.
- Tu, W., R. Cao, Y. Yue, B. Zhou, Q. Li, and Q. Li. 2018. "Spatial Variations in Urban Public Ridership Derived from GPS Trajectories and Smart Card Data." *Journal of Transport Geography* 69: 45–57.
- Van Oort, N., T. Brands, E. de Romph, and M. D. Yap. 2016. "Ridership Evaluation and Prediction in Public Transport by Processing Smart Card Data: A Dutch Approach and Example." Chap. 11 in *Public Transport Planning with Smart Card Data*, edited by F. Kurauchi and J. D. Schmöcker. Boca Raton, FL: CRC Press.
- Wang, W., J. P. Attanucci, and N. H. M. Wilson. 2011. "Bus Passenger Origin-destination Estimation and Related Analyses Using Automated Data Collection Systems." *Journal of Public Transportation* 14: 131–150.
- Wardman, M., and G. Whelan. 2011. "Twenty Years of Rail Crowding Valuation Studies: Evidence and Lessons from British Experience." *Transport Reviews* 31: 379–398.
- Whelan, G., and J. Crockett. 2009. "An Investigation of the Willingness to Pay to Reduce Rail Overcrowding." Proceedings of the First International Conference on Choice Modelling, Harrogate, April.
- Yap, M. D., O. Cats, N. Van Oort, and S. P. Hoogendoorn. 2017. "A Robust Transfer Inference Algorithm for Public Transport Journeys During Disruptions." *Transportation Research Procedia* 27: 1042–1049.
- Zhang, F., J. Zhao, C. Tian, C. Xu, X. Liu, and L. Rao. 2016. "Spatiotemporal Segmentation of Metro Trips Using Smart Card Data." *IEEE Transactions on Vehicular Technology* 65: 1137–1149.
- Zhao, J., A. Rahbee, and N. H. M. Wilson. 2007. "Estimating a Rail Passenger Trip Origin-destination Matrix Using Automatic Data Collection Systems." *Computer-Aided Civil and Infrastructure Engineering* 24: 376–387.