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Yap, Menno; Cats, Oded

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Ride-hailing vs. public transport: Comparing travel time perceptions using revealed preference data from Washington DC

Menno Yap *, Oded Cats

Department of Transport and Planning, Delft University of Technology, Delft, the Netherlands

A R T I C L E I N F O

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A B S T R A C T

Ride-hailing has become an important part of the urban mobility landscape. The main contribution of this study is to estimate how travellers perceive time when using ride-hailing compared to using conventional public transport, to better understand ride-hailing mode choice. We combine two unique datasets containing actual, individual passenger behaviour for the Washington DC area from October 2018: a large set of almost 250,000 individual ride-hailing trips made using Uber, and more than 326,000 public transport trips obtained from automated ticketing data. Contrary to previous studies our model estimations rely on over half a million directly observed passenger choices between ride-hailing and public transport, based on which we estimate a discrete choice model to infer travel time perceptions for both modes using a binomial logit model. Our results show that on average ride-hailing in-vehicle time is perceived 35% less negative than public transport in-vehicle time. We also found that waiting time for ride-hailing is valued 1.3 times more negative than ride-hailing in-vehicle time, which is about 20% less negative than the ratio between waiting and in-vehicle time found for public transport. Our study enables a more accurate modelling of ride-hailing by using mode-specific travel time coefficients derived from large-scale empirical data, which can improve the accuracy of modelling outputs and thus improve decision-making processes.

1. Introduction

In many cities around the world, ride-hailing has become an important part of the urban mobility landscape since the 2010 s. Since companies such as Uber, Lyft and Bolt started providing their services, there have been societal, political and scientific debates regarding their impact on road traffic congestion, mode choice and public transport (PT) usage (e.g. Clewlow and Mishra, 2017). Proponents argue that ride-hailing can complement conventional PT by feeding PT services or by operating at locations and times when conventional PT is not economically viable or when it does not provide a competitive alternative, and that it can contribute to a car-independent lifestyle (e.g. Rayle et al., 2016, Wang and Mu, 2018). Critics however mention the negative impact ride-hailing can have on car vehicle kilometres, road congestion and its potential cannibalisation of public transport (Tirachini, 2020, Young et al., 2020, Cats et al., 2022). An important topic in this debate is to better understand how travellers make their choice between ride-hailing and conventional public transport. Gaining more insight in how the perception of in-vehicle time and waiting time might differ between ride-hailing and PT will enable a better explanation and prediction of mode choice. Furthermore, this allows for a more accurate modelling of demand for ride-hailing services and consequentially their impact on PT, road traffic and emissions.

The characteristics of ride-hailing users are studied in several previous studies, often finding that ride-hailing is mostly used by higher educated, middle-aged (age category 20–39) travellers with a relatively high income (see for example Alemi et al., 2018, Gehrke et al., 2019, Tirachini and del Rio, 2019, Young and Farber, 2019, Young et al., 2020). However, based on a survey of nearly 1,000 ride-hailing passengers in Boston in 2017, Gehrke et al., 2019 found that trip-specific attributes (such as in-vehicle time and waiting time) are more relevant in explaining mode choice between ride-hailing and conventional PT than sociodemographic variables. This indicates that a better understanding of how these different trip attributes are valued by users for ride-hailing compared to PT is imperative to obtain a better insight in these mode choice decisions.

The topic of travel time valuation is relatively well studied for conventional urban transport modes, such as private car and regular PT. For

* Corresponding author.
E-mail addresses: M.D.Yap@TUDelft.nl (M. Yap), O.Cats@TUDelft.nl (O. Cats).

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example, Shires and Jong (2009) and Wardman (2004) quantify the value of time for private cars and PT users, as well as the ratio between out-of-vehicle time (e.g. walking and waiting time) and in-vehicle time. Abrantes and Wardman (2011) study the value of time for different journey purposes using a *meta*-analysis of several previous studies, mostly based on Stated Preference data obtained through choice experiments. For example, based on a *meta*-analysis of British studies to time valuation, Wardman (2004) suggests using walking and waiting time coefficients of respectively 2.0–2.5. More recently, ratios between waiting time and in-vehicle time for urban PT networks have also been estimated using Revealed Preference approaches based on large-scale passenger ticketing data from Automated Fare Collection (AFC) systems or based on video observations. For example, Yap et al. (2020) found a ratio of 1.5 between PT waiting and in-vehicle time in the Netherlands, while Yap and Cats (2021) found a ratio of 1.62 between these two journey time components for Washington DC. Fan et al. (2016) reported average waiting time being perceived at least 1.2 times as negative as in-vehicle time, depending on waiting time duration, amenities at the stop and personal characteristics.

In recent years there have been some studies focusing on the valuation of ride-hailing trip attributes and the mode choice between ride-hailing and conventional public or private modes. For example, Ulak et al. (2020) derived the value of convenience as perceived by taxi users in New York City based on a taxi trips dataset in Manhattan, but no other modes were considered. Kouwenhoven et al. (2023) derived the value of travel time and value of reliability in the Netherlands for different modes, such as car, taxi, train and local public transport, based on a Stated Preference study. However, ride-hailing was not considered as a separate mode in this work. Geržinič et al. (2023) used 923 responses from a Stated Preference survey to estimate how variability of ride-hailing waiting time is valued. This study specifically derived the value of unexpected waiting time for ride-hailing, without considering alternative travel modes. Chavis and Gayah (2017) used a Stated Preference approach to understand mode choice between conventional PT and ride-hailing by surveying PT users in Baltimore, whereas Dong (2020) surveyed Uber and Lyft users for the same purpose. Based on a Stated Preference experiment, Gao et al. (2019) derived that the value of in-vehicle time whilst being driven in a ride-hailing service is on average 13 % less negative compared to driving one's own private car, possibly explained by the opportunity to undertake other tasks during the trip. In another Stated Preference study, Azimi et al. (2020) studied mode choice between PT and ride-hailing based on surveys distributed amongst private car and PT users.

To the best of our knowledge, there are only a few studies which adopt a Revealed Preference approach when studying ride-hailing mode choice, in contrast to the abovementioned Stated Preference based mode choice studies. Habib (2019) estimated a mode choice model based on Toronto's 2016 household travel survey. Based on travel diaries from the sampled respondents, ~11,000 trips were used to estimate a mode choice model. However, no complete fare information of the ride-hailing trips including surge pricing was available for this study. Garcia-Melero et al. (2022) developed a Revealed Preference based mode choice model for ride-hailing by conducting online surveys with Uber users in Chile. In these 1,912 completed surveys users are asked to report the travel time and cost attributes of a recent (non-pooled) UberX trip they made. As both studies rely on afterwards reported trip attribute values, there are potential reporting errors associated as attribute values are not directly observed values from source. None of these past studies has relied on direct observations of travel choices. Buchholz et al. (2024) conducted a large scale Revealed Preference study to derive customer's willingness to pay for reduced ride-hailing waiting times. This was derived from detailed data from a ride-hailing company in Prague where drivers bid on trip requests and customers subsequently choose their preferred offer based on expected waiting time and fare. This study provides valuable insights in the trade-off between ride-hailing waiting time and fare, but it does not include the valuation of ride-hailing in-vehicle time nor positions ride-hailing time perception relative to conventional public transport.

From the literature review above we can conclude that studies to ride-hailing mode choice are predominantly based on Stated Preference approaches, and that the few Revealed Preference based models have been estimated based on incomplete and/or indirectly inferred (reported) attribute levels or focus solely on ride-hailing time valuation. This strong reliance on Stated Preference data or reported attribute values can partially be explained by the fact that ride-hailing data is owned by commercial parties, meaning that public access is often limited. Nevertheless, an inherent limitation of Stated Preference approaches is the potential discrepancy between stated mode choice behaviour in surveys compared to actual behaviour, resulting in different or possibly biased coefficients. This discrepancy can occur if respondents have difficulties imagining the hypothetical choice situation, or when lacking sufficient experience with similar circumstances in reality to fully grasp the trade-offs in the choice set (Yap et al., 2020). Whilst there have been previous studies to travel time valuation for taxis (e.g. Kouwenhoven et al., 2023, Wardman et al., 2023), there is typically limited *a priori* information available on the actual in-vehicle time, waiting time and fares before choosing a taxi. This means that the actual travel time and costs may provide less explanatory power to explain a mode choice decision. In contrast, the availability of the estimated or actual time and fare attribute levels before ordering a ride-hailing service means that the actual attribute values are suitable to use in a RP based mode choice model.

The main contribution of this study is to estimate how travellers value time for ride-hailing compared to conventional PT, thereby addressing the abovementioned limitations in the current state-of-the-art. For this purpose this study relies entirely on empirical, large-scale Revealed Preference data for both ride-hailing and public transport, instead of using Stated Preference or self-reported travel diaries. To this end we combine two unique datasets both containing actual, individual passenger behaviour for the Washington DC area for the same period between 1 and 25 October 2018:

- A large sample of almost 250,000 individual ride-hailing trips made using Uber, including the travel time and travel cost attributes corresponding to each individual trip.
- All individual public transport journeys made by bus and metro on the PT network of the Washington Metropolitan Area Transit Authority (WMATA), resulting in more than 326,000 relevant PT trips for this study.

To the best of our knowledge, this is the first study which positions travel time valuations for ride-hailing relative to conventional PT using empirical data from both modes on this scale, thus enabling a robust estimation of different travel time and cost coefficients. Contrary to previous studies our model estimations rely on more than half a million directly observed passenger mode choices between ride-hailing and PT, based on which we estimate discrete choice models to infer travel time perceptions for ride-hailing and PT.

The remainder of this paper is structured as follows. In chapter 2 we discuss our input datasets, data processing steps, choice set generation and specification of our discrete choice model. Model estimation results together with their policy implications are discussed in chapter 3. In chapter 4 we discuss the key conclusions and provide recommendations for follow-up research.

2. Methods

In this section we first discuss the ride-hailing data and the relevant data processing steps, followed by the public transport data. Next, we explain the choice set generation steps. At last, the specification of the travel mode choice model is discussed.

2.1. Ride-hailing data

The ride-hailing data used as input for this study is a large sample of actual passenger trips made by Uber in the Washington DC area between 1 and 25 October 2018. In our study we only consider non-shared UberX trips: UberPool trips where parts of the trip could have been shared with other users are not included in our research. In the current post-pandemic era we expect that primarily attitudes towards pooled trips may have changed as it would require sitting together with unknown travellers within a closed environment for an extended period of time. As our dataset stems from the pre-pandemic era, focusing solely on non-shared UberX trips makes our results robust against possible changes in post-pandemic perceptions of especially in-vehicle time. From all ride-hailing trips to/from the Washington DC area, only trips with both their origin and destination within the geo-fenced area of Washington DC metropolitan area are included, so that the same catchment area is used as served by the PT bus and metro services of WMATA. In addition, only ride-hailing trips of users for whom Washington DC is the city where they use Uber most frequently are included. This serves as indicator that users are acquainted with travel options in the Washington DC area. As we aim to estimate a discrete choice model based on Revealed Preference data, the observed travel time and cost attribute levels are used to derive preferences and to explain mode choice. This implies that travellers need to have some *a priori* knowledge or expectations about the travel times and costs of the ride-hailing service as well as the PT alternative, in order to make an informed choice between these alternatives. When there would be a large discrepancy between the *a priori* expected travel time and cost, and the *a posteriori* actual travel times and cost, estimating a choice model based on actual attribute levels might not be opportune. By only including trips from users for whom Washington DC is their most commonly used city for Uber trips, we aim to align expected and actual attribute levels as much as possible. For the same reason, ride-hailing trips to and from airports are excluded from our dataset. Furthermore, we focus on typical ride-hailing trips, excluding short trips with a duration of seven minutes or less and excluding the 5 % trips with the longest waiting time (exceeding 10 min). After applying the above filtering rules our sample contains a total of 249,628 individual ride-hailing trips.

The structure of the ride-hailing dataset is shown in Table 1. Each row reflects an individual trip i^{RH}, with the lat/lon coordinates of the origin and destination location of the trip provided. For privacy reasons the coordinates of the origins and destinations are rounded to three digits (which translates to ~50 m accuracy). The start time corresponds to the pick-up time, i.e. the moment the passenger enters the car, rounded to the nearest 5 min due to privacy reasons. Importantly, the trip duration – the time between boarding (pick-up) and alighting (drop-off) the car – is however accurately calculated in seconds without any rounding. We will refer to the trip duration as the ride-hailing in-vehicle time $t^{RH}_{ivt,i}$. The wait/walk time is the time difference between the travel request time and the start time of the trip, further indicated by variable $t^{RH}_{wtt,i}$. Given that ride-hailing provides door-to-door services, no further additional walking time is assumed beyond the registered origin and destination coordinates. Based on the available data we cannot disentangle $t^{RH}_{wtt,i}$ further into a separate walking time and waiting time component, as there is no information about the location of the passenger at the time when the request was made. It could be that the user requested the ride-hailing service whilst already waiting at the pick-up location, or for example when still in the house or at a restaurant, meaning that some walking towards the pick-up point could be involved within $t^{RH}_{wtt,i}$. Using a combined waiting + walking time can be justified further as we know from previous studies that walking and waiting time perceptions are often comparable (see for example Wardman et al., 2016). The trip fare c^{RH}_i expressed in USD corresponds to the actual fare paid for the ride including any potential surge pricing. Note that during the analysis period the announced Uber fare upon request was equal to the actual fare paid in Washington DC, meaning that the actual fare was not affected by the eventual traffic conditions along the route. As such, there is no discrepancy between the announced/anticipated fare upon travel request, i.e. when performing the ride-hailing mode choice, and the actual fare in the dataset provided.

Based on the start date and time we add a variable reflecting the day of the week (weekday vs. weekend) and the hour of travel based on the starting time of the trip. Both the origin and the destination location are clustered into an origin zone and a destination zone by using the H3 hexagonal geospatial indexing system (Uber, 2018). Aggregation of each individual ride-hailing trip to day of week, hour of the day, origin zone and destination zone is necessary, so that at a later stage the attribute levels for the corresponding, non-chosen PT alternative for this same day-hour-origin–destination cluster can be derived. To retain a high level of disaggregation we use H3 clustering resolution 9, meaning that each hexagonal zone covers 0.105 km^2. This means that the Washington DC area is composed of ~1,700 zones in our analysis.

2.2. Public transport data

The public transport data used as input to the subsequent choice modelling is constructed from all individual PT passenger movements in metro and bus in the Washington DC metropolitan area under authority of WMATA between 1–25 October 2018. We are not aware of any major planned maintenance works which took place on the public transport network during this period. Table 2 illustrates the structure of the data, where each row in the dataset reflects an individual passenger movement which is derived from the Automated Fare Collection (AFC) and Automated Vehicle Location (AVL) systems in place. As there is already a solid body of knowledge regarding how to process raw AFC and AVL data to construct PT journeys (e.g. Gordon et al., 2013; Munizaga and Palma, 2012; Trépanier et al., 2007; Zhu et al., 2017), we made use of passenger journey data which was processed using the ODX algorithm as implemented by Sánchez-Martinez (2017) and which was made available for this study purpose. In this algorithm the most plausible alighting stop is inferred for PT bus journeys using a destination inference algorithm, as passengers only tap in upon boarding buses in the DC area. For metro journeys the time and location of the gate-line entry and gate-line exit station is empirically available, based upon which the most plausible route through the metro network is derived based on actual vehicle

Table 2
An illustration of the structure of the public transport dataset.

Journey key	Sequence	Mode	Start Stop	End Stop	Start Time	End Time
141906	1	Walk / wait	048	C13-1	07:53:46	07:55:52
141906	2	Metrorail	C13-1	C08-1	07:55:52	08:03:46
141906	3	Walk / wait	C08-1	057	08:03:46	08:05:17

Table 1
An illustration of the structure of the ride-hailing dataset.

Origin lat	Origin lon	Dest lat	Dest lon	Start time (rounded to 5 min)	Wait+walk time (s)	Trip duration (s)	Trip fare ($)
38.906	−76.977	38.846	−76.969	2018–10-01 16:05	220	878	11.26

arrival and departure times from the AVL database. PT journeys are constructed from the individual passenger movements based on a journey inference (linkage) algorithm, i.e. identifying whether subsequent trips constitute successive legs of a single journey or separate journeys. Incomplete journeys are excluded from the analysis, which results in a total of 23.3 million individual passenger journeys made using PT (metro or bus) on the WMATA network in the aforementioned period. For more details on the PT data processing steps we refer the reader to Yap and Cats (2021) and Sánchez-Martinez (2017). Similar as for ride-hailing trips, short PT journeys (with an in-vehicle time of 7 min or less) and PT journeys with excessive waiting time (longer than 60 min) are excluded from the dataset.

The PT passenger movement example shown in Table 2 illustrates a passenger journey only involving a metro trip from stop C13 (King St-Old Town) to stop C08 (Pentagon City). In this case the start time at the gate-line entry (gate 048 at stop C13) and the end time at the gate-line exit (gate 057 at stop C08) are directly available from the AFC ticketing system. Based on these times the most plausible metro taken from stop C13-1 to stop C08-1 is inferred. Based on the actual arrival and departure times of this metro as recorded in the AVL data, the PT in-vehicle time t_{ivt}^{PT} equals the difference between the end time (08:03:46) and start time (07:55:52) of the *Metrorail* movement. The combined PT walking and waiting time t_{wtt}^{PT} equals the walking time from gate-line entry (07:53:46) to the platform, the platform waiting time until boarding the metro (07:55:52) plus the walking time after alighting the metro (08:03:46) until the gate-line exit (08:05:17), indicated by *walk / wait* in Table 2. Similar as for ride-hailing we refrain from disentangling PT walk/wait time further into waiting and walking time separately, as this would require making assumptions on the walking speed of individual passengers to estimate the walking time required from the station entry to the metro platform. The *Journey key* column indicates that these three passenger movements belong to one total PT journey. In the event of a PT journey which includes a bus-metro interchange, the identical journey key indicates that these passenger movements are part of one PT journey. t_{ivt}^{PT} and t_{wtt}^{PT} are then calculated by summing over the respective individual movements.

As the travel costs c_i^{PT} are not provided in the ODX database, travel costs are calculated off the fare system in place in Washington DC. Based on the distance based fare for metro and the flat bus fare applicable to the peak / off-peak time period each individual passenger is travelling, the total fare is calculated. All fares in place as per October 2018 are used, including fare caps where applicable, to provide an adequate comparison with the corresponding ride-hailing trip fare. No concessionary fares (e.g. for the elderly or children) are considered in this calculation, as no age information is available. However, for the traveller segment actively using both PT and ride-hailing, age based fare discounts are typically not expected to apply (e.g. Sikder, 2019). For a more detailed discussion on the PT fare calculation the reader is referred to Cats et al. (2022). Similar as for ride-hailing trips, the ultimate origin and destination of each PT journey is clustered into the same H3 hexagonal origin and destination zones (using clustering resolution 9) and grouped by day-hour-origin–destination cluster to make them comparable to the ride-hailing journeys.

2.3. Choice set generation

From the datasets described in **section 2.1** and **section 2.2** the chosen mode alternative (ride-hailing or PT) for each individual passenger is known, including the values of the travel time and cost attributes of this chosen alternative. To generate a choice set for our discrete choice model, in the next step we add the attribute values of the non-chosen alternative for each chosen alternative. This process is visualised in Fig. 1.

For each observed ride-hailing trip, we query Open Trip Planner (OTP) to find the most plausible non-chosen PT counterpart trip (https://www.opentripplanner.org). Based on the coordinates of the origin and destination of the ride-hailing trip and the requested departure time, the fastest PT alternative is found in OTP by searching through a detailed time-dependent graph built from the actual PT schedule and a detailed walk network. In our settings we search for the fastest PT alternative within a maximum total walking distance of 2 km, from which the attribute levels (in-vehicle time t_{ivt}^{PT} and waiting + walking time t_{wtt}^{PT}) are derived. The PT fare c_i^{PT} is calculated in a post-processing step similar to the approach discussed in **section 2.2**. We opt for using OTP to derive the attributes for the non-chosen PT alternative for each ride-hailing trip, instead of using the actual travel times and costs for the equivalent PT journey from the AFC data. If we were to rely on the AFC data to populate the non-chosen attribute values, then we could only retain ride-hailing trips for the same day-hour-origin–destination zone combinations for which there are also actual observed PT trips. Ride-hailing data for day-hour-origin–destination zone combinations without equivalent observed PT journeys would have to be excluded from the choice set as it would not be possible to populate the non-chosen attribute values, meaning a loss of valuable choice information. By querying OTP we can find the attribute values of the most feasible PT counterpart for each ride-hailing trip, which means that all

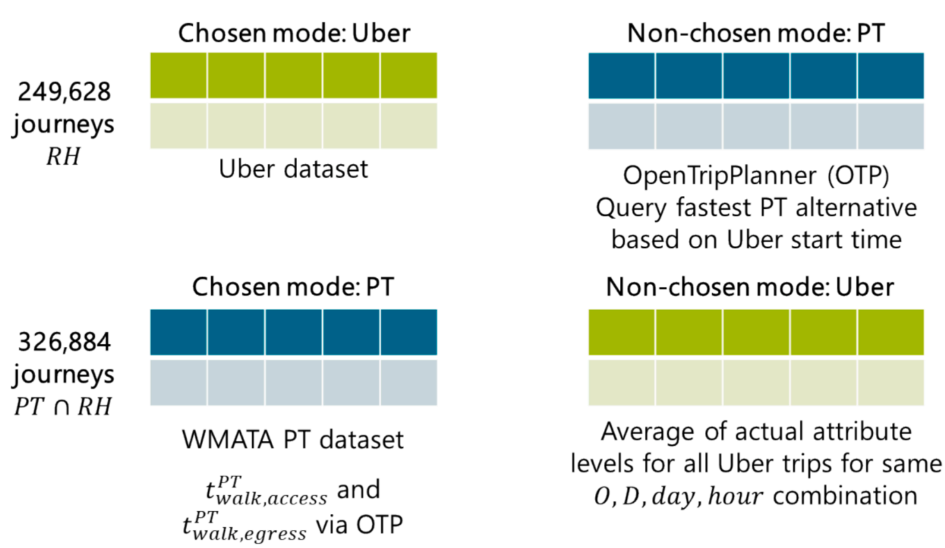

Fig. 1. Choice set generation: composing the non-chosen alternative.

249,628 observed ride-hailing trips can be retained in the choice set. Furthermore, by relying on the Open Trip Planner we can also include the first access time from the origin coordinates to the PT stop and the last egress time from the last PT stop to the destination coordinates in the PT waiting + walking time. This provides an additional advantage over using AFC data, as the latter does not contain information on access (egress) time to (from) the first (last) PT stop.

For each chosen PT trip, the attribute levels of the non-chosen ride-hailing counterpart trip are obtained by averaging the realised attribute levels for all empirical ride-hailing trips for the same day-hour-origin–destination zone combination. Contrary to populating non-chosen PT attribute values, ride-hailing travel time and cost attribute values are not publicly available. Therefore, in order to populate these non-chosen attribute values, we are constrained to the data from those day-hour-origin–destination zone combinations for which there are observed ride-hailing trips in our dataset. Consequentially, this implies that only PT journeys between zones for which there is also observed ride-hailing data can be retained, i.e. the intersection between PT and ride-hailing in terms of day-hour-origin–destination zone combinations. As a result 326,884 PT journeys are included in the choice set, amounting to more than half a million (576,512) observed ride-hailing or PT mode choices in our choice set. For consistency purposes we add the average first access and last egress walking time for the corresponding day-hour-origin–destination zone combination as derived from the OTP to the waiting + walking time t_{wtt}^{PT} for chosen PT journeys, so that in all cases access and egress time to/from the PT stop is included.

2.4. Mode choice model specification

We estimate a simple binomial logit model with PT and ride-hailing as mode choice alternatives to obtain the value ride-hailing and PT users attribute to the different journey components. **Equations (1) and (2)** show the structural part of the utility functions as specified for ride-hailing trips V^{RH} and PT trips V^{PT}, respectively. As can be seen from the utility functions, mode-specific in-vehicle time and waiting + waiting time coefficients are used to allow positioning ride-hailing time coefficients relative to PT time coefficients. Additionally, a generic cost coefficient is estimated. We add an alternative-specific constant *asc* to each utility function to capture the average utility across all variables not included in the model, which is fixed to zero for PT.

In addition to trip-specific attributes, we also extract relevant sociodemographic data based on the 2019 US Census data (Oakes et al., 2019). Based on the coordinates of the origin and destination of the chosen PT or ride-hailing trip, sociodemographic data for both the corresponding origin and destination census zone is extracted to allow for testing the importance of sociodemographic attributes. The following attributes are considered potentially relevant for our analysis: median household income, proportion unemployed, person density per km^2 and housing density per km^2. For each of these four sociodemographic attributes the average value across the origin zone and destination zone of the trip is calculated, as there is no information in our dataset what the home-end and the activity-end is of the journey. After initial testing we found that only the variable *housing density hd* (the number of houses per km^2 averaged across the census zone of the origin and destination of the journey) added plausible explanatory power to our model results, hence only this variable is included in the utility functions. β_{hd}^{PT} is fixed to zero, with β_{hd}^{RH} quantifying the additional importance of house density for RH utility relative to PT.

$$V^{RH} = \beta_{ivt}^{RH} \bullet t_{ivt}^{RH} + \beta_{ivt}^{RH} \bullet \beta_{wtt:ivt}^{RH} \bullet t_{wtt}^{RH} + \beta_c \bullet c^{RH} + \beta_{hd}^{RH} \bullet hd + asc^{RH} \tag{1}$$

$$V^{PT} = \beta_{ivt}^{PT} \bullet t_{ivt}^{PT} + \beta_{ivt}^{PT} \bullet \beta_{wtt:ivt}^{PT} \bullet t_{wtt}^{PT} + \beta_c \bullet c^{PT} + \beta_{hd}^{PT} \bullet hd + asc^{PT} \tag{2}$$

The total utility function equals the sum of the structural component of the utility function V and the error term ε, as shown by **Equation (3)**. As ride-hailing and PT are distinct modes we do not anticipate any violation of the assumption of the IID (independent and identically distributed) error terms, implying that using a standard closed-form binomial logit model to calculate mode choice probabilities (**Equation (4)** is considered adequate for the purpose of this study. Due to privacy constraints there is no information on the panel structure of our data. One could expect that among the 576,512 observed choices included in the choice set, some of these choices are repeated choices made by the same individual. Due to the correlations between mode choices made by the same individual, in these cases it would be preferred to estimate a panel effects mixed logit model instead of a standard binomial logit model. However, as there is no unique identifier of PT card IDs or ride-hailing users in the data, incorporating a panel structure is not possible. Instead, we therefore report the robust t-values as sandwich estimator to reduce the risk of overestimation of certain coefficients.

We perform maximum likelihood estimation (MLE) to find the coefficients of the variables in the utility function which best explain the observed mode choices. The maximum likelihood estimation is performed in PythonBiogeme and solved using the Newton algorithm as an iterative method for solving this nonlinear optimisation problem (Bierlaire, 2016). We express the waiting + walking time coefficient β_{wtt} (for consistency purposes for both PT and RH) as multiplicative factor of the in-vehicle time, so that waiting time perception can be interpreted directly relative to in-vehicle time perception. This means that $\beta_{wtt} = \beta_{wtt:ivt} \bullet \beta_{ivt}$, where we estimate the coefficient reflecting the ratio between waiting + walking time and in-vehicle time $\beta_{wtt:ivt}$ in our model. Important to mention is that we additionally fixed this ratio for public transport $\beta_{wtt:ivt}^{PT}$ to 1.62 times the PT in-vehicle time coefficient β_{ivt}^{PT} based on the choice model estimation results from Yap and Cats (2021). The latter estimated a PT route choice model based on the same Washington DC PT network based solely on AFC passenger demand data, where a ratio of 1.62 was found between β_{wtt}^{PT} and β_{ivt}^{PT}. This ratio was estimated entirely based on actual PT journeys for origin–destination pairs with at least two different observed PT paths. This means that these estimation results were not partially relying on data obtained from OpenTripPlanner to obtain the attribute values for the non-chosen alternative, but rather that attribute values for both the chosen and non-chosen PT path were derived entirely from observed PT data. Furthermore, as PT lines often operate with a similar service frequency, in some cases it can be difficult to find a meaningful or statistically significant waiting time coefficient due to the limited variation in actual PT waiting time values in the RP choice set. Therefore, adopting a pre-specified ratio between β_{wtt}^{PT} and β_{ivt}^{PT} as previously established is preferred in this case. As the objective of our study is to position ride-hailing preferences relative to PT, fixing solely the PT waiting time coefficient does not further influence the results.

$$U^{RH} = V^{RH} + \varepsilon^{RH} \tag{3}$$

$$P^{RH} = \frac{1}{1 + e^{V^{PT}}} \tag{4}$$

3. Results and discussion

This section shows the empirical results and model estimation results first, followed by a discussion on the results, study limitations and the study implications.

3.1. Results

3.1.1. Empirical results

By fusing the empirical ride-hailing and PT data sources, we can illustrate the spatial and temporal mode share in Washington DC (Fig. 2). The mode share of Uber as ride-hailing provider is shown in relation to the sum of Uber and PT usage for different areas of Washington DC and for different time periods on a weekday, based on the origin zone of the journey. For the visualisation of the empirical results

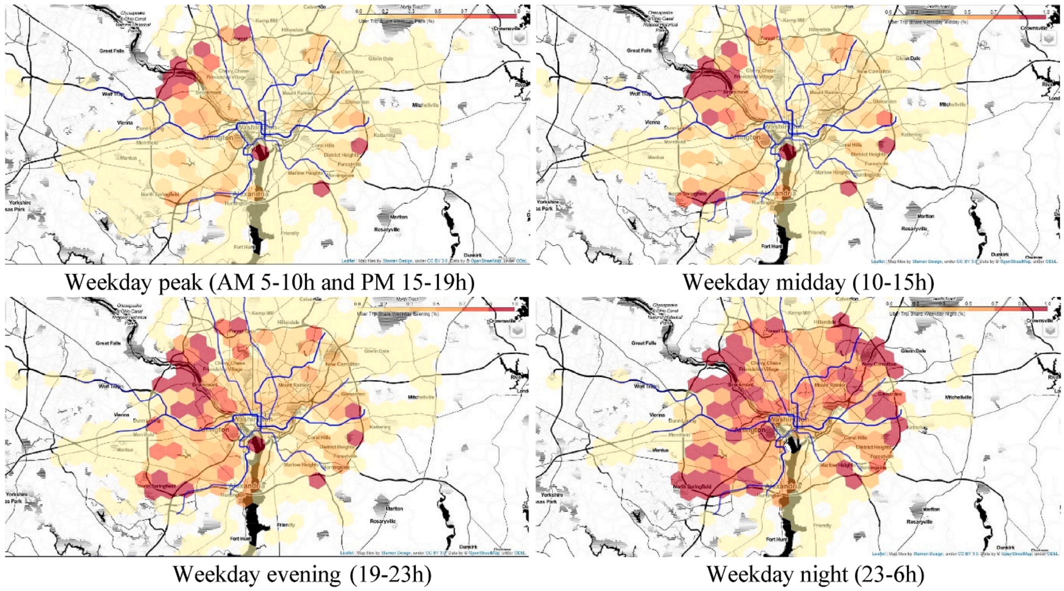

Fig. 2. Uber demand share as percentage of Uber and public transport demand. Metro lines are shown in blue; darker red colours indicate a higher Uber demand share.

in Fig. 2 we use a higher spatial aggregation level of trip origins based on H3 resolution 7. Note that only trips made by Uber (for ride-hailing) and WMATA (for public transport) are included in this figure, thus excluding any trips made by private car, walking, taxi or other ride-hailing providers. Remarkably, Uber ride-hailing trips make up the majority of all trips for a considerable number of spatial–temporal combinations.

It can clearly be observed that the share of Uber ride-hailing increases during time periods and for areas with limited or no rail based PT supply, such as the weekday evening and night compared to weekday peak hours and midday. For example, areas near the main ring highway around DC typically have a higher Uber ride-hailing share, as well as areas in the north-western part of the city near the Potomac River where rail based PT supply (indicated in blue in Fig. 2) is limited. The high share of Uber ride-hailing in the evening and night may also be explained by perceived safety concerns which might be experienced by some users whilst travelling in the dark, for example when having to wait at a quiet or unlit PT stop for the bus or metro to arrive. Additionally, the PT share is highest during the AM and PM peak periods where PT is generally most competitive in terms of frequencies and speed, suggesting a stronger preference for PT during peak hours compared to ride-hailing. A possible explanation can be that especially rail bound PT is not affected by road traffic congestion, resulting in faster and more reliable journey times compared to ride-hailing, where the risk on congestion adds additional uncertainty to the expected arrival time at the destination.

3.1.2. Model estimation results

In Table 3 the results from our estimated discrete choice model are reported. The model – with a sample size of 576,512 choices and 6 estimated coefficients – converged after 23 iterations in less than 2 min on a regular i7 PC. The Rho-square and Rho-square-bar are 0.97. The Akaike Information Criterion (AIC) is 6,952,290, whereas the Bayesian Information Criterion (BIC) equals 6,953,358. By inspecting the estimated coefficients we can conclude that the signs of all coefficients align with expectations, with generally negative signs for time and cost coefficients. All estimated coefficients have high absolute robust t-values with robust p-values for all coefficients smaller than 0.01, indicating that the found results are statistically highly significant. The correlations between the coefficients are generally low, with no correlation coefficient being higher than 0.55.

Table 3
Estimation results.

Coefficient	Name	Value (t-value)
β^{PT}_{ivt}	in-vehicle time PT (minutes)	−0.0548** (−158)
$\beta^{PT}_{wtt:ivt}$	ratio waiting + walking time to in-vehicle time PT	1.62 (fixed)[a]
β^{RH}_{ivt}	in-vehicle time ride-hailing (minutes)	−0.0357** (−69.5)
$\beta^{RH}_{wtt:ivt}$	ratio waiting + walking time to in-vehicle time ride-hailing	1.32** (30.7)
β_c	fare (USD)	−0.0775** (−71.0)
β^{RH}_{hd}	housing density (1,000 housing units / km^2) ride-hailing	−0.133** (−90.9)
β^{PT}_{hd}	housing density (1,000 housing units / km^2) PT	0.0 (fixed)
asc^{RH}	alternative-specific constant ride-hailing	−0.273** (−18.5)
asc^{PT}	alternative-specific constant PT	0.0 (fixed)

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

[a] *Estimated in Yap M. & Cats O. (2021). Taking the path less travelled: Valuation of denied boarding in crowded public transport systems. Transportation Research Part A, 147, 1–13.*

3.2. Discussion

When comparing the in-vehicle time coefficient for PT β^{PT}_{ivt} and the in-vehicle time coefficient for ride-hailing β^{RH}_{ivt}, the ratio $\beta^{RH}_{ivt}/\beta^{PT}_{ivt}$ equals 0.65. This implies that one minute travelling in a ride-hailing service is on average perceived 35 % less negative than travelling one minute in a conventional PT vehicle. Formulated from the ride-hailing perspective, oppositely this means that on average PT in-vehicle time is perceived (−0.0548/-0.0357 =) 54 % more negative than ride-hailing in-vehicle time. Our model results provide strong quantitative evidence on the extent to which travellers value in-vehicle time in a ride-hailing service as less negative than PT in-vehicle time. For both PT and ride-hailing the traveller has the ability to perform other tasks (such as phone calls), but ride-hailing has a competitive advantage over PT in the sense that the vehicle is not shared with other, unknown, passengers. Furthermore, using ride-hailing means there is no risk of crowding or not having a seat, which can be important especially compared to using crowded PT systems in peak hours.

We find an estimated coefficient of 1.32 for the ride-hailing waiting + walking time relative to the ride-hailing in-vehicle time $\beta^{RH}_{wtt:ivt}$. This coefficient indicates that ride-hailing users value waiting + walking time for the ride-hailing service on average 32 % more negative compared to in-vehicle time on-board the ride-hailing service. The equivalent ratio of 1.62 for PT derived in Yap and Cats (2021) indicates that PT users value waiting + walking time on average 62 % more negative than uncrowded PT in-vehicle time. This shows that ride-hailing waiting time relative to the in-vehicle time is perceived about 20 % less negative than PT waiting time relative to in-vehicle time, although the difference between these ratios is not as distinct as the difference between the estimated in-vehicle time coefficients. Waiting time for ride-hailing has the advantage that the real-time position of the car is always shown via the app after requesting a trip. Furthermore, users have the ability to contact the driver directly via the app if necessary. We argue that provision of real-time information takes away some degree of uncertainty associated with waiting time, especially when comparing to waiting time for PT services without real-time arrival information provision, resulting in a less negative waiting time valuation. Another possible factor is that a PT passenger has to be alert and aware of the PT departure time when waiting, as the responsibility for not missing the PT vehicle lies entirely with the passenger. When using ride-hailing one knows that the driver might wait a few minutes after arriving at the requested location, meaning there is a joint responsibility between user and driver to make the trip happen. This could imply that a lower level of alertness is required from the ride-hailing user whilst waiting or walking, possibly reducing the perceived waiting time. On the other hand, one can argue that waiting for regular PT has an advantage over ride-hailing as the PT stop is a dedicated, clearly indicated location with certain facilities such as benches, cover or other amenities. As the pickup location for ride-hailing can be virtually any location where the vehicle is allowed to stop, the pickup point might be perceived as less clear and provides fewer facilities to the user. However, given that the waiting time to in-vehicle time ratio for ride-hailing of ~1.3 is about 20 % lower compared to this ratio of ~1.6 for PT, our study results suggest that the overall balance falls in favour of ride-hailing in terms of waiting time valuation.

The value of travel time (VOTT) for ride-hailing users can be computed by dividing the ride-hailing in-vehicle time coefficient β^{RH}_{ivt} by the fare coefficient β_c. As times are currently expressed in minutes, converting to hours results in an average VOTT of $27.6 per hour for ride-hailing users. This is somewhat higher than the typical range for hourly value of times between $10.00 and $17.00 used by the US Department of Transportation (DoT, 2016). This may suggest that the average customer segment using ride-hailing has a higher than average time valuation. As we estimated a generic fare coefficient, our results indicate a 35 % reduction in VOTT for ride-hailing compared to PT – which is directly associated with the 35 % less negative ride-hailing in-vehicle time valuation compared to PT. For a more complete comparison in VOTT between ride-hailing and PT users, a more detailed follow-up study is recommended where mode-specific fare coefficients are estimated and where heterogeneity in VOTT both between modes and within each mode is explicitly accounted for. For that purpose, a more detailed fare calculation for each individual PT passenger journey is recommended, which includes the impact from concessionary fares and monthly or annual travel passes on the actual and perceived PT fares.

At last, the negative coefficient for ride-hailing for the average housing density β^{RH}_{hd} suggests an overall additional preference for PT in areas with higher housing densities relative to ride-hailing. We can expect that high-density areas are typically better served by public transport compared to low-density areas, as a certain degree of demand concentration is essential for PT systems to operate in an economic way. This coefficient therefore might reflect the overall better PT quality in high-density areas, above and beyond the associated travel time components already accounted for in the utility function.

3.3. Study limitations

Given that the exact origin and destination coordinates of the PT journeys are not empirically known, in our study we used the average first access and last egress walking time for the corresponding day-hour-origin–destination zone combination as derived from the OTP for the matching ride-hailing trip. If the corresponding ride-hailing trips originate or terminate on average further from the PT stops or stations than the PT journeys, this may result in a slight overestimation of the assumed PT access or egress walking time. However, given that the matching between ride-hailing and PT journeys occurs using a relatively high level of disaggregation (H3 clustering resolution 9, with each zone covering an area of 0.105 km^2), the impact on the total PT waiting + walking time is expected to be limited – especially because the access / egress walking time is only a subset of the total PT walking and waiting time t^{PT}_{wtt} which also includes waiting time and station walking time.

As the ratio between PT waiting time and in-vehicle time is fixed to 1.62 times the PT in-vehicle time coefficient in our study, we have performed a sensitivity analysis to this assumption. As choice probabilities in discrete choice modelling are driven by the difference in utility between the RH and PT alternatives rather than their absolute utility, the estimated RH coefficients change when changing $\beta^{PT}_{wtt:ivt}$. When using a PT waiting time to in-vehicle time ratio $\beta^{PT}_{wtt:ivt}$ of 1.50 and 1.75, we find that the estimated ride-hailing waiting time to in-vehicle time ratio $\beta^{RH}_{wtt:ivt}$ equals 1.26 and 1.37, respectively. From this we can conclude that ride-hailing waiting time relative to ride-hailing in-vehicle time is consistently perceived about 20 % less negative than PT waiting time relative to PT in-vehicle time.

In our model we have specified bespoke alternative-specific constants and time coefficients for PT and ride-hailing. Even though subway and bus may be perceived differently by passengers, we have not made a further distinction within the PT mode between bus and subway given the research focus to obtain a better understanding of mode choice between PT and ride-hailing. A suggested future improvement in the model specification is the introduction of mode-specific alternative-specific constants for bus and subway, as well as mode-specific time coefficients for bus and subway separately.

3.4. Study implications

Our study results allow policy makers to position ride-hailing services relative to conventional PT and – indicatively – to private car in terms of in-vehicle time perception. As mentioned in chapter 1, Gao et al. (2019) found that on average in-vehicle time in ride-hailing is perceived as 13 % less negative compared to in-vehicle time when driving a private car, presumably due to the ability to undertake other tasks whilst being driven. In Wardman (2004) it was found that PT in-vehicle time is valued 1.3–1.5 times higher than in-vehicle time in a private car, depending on the journey purpose. When combining these two ratios from both studies, PT in-vehicle time would be expected to be valued ~1.5–1.7 times more negative than ride-hailing in-vehicle time. As abovementioned, our estimation results show that on average PT in-vehicle time is valued 1.54 times more negative than ride-hailing in-vehicle time, thus pointing into the same direction. Taking this together we can conclude that the private car can be positioned between ride-hailing and PT in terms of in-vehicle time perception, although the private car in-vehicle time valuation sits closer to ride-hailing than to regular PT. This is visualised in Fig. 3, which shows the in-vehicle time perception ratios between ride-hailing, private car and PT. As illustration, the figure shows the in-vehicle time ratio between ride-hailing and private car found in Gao et al. (2019), scaled relative to the ride-hailing in-vehicle time coefficient set to 1.00 (1.00/(1–0.13) = 1.15). Furthermore, it shows the in-vehicle time ratio between private car and PT as found in Wardman (2004), scaled against the private car in-vehicle time which is set equal to 1.15, resulting in PT in-vehicle time ratios between

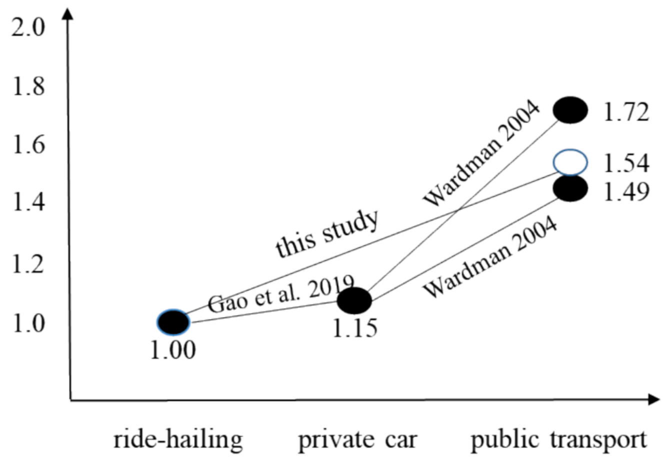

Fig. 3. In-vehicle time perception ratios between ride-hailing, private car and public transport.

1.49 (1.15·1.3) and 1.72 (1.15·1.5). Finally, the in-vehicle time ratio between ride-hailing and PT as found in our study is shown, scaled to the ride-hailing in-vehicle time equalling 1.00, resulting in a PT in-vehicle time coefficient of 1.54 (−0.0548/-0.0357).

A second implication of our study results is that it enables a more accurate modelling, and thereby forecasting, of ride-hailing services and their impacts on PT ridership and road traffic congestion. Currently, in the absence of bespoke coefficients and ratios between coefficients for ride-hailing based on observed choice behaviour, transport models aiming to model ride-hailing typically apply the same coefficients and ratios between coefficients as for PT or private car, or use Stated Preference based estimated coefficients. For example, when assessing accessibility benefits provided by ride-hailing in addition to regular PT, Cats et al. (2022) apply the default PT waiting time to in-vehicle time ratios to ride-hailing as well. Kucharski and Cats (2022) use ride-hailing perception coefficients derived from a Stated Preference study (Geržinič et al. 2022) when simulating ride-hailing services with MaasSim. Our study results enable a more accurate modelling of ride-hailing as a distinct mode with bespoke travel time coefficients derived from observed mode choices, thereby contributing to the generation of more accurate modelling results that provide a sound empirical underpinning in support of decision-making processes.

4. Conclusions

The main objective of this study is to estimate how travellers perceive time for ride-hailing services compared to conventional public transport. In contrast to previous research on ride-hailing mode choice which often relies on Stated Preference approaches or self-reported samples, our study uses empirical, large-scale Revealed Preference data containing observed choices of both ride-hailing and public transport to understand travellers' time valuations. Our estimated choice model is based on more than half a million actual ride-hailing and PT choices, resulting from Uber ride-hailing data and WMATA public transport demand data in the Washington DC metropolitan area.

Based on the model outputs we can conclude that in-vehicle time in ride-hailing is perceived substantially less negative compared to in-vehicle time on-board PT. Our findings suggest that ride-hailing in-vehicle time is perceived 35 % less negative, providing strong quantitative evidence for users' preferences for ride-hailing. We also found that waiting time for ride-hailing is valued roughly 1.3 times more negatively than ride-hailing in-vehicle time, which is about 20 % less negative than the ratio between waiting and in-vehicle time found for PT. Our study enables a more accurate modelling of ride-hailing by using bespoke, mode-specific travel time coefficients derived from large-scale empirical data, which can improve the accuracy of modelling outputs and thereby improve decision-making processes.

We formulate two main directions for follow-up research. First, heterogeneity in travel preferences can be explored in future research. For example, taste heterogeneity could be further explored by estimating mixed MNL models to understand the variance in ride-hailing in-vehicle time and waiting time valuation between different users. Furthermore, latent class models could be estimated to derive segmented ride-hailing coefficients. Second, when data concerning attributes of individual users would be available, it is recommended to add user-specific characteristics such as gender, age, education level and income to the discrete choice model. Instead of relying on average sociodemographic data for the origin and destination area of a certain trip, accounting for personal characteristics could potentially increase the proportion of variance explained by the choice model.

CRediT authorship contribution statement

Menno Yap: Conceptualization, Methodology, Data curation, Formal analysis, Writing – original draft, Writing – review & editing. **Oded Cats:** Conceptualization, Formal analysis, Writing – review & editing, Project administration and Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. This research has not been commissioned by Uber. The authors did not receive any financial compensation from Uber for performing this study.

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