Public Transport Crowding Valuation in a Post-Pandemic Era

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ABSTRACT

The main contribution of this study is to derive the crowding valuation of public transport passengers in a post-pandemic era entirely based on observed, actual passenger route choices. We derive passengers' crowding valuation for the London metro network based on a revealed preference discrete choice model using maximum likelihood estimation. We find that after the passenger load on-board the metro reaches the seat capacity, the in-vehicle time valuation increases by 0.422 for each increase in the average number of standing passengers per square metre upon boarding. When comparing this result to a variety of crowding valuation studies conducted before the pandemic in London and elsewhere, we can conclude that public transport passengers value crowding more negatively since the pandemic. Our study results contribute to a better understanding on how on-board crowding in urban public transport is perceived in a European context since the outbreak of the COVID-19 pandemic.

Keywords: COVID-19; Crowding; Public Transport; Revealed Preference; Smart Card Data.
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1. INTRODUCTION

In many urban public transport (PT) systems worldwide high passenger volumes result in high crowding levels on-board PT vehicles. Over the last two decades, many studies have been performed to public transport crowding valuation, by inferring the PT in-vehicle time crowding multiplier as a function of the on-board load factor or standing density (average number of standing passengers per m^2). Initially, most of these studies relied on stated preference (SP) approaches where respondents were asked in (online) surveys to indicate which route or mode choice alternative they would choose based on hypothetical crowding scenarios (e.g. Batarce et al. 2016, Tirachini et al. 2017, Wardman and Whelan 2011, Li and Hensher 2011). In more recent years there is an increasing number of studies using revealed preference (RP) for this purpose. With the availability of large-scale passenger data from Automated Fare Collection (AFC) systems and/or Automated Passenger Count (APC) systems such as load-weigh systems, passengers' crowding valuation can be derived from empirically observed route and mode choice behaviour. RP based crowding studies have been applied to case studies in Singapore (Tirachini et al. 2016), Hong Kong (Hörcher et al. 2017), the Netherlands (Yap et al. 2020) and Washington, DC (Yap and Cats 2021).

All abovementioned studies estimate the perception of PT crowding based on data before the outbreak of the COVID-19 pandemic. One can expect that passengers are perceiving crowding more negatively since the start of the pandemic as crowded environments generally pose a higher risk of contracting COVID-19. It is thus of utmost importance to understand how PT passengers perceive on-board crowding in this post-pandemic era, as changes in crowding perception might influence route and mode choice and might hamper a full demand recovery on PT routes being perceived as (over)crowded, imposing in effect new de-facto capacity limits. More recently, a few studies have been performed which assess passengers' post-pandemic crowding perception based on stated preferences elicited from choice experiments (Bansal et al. 2022, Basnak et al. 2022, Flügel and Hulleberg 2022, Shelat et al. 2022). However, as of yet no studies have been performed which use observed passenger route choices from large-scale AFC and APC systems to re-establish public transport crowding perception in the aftermath of the pandemic based on actual passenger behaviour rather than based on stated behaviour in surveys or choice experiments.

The main contribution of our study is deriving the crowding valuation of public transport passengers in a post-pandemic era entirely based on observed, actual passenger route choices. The results of our revealed preference approach thereby add to the emerging evidence from studies which derive post-pandemic crowding perceptions from SP surveys (see **Table 1**). By relying on large-scale, empirical passenger demand data, we derive crowding valuations based on more than 20,000 observed passenger journeys in the London PT network.

Table 1. Study contribution

PT crowding studies	Stated Preference	Revealed Preference
Pre-pandemic	Li and Hensher (2011) Wardman and Whelan (2011) Batarce et al. (2016) Tirachini et al. (2017)	Tirachini et al. (2016) Hörcher et al. (2017) Yap and Cats (2021)
Post-pandemic	Bansal et al. (2022) Basnak et al. (2022) Flügel and Hulleberg (2022) Shelat et al. (2022)	This study

2. METHODOLOGY

Data input

As input for our study we use passenger demand and occupancy data derived from the urban PT network of the Greater London Area, which is under the authority of Transport for London (TfL). For metro journeys in London each row in the AFC data consists of the location and time of the first station entry and of the last station exit. For buses only the boarding stop, time and bus route are empirically available, whereas the alighting bus stop is inferred. The data format for metro and bus journeys is illustrated in **Table 2**. As metro crowding information is not directly available from AFC data, we rely on APC data obtained from load-weigh data for the lines where the rolling stock is equipped with load-weigh systems. This provides on-board passenger loads for each line segment by train and on average per 15-minute time interval. As London buses are not equipped with APC systems, bus crowding information can only be inferred. Therefore, we only focus on estimating the crowding valuation for metro journeys for which we can rely directly on APC data, while keeping the bus data in the passenger journey dataset.

Table 2. An illustration of the structure of the AFC dataset

Mode	Route	Start Time	Start Stopcode	End Time	End Stopcode
Metro	-	2022-06-15 08:01:12	778	2022-06-15 08:19:53	729
Bus	43	2022-06-17 16:44:05	BP3065	2022-06-17 16:59:22*	BP2336*

** inferred, not empirically available*

In this study we estimate three different models:

- A pre-pandemic off-peak model based on 3-7 February 2020. We use this as an un-crowded pre-pandemic baseline model.
- A post-pandemic off-peak model based on 13-17 June 2022, used to assess whether base level in-vehicle time and waiting/walking time valuations have changed since the COVID-19 pandemic.
- A post-pandemic peak model based on the same period 13-17 June 2022. This model, focusing on AM and PM journeys, estimates the post-pandemic metro crowding valuation based on load-weigh data which is available for this period.

During the selected post-pandemic period 13-17 June 2022 there were no COVID related restrictions in place anymore in London. Additionally, no capacity constraints, social distancing or mandatory face covering were in place when travelling by PT. This implies that June 2022 reflects a more steady-state situation in the post-pandemic era.

Choice set generation

To generate a choice set we apply the following criteria and filtering rules:

- Exclude incomplete and unrealistic journeys.
- Include metro journeys entirely made on lines for which load-weigh data is available (Central and Victoria Line).
- Include metro journeys between station pairs with unambiguous routing, to reliably infer the in-vehicle time and waiting time corresponding to the route a passenger took.
- Include journeys made in the off-peak for the two uncrowded models (10-14h or 20-23h), and journeys in the AM peak (6-10h) or PM peak (15-19h) for the crowding model.
- Only include origin-destination pairs with a sufficient number of observations for at least two different observed paths, as we rely entirely on observed passenger route choices to derive crowding perceptions.
- For the crowding model, only include OD pairs with sufficient crowding levels (at least a load factor of 50%) for at least one of the paths.
- Exclude OD pairs where one route option is dominant over the other paths.

The resulting choice set inputs for all three models are summarised in **Table 3**.

Table 3. Choice set description

	Model 1 Pre-pandemic uncrowded model	Model 2 Post-pandemic uncrowded model	Model 3 Post-pandemic crowding model
Observations	50,494	46,400	20,970
Number of OD pairs	407	377	60
Number of paths	820	764	126
Average number of paths per OD pair	2.01	2.03	2.10
Average number of observations per OD pair	124	123	350

Model specification

We adopt a standard utility maximisation framework. To prevent biased estimates due to possible correlations between unobserved components of the different path alternatives $a_{od} \in A_{od}$, we explicitly account for overlap between paths using a path size correction factor as proposed by Ben-Akiva and Bierlaire (1999). Therefore, the total disutility of each path $U(V, r, \varepsilon)$ is composed of the structural, deterministic utility component V, a path size factor r and a random error term ε (**Eq.1**). The probability P_a for choosing each path a can then be calculated using the closed-form function shown in **Eq.2**.

$$U_{a_{od}} = V_{a_{od}} + \beta_{psl} \cdot r_{a_{od}} + \varepsilon_{a_{od}} \tag{1}$$

$$P_{a_{od}} = \frac{\exp(V_{a_{od}} + \beta_{psl} \cdot r_{a_{od}})}{\sum_{a_{od} \in A_{od}} \exp(V_{a_{od}} + \beta_{psl} \cdot r_{a_{od}})} \tag{2}$$

The structural part of the utility function V is a vector of observable route attributes with their corresponding weights as defined for the uncrowded off-peak models 1 and 2 (**Eq.3**) and for the crowding model (**Eq.4**). We specify mode-specific in-vehicle time coefficients β_{ivt}^{b} for bus and β_{ivt}^{m} for metro, so that potential mode-specific differences in in-vehicle time valuation can be captured. A generic waiting/walking out-of-vehicle time coefficient β_{wtt} is specified in the utility function, in such a way that β_{wtt} directly reflects the ratio between waiting/walking time and in-vehicle time valuation. We use the standing density on-board the metro d^{m} as a crowding metric, which reflects the average number of standing passengers per square metre as derived from load-weigh data for each route segment per 15-minute time interval. The standing density equals zero if the passenger load q is smaller than the seat capacity κ – implying that all passengers can have a seat – and increases up to 4 standing passengers per m^2 when all surface available for standing θ has been used. In this study we test three different metrics for capturing the crowding perception associated with the standing density: the average standing density across all links of a passenger journey (**Eq.5**), the standing density at the first link of a passenger journey upon boarding (**Eq.6**), and the maximum standing density (over all links $e_i \in E_i$) at the busiest point of the passenger journey (**Eq.7**). This enables us to assess which formulation of standing density is most important for passenger's crowding valuation. The coefficient β_{d}^{m} is specified such that it reflects the in-vehicle time crowding multiplier as function of the standing density.

$$\begin{aligned} V = {} & asc^{b} \cdot b \ + \beta_{ivt}^{b} \cdot t_{ivt}^{b} + \beta_{ivt}^{b} \cdot \beta_{wtt} \cdot t_{wtt}^{b} + \\ & asc^{m} \cdot m + \beta_{ivt}^{m} \cdot t_{ivt}^{m} + \beta_{ivt}^{m} \cdot \beta_{wtt} \cdot t_{wtt}^{m} \end{aligned} \tag{3}$$

$$\begin{aligned} V = {} & asc^{b} \cdot b \ + \beta_{ivt}^{b} \cdot t_{ivt}^{b} + \beta_{ivt}^{b} \cdot \beta_{wtt} \cdot t_{wtt}^{b} + \\ & asc^{m} \cdot m + \beta_{ivt}^{m} \cdot t_{ivt}^{m} \cdot (1 + (\beta_{d}^{m} \cdot d^{m})) + \beta_{ivt}^{m} \cdot \beta_{wtt} \cdot t_{wtt}^{m} \end{aligned} \tag{4}$$

$$d_i^{avg} = \max\left(\frac{\sum_{e_i \in E_i} \frac{q_e - \kappa_e}{\theta_e}}{|E_i|}, 0\right) \tag{5}$$

$$d_i^{first} = \max\left(\frac{q_{e_1} - \kappa_{e_1}}{\theta_{e_1}}, 0\right) \tag{6}$$

$$d_i^{max} = \max\left(max\left(\frac{q_{e_i} - \kappa_{e_i}}{\theta_{e_i}}, 0\right)\right) \quad \forall\, e_i \in E_i \tag{7}$$

3. RESULTS AND DISCUSSION

Results

Maximum likelihood estimation is performed to infer the coefficients which best explain the observed passenger route choices for the three different models. The Newton algorithm is used as iterative method to solve this non-linear optimisation problem. From the model estimation summary shown in **Table 4**, it can be seen that the Rho-square-bar of crowding model 3 is 37% higher compared to the Rho-square-bar of uncrowded post-pandemic model 2. Model estimation results are presented in **Table 5**. The signs of all coefficients are plausible and in line with a-priori expectations and findings reported by previous studies. As we don't have access to information on the panel structure of the data, we report the robust t-statistic and robust p-value as sandwich estimator with the aim of preventing an overestimation of the model coefficients. The absolute value of the robust t-value is larger than 1.96 for all estimated coefficients, which confirms that our results are statistically significant.

Table 4. Model estimation summary

	Model 1 Pre-pandemic uncrowded model	**Model 2 Post-pandemic uncrowded model**	**Model 3 Post-pandemic crowding model**
Observations	50,494	46,400	20,970
Number of estimated parameters	6	6	6
Initial log-likelihood	-35,339	-33,177	-12,209
Final log-likelihood	-28,182	-25,936	-8,551
Rho-square	0.203	0.218	0.300
Rho-square-bar	0.202	0.218	0.299
Akaike Information Criterion (AIC)	56,377	51,884	17,115
Bayesian Information Criterion (BIC)	56,430	51,937	17,162

Table 5. Model estimation results

	Model 1 Pre-pandemic uncrowded model	**Model 2 Post-pandemic uncrowded model**	**Model 3 Post-pandemic crowding model**
Coefficients	**Value (robust t-value)**	**Value (robust t-value)**	**Value (robust t-value)**
asc^b – alternative specific constant bus	-0.677** (-21.0)	-0.792** (-21.2)	-0.635** (-16.1)
asc^m – alternative specific constant metro	+0.677** (+21.0)	+0.792** (+21.2)	+0.635** (+16.1)
β_{ivt}^b – in-vehicle time bus	-0.0653** (-23.0)	-0.0458** (-17.2)	-0.0399** (-14.9)
β_{ivt}^m – in-vehicle time metro	-0.0520** (-13.9)	-0.0388** (-9.07)	-0.0220** (-12.5)
β_{wtt} – ratio wait/walk time : in-vehicle time	+1.94** (+17.6)	+1.93** (+11.5)	+1.93 (fixed)[1]
β_{psl} – path-sized logit factor	-0.438** (-3.54)	-0.757** (-9.18)	-0.573** (-5.95)
β_d^m – standing density metro			+0.422* (+2.21)

*robust t-values in parentheses. * robust p < 0.05; ** robust p < 0.01*

[1] Fixed for the ratio wait/walk time : in-vehicle time as found in uncrowded post-pandemic model 2 estimated for the same time period

Discussion on uncrowded models

Based on the ratio between the metro and bus in-vehicle time coefficients β_{ivt}^m:β_{ivt}^b of the uncrowded pre-pandemic **model 1**, we find that on average uncrowded in-vehicle time on-board a metro is perceived 20% less negatively than uncrowded bus in-vehicle time. The same ratio for post-pandemic uncrowded **model 2** shows that metro in-vehicle time is now on average valued 15% less negatively compared to bus in-vehicle time. Whilst this still confirms a generic passenger preference for metro over bus regarding in-vehicle time, this result suggests that the relative attractiveness of the metro compared to bus has decreased somewhat in terms of in-vehicle time. A possible explanation is that since the COVID-19 outbreak passengers value travelling in enclosed, underground environments such as a metro system more negatively than pre-pandemic, as these might be perceived as areas with higher infection risks. In contrast, bus travel on the surface with frequent door openings at stops and the possibility for passengers to open windows can be perceived as a travel mode providing better ventilation and thus reducing COVID-19 infection risks.

β_{wtt}, the coefficient which reflects the ratio between waiting/walking time and uncrowded in-vehicle time, equals 1.94 for the pre-pandemic model. This implies that on average passengers value one minute of out-of-vehicle (walking or waiting) time as almost two minutes of in-vehicle time. In the post-pandemic model we see that on average out-of-vehicle time is perceived 1.93 times more negatively compared to uncrowded in-vehicle time. As β_{wtt} remains almost unchanged between the pre-pandemic and post-pandemic off-peak models, we can conclude that PT waiting/walking time valuation relative to in-vehicle time did not change since the COVID-19 pandemic.

Discussion on crowding model

For the post-pandemic crowding model the estimated metro crowding coefficient β_d^m is significant at a 95% significance level, with the robust t-statistic of 2.21 being larger than 1.96. The value of this coefficient implies that after the passenger load on-board the metro reaches the seat capacity, the in-vehicle time valuation increases by 0.422 for each increase in the average number of standing passengers per square metre. When we linearly extrapolate the estimated crowding coefficient – as observed crowding levels averaged per 15-minute interval in our choice set did not exceed 3 standing passengers per m^2 – we can estimate that the in-vehicle time multiplier would be equal to 2.69 when a train operates at full capacity (assumed at 4 standing passengers per m^2). The model using the crowding level upon boarding (d^{first}) was the only model resulting in a statistically significant standing density crowding coefficient. This suggests that the PT crowding level upon boarding best captures passengers' crowding valuation. An explanation for this is that the crowding level upon boarding is related to the passenger's seat probability, as this is an important determinant of whether a passenger will be able to have a seat during the entire journey.

In **Figure 1** we compare the in-vehicle time crowding curve as derived from our model to previous studies. Compared to the three pre-pandemic RP studies performed based on large-scale AFC data (Singapore, Hong Kong,Washington DC) we can conclude that our post-pandemic crowding multiplier found for London is substantially higher. The same conclusion is reached when comparing the SP results between a pre-pandemic and post-pandemic study conducted in Santiago de Chile. Specifically for London we refer to two pre-pandemic studies on crowding valuation. The first one is a RP study performed in the 1990s by Transport for London. The resulting crowding multiplier of 2.32 at 4 standing passengers per m^2 is notably higher than other pre-pandemic studies, although this study has been performed several years ago using a different methodology than more recent RP studies. We can derive a more recent average pre-pandemic crowding multiplier for London using the SP based coefficients estimated for seated and standing passengers by Whelan (2009), which results in an average pre-pandemic in-vehicle time multiplier of 1.77. Our equivalent RP based estimated crowding multiplier for London in the post-pandemic era of 2.69 provides strong evidence that PT passengers value metro crowding substantially more negatively in London since the COVID-19 outbreak compared to both pre-pandemic studies in London, despite their differences in methodology. The crowding valuation found in our study is comparable to the post-pandemic crowding valuation derived from SP research for Santiago de Chile by Basnak (2022), which gives confidence in the magnitude of our estimated crowding coefficient.

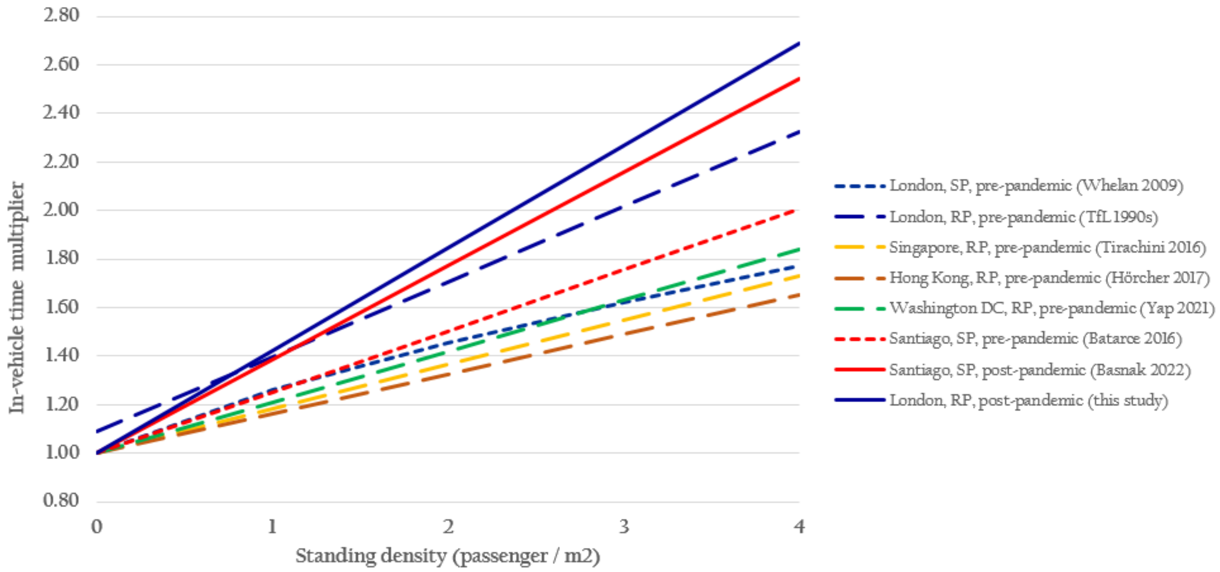

Figure 1. In-vehicle time crowding multiplier as function of standing density

4. CONCLUSIONS

Based on the three estimated discrete choice models we can formulate three main conclusions. First, the average post-pandemic out-of-vehicle time valuation remains unchanged at almost twice the uncrowded in-vehicle time valuation. Second, whilst our study results confirm that there is a generic passenger preference for metro over bus regarding in-vehicle time, we find that the relative attractiveness of metro compared to bus has decreased somewhat post-pandemic in terms of in-vehicle time. This possibly echoes a more negative perception of metro travelling in a more enclosed, underground environment compared to bus travel. Third, our crowding model estimation results show that passengers' average in-vehicle time valuation increases by 0.422 for each increase in the average number of standing passengers per square metre. In contrast, this same value equals 0.22 as average across the six studies to pre-pandemic crowding valuation as reported in **Figure 1**. Compared to the results of these SP and RP studies conducted before the pandemic in London and elsewhere we thus clearly see a steeper slope of the post-pandemic crowding curve as found in our study, based on which we can conclude that PT passengers value crowding more negatively since the COVID-19 pandemic.

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