Willingness to share rides in on-demand services for different market segments

Presented at Thredbo 16 (International Conference Series on Competition and Ownership in Land Passenger Transport), 2019, Singapore

María J. Alonso-González [a*], Oded Cats [a], Niels van Oort [a], Sascha Hoogendoorn-Lanser [b], and Serge Hoogendoorn [a]

[a] *Dep. Transport and Planning, Faculty of Civil Engineering and Geosciences, Delft University of Technology, P.O. Box 5048, 2600 GA Delft, The Netherlands*
[b] *KiM Netherlands Institute for Transport Policy Analysis, Postbus 20901, 2500 EX The Haag, The Netherlands*

* Corresponding author: Dep. Transport and Planning, Faculty of Civil Engineering and Geosciences, Delft University of Technology, P.O. Box 5048, 2600 GA Delft, The Netherlands, +31 (0)152784066, m.j.alonsogonzalez@tudelft.nl

JEL classification: L920, R400, R410, O180

Keywords: On-demand transport; Demand Responsive Transport; DRT; Willingness to share; Ridesplitting; Discrete Choice Model; Latent Class Analysis; Market segmentation; Stated Preference

ABSTRACT

The impact of on-demand urban transport services on traffic reduction will depend on the willingness to share (WTS) of individuals. However, the extent to which individuals are willing to share remains largely unknown. By means of a stated preference experiment, this study analyses the WTS of respondents by comparing their preferences towards individual and pooled rides. Urban Dutch individuals are the target population of this study. In our research, we: 1) quantify the WTS in on-demand services with different number of passengers to disentangle the sharing aspect from related time-cost considerations (e.g. detours); 2) investigate which distinct (latent) market segments exist in regards to the WTS and value of time (VOT) for these on-demand services, and 3) analyse which socioeconomic characteristics and travel patterns can help explain taste variations. Despite the large majority of current on-demand rides being individual, we found that less than one third of respondents have strong preferences for not sharing their rides. Also, we found heterogeneity not only in the values of the WTS of individuals, but also in the way this disutility is perceived (per-ride or proportional to the in-vehicle time).

1. Introduction

The new on-demand mobility services appearing in cities can lead a shift from the current ownership paradigm into a service paradigm (ITF, 2017). Among the different existing on-demand services, ridesourcing services, such as Uber and Lyft, play an important role due to their substantial uptake all over the world, with Uber alone fulfilling 14 million trips a day (Uber, 2019). Ridesourcing services include not only individual but also pooled rides (different people share the same ride, which is also referred to as ridesplitting (Stocker and Shaheen, 2016). These pooled on-demand services are also known as Demand Responsive

Transport (DRT) services. Research has shown that the vast majority of the performed urban rides could be shared, with individuals incurring in very little extra time disutility (Tachet et al., 2017), yet still only around 20% of the on-demand rides in cities where the pooled option is offered are chosen to be shared (Chen et al., 2018), (Uber, 2018).

Why is the percentage of pooled trips not higher? Chen et al. (2017) name travel time and cost as main variables to explain whether an on-demand trip is preferred to be shared or not. Another study highlights trust as main influencing factor to consider sharing rides (Amirkiaee and Evangelopoulos, 2018). In this line, Morales Sarriera et al. (2017) found that safety concerns, feelings of prejudice and the fear of having negative social interactions deterred individuals from choosing a pooled ride. This leads us to our research question: What is the monetary disutility associated with sharing an on-demand ride with (different numbers of) other passengers (i.e., the willingness to share (WTS)), and how does it differ for different individuals?

A few previous studies have also quantified preferences towards individual or pooled on-demand services (Krueger et al., 2016), (Lavieri and Bhat, 2019), (Liu et al., 2018), (Steck et al., 2018). Our study adds to them by accounting for the impact of different number of additional passengers in the WTS and by identifying latent classes that capture the existent heterogeneity surrounding WTS. Lavieri and Bhat (2019) also includes a varying number of passengers, but they consider this disutility to increase linearly for all individuals with an increasing number of passengers. Our study also differentiates from theirs in vehicle automatization (manned versus autonomous), the target sample (the general population versus commuters exclusively) and the research setting (the Netherlands versus the USA).

Demand data regarding on-demand service is rarely public given the competitive market in which these services operate (Clewlow and Mishra, 2017). Moreover, unlike in the USA or China, there are, at the time of writing, no large scale pooled on-demand services active in the Netherlands, yet. Therefore, a stated preference survey is set up for this research. We summarise the aims of the current research as follows:

- Quantify the WTS in on-demand services with different number of passengers to disentangle the sharing aspect from related time-cost considerations (e.g. detours) in relation to choosing between individual and pooled rides.
- Understand if distinct segments exist in regards to the WTS and value of time (VOT) for these on-demand services.
- Analyse if socioeconomic characteristics and travel patterns can help explain taste variations.

The rest of the paper is organised as follows: Section 2 presents the research methodology; Section 3 analyses the results, and Section 4 covers the final discussion and conclusions.

2. Methodology

The methodology of the paper involves three distinct parts: a design phase (Section 2.1), a descriptive analysis phase (Section 2.2), and a discrete choice analysis phase (Section 2.3).

2.1 Survey design

To quantify the willingness to share rides in on-demand services, we design a Stated Preference (SP) experiment. SP experiments present respondents with hypothetical situations and have been widely used in the transportation literature to obtain behavioural information in scenarios that differ from the status-quo. We opt for a labelled experiment with two alternatives (individual ride or shared ride). And we include in-vehicle time, trip cost, and the number of additional passengers of the pooled alternative as SP attributes. Figure 1 shows an example of a choice task. The SP setting is either a commuting trip (shown to 70% of the working respondents with commutes of at least 2 km who do not require their own private vehicle to commute) or a free-time trip (shown to the remaining respondents).

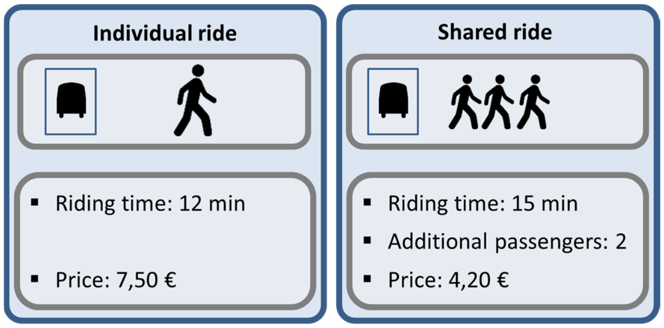


Figure 1. Example of a scenario of the stated preference experiment

This SP experiment is the last part of a more extensive survey focused on pooled on-demand services. These services are presented to respondents as depicted in Figure 2. The individual alternative is introduced only at this stage of the survey. To increase realism, the individual alternative is constrained to be always quicker (no existing high occupancy vehicle lanes in our context) and more expensive than the pooled option.

Figure 2. Included description of pooled on-demand services (booking offered via phone call and sms to respondents without mobile internet). Layout inspired by (Kim et al., 2017)

An orthogonal fractional factorial design with blocking and its foldover are used for the experimental design of the SP experiment. This results in six blocks with four scenarios each. The foldover design was included to get uncorrelated two-way interactions, given that the disutility to have extra passengers may be correlated with the time and/or cost attributes (we refer the reader to ChoiceMetrics (2012) for information regarding experimental SP designs). For the attribute levels, we consider two set of values, depending on the length of the respondent's reference trip (≤12km or >12km), following the approach used in Arentze and Molin (2013). Attribute levels for time and cost for both versions were chosen such that similar values of time could be obtained in the model estimation. Attribute levels can be found in Table A. 1.

Besides the SP experiment, we include a series of attitudinal indicators. They cover attitudes towards the three attributes included in the SP experiment (privacy, cost, and time) and serve two aims in our study: 1) understand if respondents' differences in preferences towards individual and pooled services stem from different time-cost attitudes and/or differences in privacy attitudes, and 2) understand the main cause underlying non-trading behaviour.

2.2 Descriptive analysis of non-trading behaviour

Despite including a wide range of trade-offs in SP experiments, non-trading behaviour (individuals who recurrently choose one of the alternatives throughout the whole experiment) occurs, especially in labelled experiments, and can influence the choice modelling results (Hess et al., 2010). A descriptive analysis of non-trading behaviour can help understand this phenomenon and improve the analysis and interpretation of the discrete choice model.

Three main reasons lie behind non-trading behaviour (Hess et al., 2010): 1) individuals with strong preferences for a particular alternative for which the offered trade-offs are not sufficient to switch to a different alternative, 2) non-utility maximising behaviours stemming for example from fatigue or boredom, and 3) strategic behaviour trying to influence policy decisions. While we have little reason to believe strategic behaviour could play a role in our SP experiment, both strong preferences and fatigue could be causes for non-trading (especially given that the sharing SP experiment was the last part of a longer survey). Individual validation of the underlying cause is not possible. However, given the existing link between attitudes and behaviour (Molin et al., 2016), we can analyse the attitudinal indicators to shed light on the main reason behind the exhibited non-trading behaviour.

We first perform an exploratory factor analysis on the attitudinal indicators to check if they load on the three main factors we had expected them to; these being privacy, cost and time (corresponding to the three attributes present in the SP experiment). Then, we examine differences in the means of the attitudinal indicators between 'traders', 'individual non-traders' and 'pooled non-traders' using ANOVA and independent t-tests. We assume that if statistical differences in the means of the attitudinal indicators exist among the three groups, non-trader individuals are utility maximisers with strong preferences towards one of the two alternatives. Otherwise, we argue that fatigue may be the main cause for the existing non-trading behaviour and remove non-traders from the posterior discrete choice analysis.

If an underlying attitudinal explanation is found in the SP non-trading behaviour, we further investigate whether 'traders', 'individual non-traders' and 'pooled non-traders' differ from each other in their individual characteristics (either socioeconomics or travel patterns) or if some trip characteristic may influence non-trading behaviour. We analyse if any statistical significance exists by means of chi-square tests.

2.3 Discrete choice analysis

We analyse the SP experiment using discrete choice modelling under the Random Utility Maximisation framework. We analyse different model specifications for the sharing attribute, including interactions with both cost and time. We also test whether both trip purposes should be modelled separately, and the addition of different individual characteristics to the utility function. The final model specification is a mixed logit model where we account for the panel nature of the data (correlation existing among the different observations of the same individual). BIOGEME software (Bierlaire, 2003) is used for model estimation. We estimate the parameters on 80% of the sample and use the remaining 20% for validation purposes.

We also perform a latent class choice model (LCCM) to analyse if distinct segments with different values for the model parameters exist. LCCMs are based on the assumption that there is a (latent) discrete variable that can explain the existent heterogeneity among respondents, and individuals are allocated to different classes in a probabilistic fashion. Personal characteristics (e.g., socioeconomic characteristics) can be added to the model to better forecast the probability of each individual to belonging to the different classes. Different statistical indicators can help decide on the number of classes to include in the model. We base this decision on the BIC (Bayesian Information Criterion) index. We refer the reader to Walker and Ben-Akiva (2002) and Hess (2014) for more information on LCCM and their mathematical specification. We use the dedicated latent class software LatentGOLD (version 5.1) (Vermunt and Magidson, 2016) for the LCCM specification. Same as before, we estimate the model on 80% of the sample and use the remaining 20% for model validation.

3. Results

We divide the results section in three parts. Section 3.1 describes the data collection and sample; Section 3.2 analyses the non-trading behaviour, and Section 3.3 reports the choice modelling analyses.

3.1 Data collection and sample description

The survey was distributed on-line on May 2018 (in Dutch). Prior, initial modelling of an on-line pilot performed on April 2018 validated that the chosen SP attribute levels were adequate for our modelling purposes. Target respondents were individuals aged 18 years and older with a mobile telephone living in highly urbanised areas in the Netherlands (understood as areas with more than 1,500 inhabitants/km^2 (Centraal Bureau voor de Statistiek (CBS), 1992)). Survey respondents were recruited from a household panel designed for the longitudinal study of travel behaviour in the Netherlands: the Netherlands Mobility Panel (MPN) (Hoogendoorn-Lanser et al., 2015). This provided access to information on socioeconomic and mobility characteristics of respondents. All individuals invited to fill in the survey of this study belonged to different households.

A total of 1077 respondents finished the questionnaire, of which 1006 (93%) were considered valid after data cleaning (based on survey completion time and straight lining checks throughout the whole survey). Table 1 shows the socioeconomic characteristics of the sample, the target population (highly urbanised areas in the Netherlands), and the overall Dutch values. Gender and the two urbanisation levels are well represented in our sample. Age is also adequately represented, even if middle aged adults are a bit underrepresented and the elderly population slightly overrepresented. Shares for education, working status and household composition can only be compared to the national values. As expected, our (sub)urban sample has a higher percentage of higher educated individuals, working respondents and single households. In general, we consider our sample to adequately represent the target population.

Out of the 1006 respondents, 308 were directed to the commuting trip purpose and 698 answered the survey for the free-time trip. The free-time trip purpose subsample had 42% of working individuals. Differences in working status between both subsamples led to differences in age and education levels (higher proportion of older and low educated individuals in the leisure subsample).

Table 1. Comparison between the survey sample and the Dutch population. Sources for the population data: (Centraal Bureau voor de Statistiek (CBS), 2018a)**,** (Centraal Bureau voor de Statistiek (CBS), 2018b)**,** (Centraal Bureau voor de Statistiek (CBS), 2018c)**,** (Centraal Bureau voor de Statistiek (CBS), 2018d)

Socio-economic variable	Category	Total sample (N=1006)	Dutch (very) high urbanised areas	Dutch 2018 shares
Gender	Male	48,2%	48.9%	49,6%
	Female	51,8%	51.1%	50,4%
Age	18* to 39	38,1%	38.1%	31,8%
	40 to 64	35,6%	42.0%	44,0%
	65 and above	26,3%	19.8%	24,2%
Education	Low	25,2%		31,5%
	Average	32,5%		37,8%
	High	42,0%		29,2%
	Unknown	0,2%		1,4%
Work status	Working	59,9%		50,9%
	No working	40,1%		49,1%
Household	1 person household	49,0%		38,2%
	> 1 person household	51,0%		61,8%
Urbanisation level	>2500 inhab./km²	46,9%	48,2%	23,3%
	1500-2500 inhab./km²	53,1%	51,8%	25,1%

* 18 to 39 for the share sample, but 20 to 39 for the Dutch population 2018 values

3.2 Non-trading behaviour

A significant share of respondents exhibited a non-trading behaviour in the SP experiment (around 30%, 15% “individual-only” and “15% “pooled-only”). Initial choice modelling analysis showed an average value of time of around 15 Euro/h, and all blocks contained scenarios with values of time that ranged from less than 5 Euro/hour to over 30 Euro/hour. Therefore, we consider the included trade-offs adequate and analyse the attitudinal indicators to distinguish if strong preferences or fatigue mainly underlie non-trading behaviour.

The included attitudinal indicators cover the three attributes included in the SP experiment : privacy, cost and time. Previous research found that cost sensitive individuals tend to also be more interested in shared modes (Burkhardt and Millard-Ball, 2006). We therefore also cover multimodality attitudes in our statements. Time related statements focus on the causes of the increase of time in pooled rides. An exploratory factor analysis (EFA) (principal axis factoring with direct oblimin rotation used, extracting factors with eigenvalues greater than one) confirms that all indicators load as expected. Sampling adequacy and correlation between items proves adequate (Kaiser-Meyer-Olkin measure KMO=0.797 and Bartlett's test of sphericity $p<0.001$). Table 2 shows the indicator loadings from the rotated pattern matrix, as well as the average and standard deviation of the individual indicators for the "individual-only" respondents, "pooled-only" individuals, "traders", and the whole sample.

The means of all attitudinal indicators display the same trend: "individual-only" respondents are the most privacy and time sensitive, and the least cost sensitive; the opposite holds for the "pooled-only" respondents. ANOVA tests confirm that these differences are significant for all indicators at the 95% confidence level or beyond. This difference is largest between the "individual-only" and the "pooled-only" groups, significant at the 99% level (independent t-test). Further, pair-wise comparison between "individual-only" and "traders" showed statistically different means in all indicators (in all but one at the 99% level) while differences between "pooled-only" and "traders" are sometimes insignificant, as shown in Table 2. "Pooled-only" individuals and "traders" have similar attitudes towards privacy statements that evoke strong attitudes (uneasiness or sense of identity) and multimodality. Differences in the other privacy indicators, as well as in their attitudes towards cost and time, do exist. Because of the encountered significant differences among groups, , we consider the existence of strong preferences as main underlying cause for the non-trading behaviour, and accept non-traders as valid respondents in the posterior choice modelling analysis. The three factor scores (calculated as average sum of the indicators) are computed for posterior consideration to describe the classes in the LCCM.

Table 2. EFA loadings, mean and standard deviation of the attitudinal indicators and significance of independent t-tests between traders and each of the non-trading groups (equal variance not assumed.) (Legend: "individuals-only" vs "traders" p ≤0.01 **, p ≤0.05 *; "pooled-only" vs "traders" p ≤0.01 (++), p ≤0.05 (+).)

Attitudinal statement (and source where applicable)	EFA loadings (pattern matrix)	Mean (sd) of total sample	Mean (sd) of "individual-only"/ "trading"/ "pooled-only" respondents	t-test signific. (2-tailed)
Privacy attitude				
It makes me uncomfortable to ride with strangers on public transport (modified from (Rubin, 2011))	0.622	2.31 (0.90)	2.67/2.26/2.13 (0.98/0.88/0.84)	** ( )
I think the public transport is not so clean or decent	0.571	3.06 (0.93)	3.31/3.06/2.86 (0.96/0.91/0.94)	** (+)
I like the privacy in the car or bike	0.438	3.76	4.07/3.74/3.53	** (+)

(modified from (Spears et al., 2013))		(0.87)	(0.79/0.85/0.97)	
People like me only use their own bike and/or car	0.407	3.08 (1.13)	3.41/3.03/3.01 (1.12/1.12/1.13)	** ( )
Cost sensitivity and multimodal mind-set				
I would use the car less if there would be a cheaper alternative	0.602	3.29 (1.05)	2.95/3.31/3.53 (1.06/1.03/1.00)	** (+)
I choose to travel with public transport or to share rides to reduce my trip costs	0.583	3.30 (0.98)	2.64/3.37/3.61 (1.03/0.91/0.93)	** (++)
I am willing to try new ways to travel	0.534	3.46 (0.83)	3.14/3.51/3.55 (0.99/0.79/0.83)	** ( )
I often compare different travel options and transport modes before choosing how to travel (modified from (Atasoy et al., 2010))	0.500	2.78 (1.04)	2.56/2.81/2.88 (1.12/1.03/0.99)	* ( )
I do not mind which transport mode I use, as long as it suits my trip needs	0.401	3.44 (1.01)	3.14/3.48/3.53 (1.15/0.98/0.94)	** ( )
In-vehicle time flexibility attitude				
I would not mind if other travellers get in or off the FLEXI vehicle during my ride (reversed) (modified from (Al-Ayyash et al., 2016))	0.674	2.50 (0.96)	3.13/2.43/2.23 (1.07/0.89/0.89)	** (+)
I would find it annoying that FLEXI does not drive the fastest route (e.g., FLEXI's route is 18 minutes instead of 15 minutes) (modified from (Al-Ayyash et al., 2016))	0.578	2.91 (0.96)	3.27/2.88/2.66 (1.08/0.91/0.98)	** (++)

In addition, we examine if distinct characteristics exist that differentiate these three groups. We consider socioeconomic characteristics (gender, age, employment status, education level, personal net income, household composition and urbanity level), travel patterns (usage frequency of different modes of transport), and trip characteristics (trip purpose and length).

Chi-square tests suggest that "individual-only" and "pooled-only" individuals differ in a series of characteristics ($p<0.05$). "Pooled-only" individuals are more often female (56% of "pooled-only" vs 42% for "individual only"), and have lower incomes. They also use car less frequently and bike more frequently, which fits their lower incomes. A higher percentage of "individual-only" individuals never use the train or the bus/tram/metro (41% and 37% respectively, versus 30% and 24% for "pooled-only" respondents), which explains their higher reluctance to share rides. Regarding trip characteristics, a higher share of "pooled-only" individuals are in the short version (≤12km) of the survey (55% vs 39%), which can indicate that the disutility involved in sharing rides depends on the in-vehicle time.

Interestingly, differences between traders and non-traders also exist. The largest age group for traders is 18-34 years old (33% for traders, 22% for non-traders), while individuals aged

65 and older are the most frequent among non-traders (34% vs 23%). This indicates that younger individuals are more open to using different mode alternatives. Traders have also more often a working status (63% vs 53%) and are higher educated, which can partly be due to the larger presence of younger individuals among traders. Traders are also more multimodal in general, with a lower number of them never using the train, bus/tram/metro or the bike (28%, 23% and 11% respectively, versus 36%, 30% and 16% for non-traders).

3.3 Choice model estimation of individual versus pooled on-demand trips

We perform a choice modelling analysis on 80% of our sample (805 individuals randomly drawn). We model a mixed logit model with a random component to account for the panel structure in the data. We conclude that the sharing attribute is best modelled with a common dummy coded parameter for the case of one or two passengers, and interacting with the total pooled in-vehicle time for the four extra passenger specification. This interaction explains the higher percentage of individual choices for the longer distance version of the experiment. Additionally, time taste heterogeneity between working and non-working individuals is added to the model, to account for the higher time disutility for the earlier group. Accounting for high income individuals, zero usage of bus/tram/metro (BTM), and bike usage frequency also improves model fit. These variables added to the utility function of the individual alternative. A likelihood ratio test (Ben-Akiva and Lerman, 1985) indicates that both trip purposes are best to be considered together in one single model (unlike in Lavieri and Bhat (2019)).

Table 3 shows the specification of the final mixed logit (ML) model (final rho-square 0.285), which was estimated using 10,000 Halton draws. All parameters are significant at the 0.05 level and have the expected signs. There is a higher preference for the individual alternative (the one with the shorter in-vehicle time) among working respondents, given their additional 20% time disutility. The value of time (time-price trade-off) of these two groups is 14,50 Euro/hour and 12.00 Euro/hour for working and not-working individuals respectively (see Table 4). The sharing disutility is equal for pooled trips with one or two extra passengers. Rides with four extra passengers, on the other hand, are always associated with a higher disutility than those with one or two passengers. It is also higher the longer the in-vehicle time is, starting at 20% higher than the 1 or 2 passenger scenario for 13 minute rides (the shortest trip included in the experiment). Also, in line with expectations, having high income, never riding bus/tram/metro and not riding bike frequently increase the utility of the individual alternative.

To better understand taste variation, we perform a LCCM analysis, with the ML specification as starting point. The four class model minimises the BIC index, and is adopted. The final specification, shown in Table 3, includes different pooling parameters for different classes. This indicates that the sharing attribute is best modelled using different specifications for different individuals. All time and cost parameters are significant at the 95% level and have the expected negative signs. Parameters related to the number of additional passengers are also negative, with a higher disutility the larger the number of extra passengers in the vehicle, as expected. The majority of the passenger related attributes are also significant at the 95% level. Three of the classes include an alternative specific constant (ASC) in their model specification. The positive sign in two of them implies a preference towards the pooled alternative over the individual one when time and cost parameters are 0 and there is one extra passenger in the pooled option. A first explanation could be that the two classes prefer sharing their vehicle (e.g., environmental or social considerations). However, individuals in this classes do experience a higher disutility when sharing the vehicle with two individuals than with one, and with four individuals than with two (negative related dummy coded parameters, largest for the four extra passenger specification). Therefore, we conclude that the positive ASC is not due to a preference towards sharing the vehicle, but it is linked to the cost-saving characteristic of the pooled alternative. The LCCM also includes four active covariates, which help define the classes and forecast class membership: being an working individual, having a high personal income, never using bus/tram/metro and being aged 18-34. Three of them also played a role in the ML specification, underscoring their relevance in explaining preference heterogeneity in our SP experiment.

Table 3. Parameter values (and robust t-tests) of the mixed logit (ML) and parameter values (and z-value) of the latent class choice model (LCCM) (p-value: ≤ 0.01 *, ≤ 0.05 **, ≤ 0.1*) (N/A indicates that no parameter was estimated). N/A: not applicable (constrained by specification).**

	Mixed logit model (multino-mial logit with panel effect)	Latent Class Choice Model			
Indicators		1LC (29%): “It’s my ride”	2LC (28%): “Sharing is saving”	3LC (24%): “Time is gold”	4LC (19%): “Cheap and half empty, please”
Stated preference attributes					
Time	-0.318 (-11.05) ***	-0.1936 (-3.14) ***	-0.2685 (-5.56) ***	-1.3185 (-3.01) ***	-2.0418 (-2.23) **
Additional time working individuals	-0.0662 (-2.68) ***	N/A	N/A	N/A	N/A
Cost	-1.59 (-17.17) ***	-0.6843 (-4.24) ***	-1.1492 (-5.95) ***	-3.0138 (-2.50) **	-15.7452 (-2.03) **
ASC pooled alternative (i.e., pooled and cheaper)	N/A	-1.7265 (-2.84) ***	2.1580 (4.57) ***	3.0540 (2.99) ***	N/A
1 or 2 extra passengers	-0.693 (-2.46) ***	N/A	N/A	N/A	N/A
2 extra passengers (dummy)		-0.3762 (-2.06) **	-0.3762 (-2.06) **	-0.3762 (-2.06) **	N/A
4 extra passengers (dummy)		N/A	-0.6818 (-2.37) **	-1.9873 (-1.65) *	N/A
4 extra passengers (per minute in-vehicle time)	-0.0636 (-5.68) ***	-0.0555 (-3.47) ***	N/A	N/A	N/A
Number of passengers (exponential)		N/A	N/A	N/A	-0.4661 (-1.89) *
Sigma panel	2.37 (15.19) ***	N/A	N/A	N/A	N/A
Personal attributes included in the utility function					
High income	0.880	N/A	N/A	N/A	N/A

	(2.97) ***					
BTM never used	0.522 (2.09) **		N/A	N/A	N/A	N/A
Frequency bike	-0.171 (-2.74) ***		N/A	N/A	N/A	N/A
Model for classes						
Intercept	N/A		0.3599 (2.31) **	0.1457 (0.81)	0.0391 (0.19)	-0.5447 (-2.44) **
Covariates						
Working individual	N/A		0.0681 (0.89)	-0.2531 (-2.84) ***	0.1211 (1.20)	0.0640 (0.56)
BTM never used	N/A		0.2218 (2.93) ***	-0.0363 (-0.38)	-0.0287 (-0.28)	-0.1567 (-1.30)
High personal income	N/A		0.2625 (2.83) ***	-0.0640 (-0.51)	0.0424 (0.33)	-0.2409 (-1.53)
Young individual (18-34 years old)	N/A		-0.1920 (-2.24) **	0.0722 (0.74)	0.2244 (2.43) **	-0.1046 (-0.85)

To better understand the main differences between the classes, we calculate the values of time (VoT) associated with each of the parameters (Table 4) and depict percentage differences between classes regarding socioeconomic and mode use characteristics (Figure 3). We also attach a motto to each class, as follows:

- LC 1 (29% of the sample [1]): “It’s my ride”. Individuals in this class experience the highest disutility related to sharing their ride. This preference is confirmed with the attitudinal indicators: this class has the strongest attitude towards privacy, the highest sharing-related time sensitive attitude, and the lowest price sensitive attitude of all classes (factor scores of 3.29, 3.04 and 3.04, versus 3.06, 2.71 and 3.24 respectively). “Individual-only” respondents are to be found in this class, amounting to over half of this class’ respondents. Sharing disutility for rides shared with four other passengers is proportional to the in-vehicle time (as specified for the ML model) for individuals in this class. Individuals in the other three classes (less adverse to share) perceive it as a per-ride fix disutility. Individuals in this class tend to be male, middle aged (35-64), and have high personal incomes. Regarding current mobility, they differ from the other classes in their higher car usage, and lower bike and public transport usage.
- LC 2 (28%): “Sharing is saving”. They are the most positive towards the pooled alternative, which can be explained by their price sensitivity (the pooled option offers them always cheaper rides) and low sharing reluctance. These two characteristics explain why “pooled-only” respondents are to be found (almost exclusively) in this

[1] Note that latent class models allocate individuals to classes in a probabilistic and not in a deterministic manner. An individual could, for example, belong to classes one to four with weights 0.5, 0.3, 0.1 and 0.1 respectively (the sum will always amount to one and an individual can have the same probability to belonging to different classes). All percentages regarding class size or class profile mentioned here refer to the sum of these probabilistic distributions of individuals.

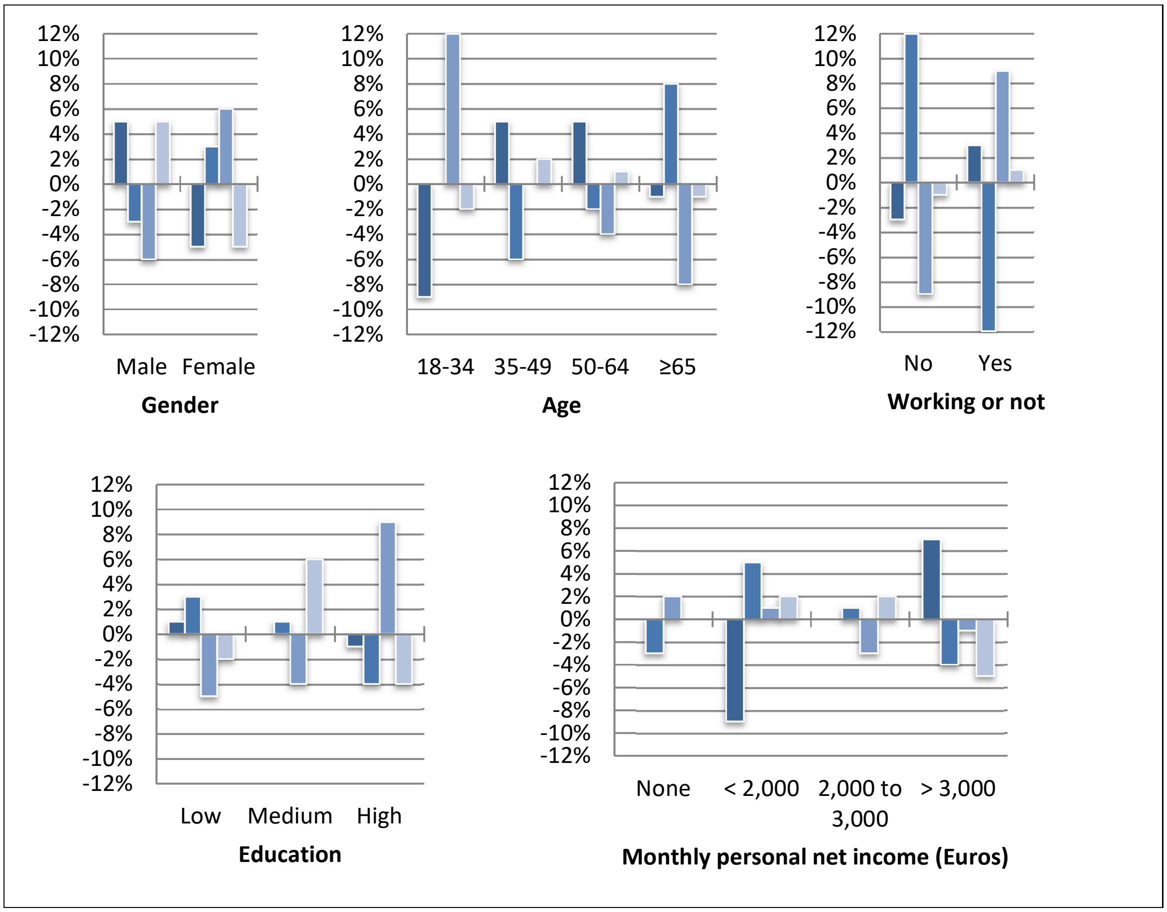
class. This class characterises for the larger shares of individuals aged 65 and older, female and not working.

- LC 3 (24%): “Time is gold”. These individuals display the highest value of time. They differentiate from “It’s my ride” individuals in their higher acceptance towards pooling. This higher acceptance explains why despite having a somewhat lower value of time, “it’s my ride” individuals have a more time sensitive attitude towards increases in time caused by sharing their ride (3.04 versus 2.68). Their strong time sensitivity, together with the little disutility they link to pooling per se cause the ASC of this class to have a positive sign. Note, however, that the lowest added time for the pooled alternative is three minutes, and “time is gold” individuals already associate a larger disutility towards pooling for the three minutes extra time than the positive utility coming from the ASC, implying that if no cost differences would exist, the individual alternative is preferred for the time situations included in the SP. Respondents also seem to be more time sensitive (and thus be in this class) for shorter trips (i.e., for the ≤12km version of the SP experiment), with 55% of individuals in this class having had the short version, versus 45-50% in the other three classes. Young (18-34), female, high educated individuals characterise this class. Frequent car usage in this class is also higher than the average, second to “It’s my ride” individuals.
- LC 4 (19%): “Cheap and half empty, please”. This is a very cost sensitive class, with a value of time even lower than the “Sharing is caring” class. The main difference with the second class is the more negative preference of “Cheap and half empty, please” individuals towards the pooled alternative, especially when four extra passengers are in the vehicle (the disutility regarding pooling with an increasing number of passengers increases exponentially). This explains why, despite their lower value of time, “Cheap and half empty, please” did trade between the individual and the pooled alternative in the SP experiment. This fourth class has a higher share of male and middle educated respondents than the average sample. The likelihood to belonging to this class is similar for individuals with different age groups or working situation.

Table 4. Value of Time (VOT) and Willingness to Share (WTS) values for the estimated models

VOT and WTS values	ML model		1LC: “It’s my ride”	2LC: “Sharing is saving”	3LC: “Time is gold”	4LC: “Cheap and half empty, please”
VOT (Eur/h)	N/A		16.98	14.02	26.25	7.78
VOT (non-working individuals) (Eur/h)	12.00		N/A	N/A	N/A	N/A
VOT (working individuals) (Eur/h)	14.50		N/A	N/A	N/A	N/A
ASC_pooled_alternative/beta_cost	N/A		2.52	-1.88	-1.01	N/A
WTS 1 additional pax (Eur/trip)	0.44		N/A	N/A	N/A	0.08
WTS 2 additional pax (Eur/trip)	0.44		0.55	0.33	0.12	0.44
WTS 4 additional pax (Eur/trip)	N/A		N/A	0.59	0.66	6.47
WTS 4 additional pax (Eur/h)	2.40		4.87	N/A	N/A	N/A

Finally, we validate the obtained models comparing the prediction rate of both the estimation and the validation subsamples. For the ML model, we obtain 71% right predicted choices for the estimation sample and 73% for the validation sample, which indicates a good prediction performance for both the in-sample and the out-of-sample data. We obtain similar prediction rates (72% and 75% for the estimation and validation samples respectively) for the LCCM using prior membership probabilities. Moreover, when using the individual's posterior membership probabilities (i.e., statistical inference using an empirical Bayes method which includes information from the observed choices and not exclusively the active covariates to determine the individual's probabilistic distribution to each of the classes), a 93% right prediction rate for both estimation and validation samples is achieved. This, in turn, suggests that the presented classes succeed in describing the existent heterogeneity of different individuals regarding preferences towards time, cost and pooling attributes when choosing between individual and pooled on-demand services.



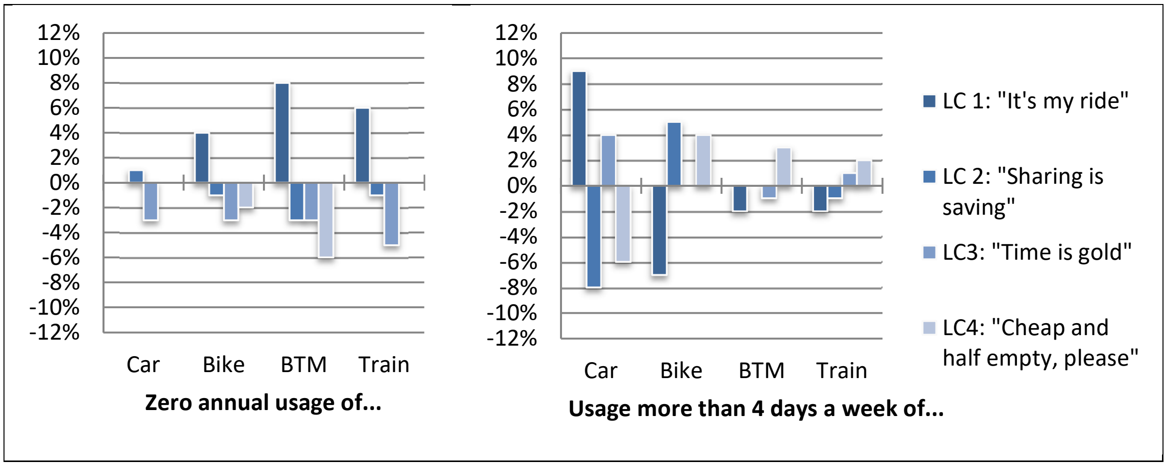


Figure 3. Class profiles regarding different socioeconomic characteristics and mode use frequency (percentage deviations from the estimation sample mean values)

4. Discussion and conclusions

New on-demand transport modes aim to improve urban mobility by shifting from the current car-centric paradigm. However, their impact on traffic reduction will depend on the willingness to share (WTS) of individuals. This study has analysed this willingness to share by comparing individuals' preferences towards individual and pooled rides. Additionally, it has identified different classes with distinct preferences regarding the WTS and value of time (VOT). Two reasons have led to our market segmentation approach: 1) there is still limited knowledge regarding the sharing aspect of on-demand services, and 2) on-demand modes allow for service differentiation, distancing from the "one size fits all" approach from current public transport. This research is set in (sub)urban areas of the Netherlands, and both commuting and free-time trip purposes have been investigated.

The research approach is as follows. We first designed a stated preference (SP) experiment that allowed us to quantify individuals' preferences towards pooled rides. We then investigated if strong preferences or fatigue was the main reason behind the existing non-trading behaviour in the experiment. We found statistical differences in time, cost and privacy attitudes regarding individuals with different trading behaviour, which pointed to the existence of strong preferences as paramount reason in non-trading. Subsequently, we performed a choice modelling analysis of the SP experiment. Two final models were selected and analysed: a mixed logit (ML) model, and a latent class choice model (LCCM).

The results of the ML model show a low willingness to pay for the increase of privacy offered by an individual ride in contrast to a pooled ride with just one or two extra passengers, in line with results from Stoiber et al. (2019) and Lavieri and Bhat (2019). This disutility is also best modelled as a per-ride disutility. On the other hand, the disutility of having four additional passengers is best modelled proportional to the in-vehicle time. This explains the larger percentage of respondents who only chose the individual alternative among those performing longer trips. It also suggests that the disutility regarding the number of passengers in a pooled ride is perceived differently depending on the number of passengers. To the best of the authors' knowledge, no prior research has included the four passenger alternative in the study of the WTS. Our study suggests that this may constitute a tipping point in the way that the sharing disutility is perceived, but further research is needed to confirm this hypothesis.

The latent class analysis identifies four distinct classes that explain taste variation. These classes have different specifications to represent how WTS, indicating that the disutility attributed to sharing is perceived differently among individuals. Individuals in "It's my ride" class (29% of the sample), attribute a high penalty to sharing (high WTS value) and have high a high value of time (VOT). As a result, they strongly prefer individual rides. Individuals in this class have different travel patterns than those in the other classes, with a higher car usage, and a lower bike and public transport usage. Individuals in the "Cheap and half empty, please" class (19%), also experience a high WTS penalty, but only when the ride is shared with four additional passengers. The remaining two classes show a low WTS penalty, and have time ("Time is gold", 24%) or cost ("Sharing is saving", 28%) as main driver in their choices. The somewhat higher shares of females in these two classes suggests a lower WTP penalty from this population segment.
Only around 20% of ridesourcing users currently opt for pooled rides (Gehrke et al., 2018) (with around 20% of the rides being pooled (Chen et al., 2018), (Uber, 2018)). Our research has identified that less than one third of individuals ("It's my ride" individuals) have strong preferences towards individual rides, and that these individuals characterise for having a more unimodal car behaviour. This suggests that: 1) the uptake of pooled rides can still increase considerably and 2) current car-centred individuals are less likely to share in the future on-demand mobility paradigm.

Based on our results, we derive the following two recommendations. First, measures that contribute to a higher cost benefit and a lower time disutility of pooled rides can have a big impact in their uptake, since cost-time considerations have been found much more important (for most respondents) than the sharing aspect. And second, a beforehand specification of the number of people that will be in the pooled ride (or a predicted estimate thereof) can also encourage individuals to use the pooled alternative. In the absence of such a prediction, users may refrain from opting for the pooled service in order to avoid the most adverse case in which they share their ride with four or more co-riders. Additionally, based on previous research, we also advise operators to ensure a feeling of safety in such pooled services (Morales Sarriera et al., 2017).

Despite the hypothetical nature of SP studies, this research provides a good understanding of preferences towards the pooling aspect of on-demand services, not possible to capture otherwise for a representative sample of the population. Future research could delve into how vehicle size, a larger number of additional passengers or uncertainties in the number of passengers affects the obtained WTS for pooled on-demand trips.

Acknowledgements

This work was funded by NWO (The Dutch Scientific Research Organization), as part of the SCRIPTS (Smart Cities Responsive Intelligent Public Transport Services) research project.

Declaration of interest

Willingness to share in on-demand services for different market segments

Declarations of interest: None

References

Al-Ayyash, Z., Abou-Zeid, M., Kaysi, I., 2016. Modeling the demand for a shared-ride taxi service: An application to an organization-based context. Transp. Policy 48, 169–182. https://doi.org/10.1016/j.tranpol.2016.02.013

Amirkiaee, S.Y., Evangelopoulos, N., 2018. Why do people rideshare? An experimental study. Transp. Res. Part F Traffic Psychol. Behav. 55, 9–24. https://doi.org/10.1016/j.trf.2018.02.025

Arentze, T.A., Molin, E.J.E., 2013. Travelers' preferences in multimodal networks: Design and results of a comprehensive series of choice experiments. Transp. Res. Part A Policy Pract. 58, 15–28. https://doi.org/10.1016/j.tra.2013.10.005

Atasoy, B., Glerum, A., Hurtubia, R., Bierlaire, M., 2010. Demand for Public Transport Services: Integrating Qualitative and Quantitative Methods, in: 10th Swiss Transport Research Conference.

Ben-Akiva, M., Lerman, S.R., 1985. Discrete choice analysis: theory and application to travel demand. Vol. 9. MIT press.

Bierlaire, M., 2003. BIOGEME: a free package for the estimation of discrete choice models, in: Swiss Transport Research Conference. https://doi.org/10.1017/CBO9781107415324.004

Burkhardt, J.E., Millard-Ball, A., 2006. Who is Attracted to Carsharing? Transp. Res. Rec. J. Transp. Res. Board 1986, 98–105. https://doi.org/10.1177/0361198106198600113

Centraal Bureau voor de Statistiek (CBS), 2018a. Bevolking; kerncijfers (in Dutch) [WWW Document]. URL https://opendata.cbs.nl/statline/#/CBS/nl/dataset/37296ned/table?ts=1541413888808 (accessed 11.5.18).

Centraal Bureau voor de Statistiek (CBS), 2018b. Bevolking; hoogstbehaald onderwijsniveau en onderwijsrichting (in Dutch) [WWW Document]. URL https://opendata.cbs.nl/statline/#/CBS/nl/dataset/82816NED/table?ts=1541415076597 (accessed 11.5.18).

Centraal Bureau voor de Statistiek (CBS), 2018c. Arbeidsdeelname; kerncijfers (in Dutch) [WWW Document]. URL https://opendata.cbs.nl/statline/#/CBS/nl/dataset/82309NED/table?ts=1541426506205 (accessed 11.5.18).

Centraal Bureau voor de Statistiek (CBS), 2018d. Regionale kerncijfers Nederland; Bevolking; Stedelijkheidsklasse (in Dutch) [WWW Document]. URL https://opendata.cbs.nl/statline/#/CBS/nl/dataset/70072ned/table?ts=1541423939562 (accessed 11.5.18).

Centraal Bureau voor de Statistiek (CBS), 1992. Sociale kerncijfers - Nieuwe maatstaf van stedelijkheid. Mens en Maatsch. (in Dutch).

Chen, X. (Michael), Zahiri, M., Zhang, S., 2017. Understanding ridesplitting behavior of on-demand ride services: An ensemble learning approach. Transp. Res. Part C Emerg. Technol. 76, 51–70. https://doi.org/10.1016/j.trc.2016.12.018

Chen, X., Zheng, H., Wang, Z., Chen, X., 2018. Exploring impacts of on-demand ridesplitting on mobility via real-world ridesourcing data and questionnaires. Transportation (Amst). https://doi.org/10.1007/s11116-018-9916-1

ChoiceMetrics, 2012. Ngene 1.1.1 User Manual and Reference Guide. Sydney, Australia.

Clewlow, R.R., Mishra, G.S., 2017. Shared Mobility: Current Adoption, Use, and Potential Impacts on Travel Behavior, in: TRB 96th Annual Meeting Compendium of Papers, Washington D.C.

Gehrke, S.R., Felix, A., Reardon, T., 2018. Fare Choices. A Survey of Ride-Hailing Passengers in Metro Boston.

Hess, S., 2014. Latent class structures: taste heterogeneity and beyond, in: Handbook of Choice Modelling. pp. 311–330. https://doi.org/10.4337/9781781003152.00021

Hess, S., Rose, J.M., Polak, J., 2010. Non-trading, lexicographic and inconsistent behaviour in stated choice data. Transp. Res. Part D Transp. Environ. 15, 405–417. https://doi.org/10.1016/j.trd.2010.04.008

Hoogendoorn-Lanser, S., Schaap, N.T.W., Olde Kalter, M.J., 2015. The netherlands mobility panel: An innovative design approach for web-based longitudinal travel data collection. Transp. Res. Procedia 11, 311–329. https://doi.org/10.1016/j.trpro.2015.12.027

ITF, 2017. Shared Mobility: Simulations for Helsinki, International Transport Forum Case-Specific Policy Analysis. Paris.

Kim, J., Rasouli, S., Timmermans, H., 2017. Satisfaction and uncertainty in car-sharing decisions: An integration of hybrid choice and random regret-based models. Transp. Res. Part A Policy Pract. 95, 13–33. https://doi.org/10.1016/j.tra.2016.11.005

Krueger, R., Rashidi, T.H., Rose, J.M., 2016. Preferences for shared autonomous vehicles. Transp. Res. Part C Emerg. Technol. 69, 343–355. https://doi.org/10.1016/j.trc.2016.06.015

Lavieri, P.S., Bhat, C.R., 2019. Modeling individuals’ willingness to share trips with strangers in an autonomous vehicle future. Transp. Res. Part A Policy Pract. 124, 242–261. https://doi.org/10.1016/j.tra.2019.03.009

Liu, Y., Bansal, P., Daziano, R., Samaranayake, S., 2018. A framework to integrate mode choice in the design of mobility-on-demand systems. Transp. Res. Part C Emerg. Technol. https://doi.org/10.1016/j.trc.2018.09.022

Molin, E., Mokhtarian, P., Kroesen, M., 2016. Multimodal travel groups and attitudes: A latent class cluster analysis of Dutch travelers. Transp. Res. Part A Policy Pract. 83, 14–29. https://doi.org/10.1016/j.tra.2015.11.001

Morales Sarriera, J., Escovar Álvarez, G., Blynn, K., Alesbury, A., Scully, T., Zhao, J., 2017. To share or not to share: investigating the social aspects of dynamic ridesharing, in: Transportation Research Board 96th Annual Meeting. pp. 109–117. https://doi.org/10.3141/2605-11

Rubin, J., 2011. Choosing Transit: The Influence of Past Travel Behavior, Attitudes and Habits on Present Choices. University of California, Berkeley.

Spears, S., Houston, D., Boarnet, M.G., 2013. Illuminating the unseen in transit use: A framework for examining the effect of attitudes and perceptions on travel behavior. Transp. Res. Part A Policy Pract. 58, 40–53. https://doi.org/10.1016/j.tra.2013.10.011

Steck, F., Kolarova, V., Bahamonde-Birke, F., Trommer, S., Lenz, B., 2018. How Autonomous Driving May Affect the Value of Travel Time Savings for Commuting. Transp. Res. Rec. https://doi.org/10.1177/0361198118757980

Stocker, A., Shaheen, S., 2016. Shared Automated Vehicles : Review of Business Models.

Stoiber, T., Schubert, I., Hoerler, R., Burger, P., 2019. Will consumers prefer shared and pooled-use autonomous vehicles? A stated choice experiment with Swiss households. Transp. Res. Part D Transp. Environ. https://doi.org/10.1016/j.trd.2018.12.019

Tachet, R., Sagarra, O., Santi, P., Resta, G., Szell, M., Strogatz, S.H., Ratti, C., 2017. Scaling Law of Urban Ride Sharing. Sci. Rep. 7, 42868. https://doi.org/10.1038/srep42868

Uber, 2019. Uber - Facts & Figures as of December 2018 [WWW Document]. URL https://www.uber.com/en-GB/newsroom/company-info/ (accessed 5.16.19).

Uber, 2018. Introducing uberPOOL: A New Way to Share [WWW Document]. URL https://www.uber.com/en-AU/newsroom/uberpoolau/ (accessed 5.17.19).

Vermunt, J.K., Magidson, J., 2016. Technical Guide for Latent GOLD 5 . 1: Basic, Advanced, and Syntax, Statistical Innovations Inc.

Walker, J., Ben-Akiva, M., 2002. Generalized random utility model. Math. Soc. Sci. 43, 303–343. https://doi.org/10.1016/S0165-4896(02)00023-9

Appendix

Table A. 1. Attribute levels of the SP experiment

	Short version			Medium version		
	Level 1	Level 2	Level 3	Level 1	Level 2	Level 3
Expected time (Individual ride) [min]	10	15	18	20	25	28
Extra expected time (Shared ride) [min]	3	6	9	4	7	12
Number of other additional passengers (Shared ride) [add. passenger]	1	2	4	1	2	4
Cost (Shared ride) [Euro]	2	4	6	3	5	7
Extra cost (Individual ride) [Euro]	0.5	2.2	3	0.6	2.2	3