Modelling the role of consideration of alternatives in mode choice: An application on the Rome-Milan corridor

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Abstract

In this paper, we investigate the role of consideration of alternatives in mode choice models. Consideration effects provide additional insights into the travellers' decision-making process and can help policymakers and private operators to make better informed decisions. On the Rome-Milan corridor in Italy, where seven alternative modes of transport are available, we administered a stated choice (SC) experiment. The available modes of transport vary substantially in terms of their characterising attributes, particularly travel time. Answers to supplementary questions on consideration of the different modes of transport and on the presence of thresholds on the travel time attribute indicate travellers are less likely to consider the *slower* modes. Two model specifications, in which consideration for the slower alternatives is treated probabilistically using both sets of response to supplementary questions on consideration and thresholds, are proposed and contrasted against a model formulation which assumes all alternatives are considered. Accounting for consideration of alternatives has direct reflections on choice probabilities and parameter estimates, and indirect effects on willingness-to-pay measures. We also observe that elements conventionally attributed to unobserved preference heterogeneity can possibly be ascribed to consideration effects.

Keywords: Consideration of alternatives, mode choice, willingness-to-pay

1. Introduction

The question which of the available alternatives an individual decision-maker considers when making a choice has been a topic of interest in the transportation and marketing literature over the last decades (Manski, 1977; Swait and Ben-Akiva, 1987a-b; Shocker et al., 1991; Roberts and Lattin, 1997; Swait, 2001a-b; Cantillo and Ortúzar, 2005; Hauser, 2014). Behaviourally, considering only a subset of the available alternatives is consistent with the use of task-simplifying heuristics. The latter can be driven by, amongst other things, (self-imposed) thresholds on attributes (e.g. maximum price levels), or searching costs.

From an industry perspective, a more comprehensive understanding of the role consideration plays in the decision-making process might provide new opportunities to develop more effective marketing and pricing strategies (Pancras, 2010; Draganska and Klapper, 2011). Demand models not accounting for consideration have been shown to provide less precise - or even biased - parameter estimates and forecasts of consumer choices (Williams and Ortúzar, 1982; Swait, 1984).

In this paper, we aim to provide additional evidence that accounting for consideration effects in choice models provides insights in terms of individuals' preferences and allows for a more realistic representation of the consumer's decision-making process. In particular, we collect information on consideration of alternatives and thresholds on attributes during a stated choice (SC) experiment in the context of mode choice decisions on the Rome-Milan corridor, in Italy. Here, seven alternatives (i.e. modes of transport) are available to travellers. However, the alternatives vary significantly in terms of their characterising attributes, particularly travel time, and the additional information on consideration indicate that travellers are indeed less likely to consider the *slower* modes.

We propose two model specifications embedded in Manski's two-stage framework (1977). In order to identify consideration probabilities, we alternatively make use of respondents' stated consideration of alternatives and stated thresholds on travel time. The model specifications are contrasted against a more traditional formulation where all alternatives are assumed to be considered. The respective models are contrasted in terms of parameter estimates and model fit. In addition, we also explore the implications of accounting for consideration effects on willingness-to-pay measures and forecasted market shares.

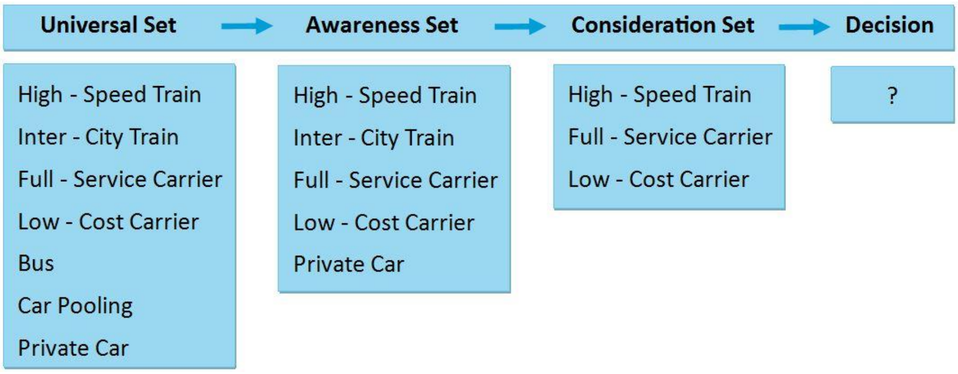
Treating the consideration of *slower* alternatives probabilistically, by definition, increases the choice probability of the *faster* ones. We observe reflections of this on parameter estimates and willingness-to-pay measures, particularly in the first model, where direct (stated) indicators of consideration are used. The second approach shows an improvement in model fit, which is due to the estimation of additional parameters identifying consideration probabilities using indirect measures of it (thresholds). In both models, elements conventionally attributed to unobserved preference heterogeneity can possibly be ascribed to consideration effects.

The remainder of the paper is as follows. We review the literature on the role of consideration in the consumer's decision-making process in Section 2. Then, we describe the case study and the available data in Section 3. Section 4 lays out the empirical strategy and explains the proposed models. In Section 5, we report and discuss the estimation and forecasting results. Finally, in Section 6, we draw some conclusions from our work.

2. Literature review

The marketing literature (for a review see Shocker et al. 1991) distinguishes between the *universal* choice set - containing all the alternatives from which individuals can choose -, the *awareness* set - the subset of alternatives individuals are actually aware of -, and the *consideration* set - including only considered alternatives (see Figure 1).

Figure 1. Successive sets involved in the decision-making process. An example of transport mode choice.



In this paper, we concentrate on the consideration set, which is defined as the subset of alternatives the individual would consider, or those "acceptable" for her/him (Howard and Sheth, 1969; Wright and Barbour, 1977). Consideration sets are assumed to be relevant not only when the number of alternatives is large (e.g. residential choice and consumer goods), but also when the number of alternatives is limited (e.g. in the case of transport mode choice).

Manski (1977) proposed a two stage decision-making process, with a consideration stage preceding choice. According to his formulation, all $2^J - 1$ (where J is the number of available alternatives) possible consideration sets have a probability of being the *true* consideration set. The expected (or unconditional) choice probability is then defined as the sum of weighted conditional (upon the consideration set) choice probabilities. Here, the consideration set probabilities act as weights. Although this model is behaviourally appealing, it suffers from two main limitations. First, it becomes computationally infeasible as the number of alternatives increases. For example, with 5 alternatives, there are already 31 possible consideration sets, and this number increases to 63 with 6 alternatives, 127 with 7 alternatives etc.. Second, the question arises as to how consideration can be separated from ‘true’ preferences. That is, it is not trivial (and perhaps impossible) to identify with certainty which factors drive the two stages, i.e. consideration and choice (Horowitz and Louviere, 1995). In addition, it is not unlikely that the drivers for both stages are correlated.

Based on Manski’s two-stage model, several alternative formulations have been proposed. Gaudry and Dagenais (1979) proposed the so-called *dogit* model, aimed at overcoming the first shortcoming, and hypothesising that only a limited number of consideration sets are actually feasible. They assume that individuals might either consider all alternatives (i.e. the consideration set coincides with the universal set), or they might be captive to just one alternative (i.e. the consideration set contains only one alternative).

With respect to the second shortcoming, Swait and Ben-Akiva (1987a, 1987b) depart in their *parameterised logit captivity model* from the *dogit* model by parameterising the captivity odds as functions of socio-economic characteristics of the individual and attributes of the alternative. A similar approach has been proposed in Basar and Bhat’s (2004) *probabilistic choice set multinomial logit* model. The latter assumes that an alternative is excluded from the choice set if its consideration utility is lower than some threshold consideration utility level.

Cantillo and Ortúzar (2005) propose a two-stage semi-compensatory model where consideration is based on thresholds on attributes. In the first stage, alternatives are rejected when a threshold on an attribute is surpassed (i.e. the non-compensatory process). In the second stage, choice is based on a fully compensatory Random Utility Maximisation (RUM) model. In particular, they try to identify the distribution of attributes’ thresholds in the population.

Other authors proposed similar approaches to the one used by Cantillo and Ortúzar (2005), with the only difference being that they modelled the entire decision-making process as a single-stage process. Consideration of alternatives is no longer deterministically identified through an acceptance/rejection mechanism, but rather treated on a continuous scale in the utility function. For example, Cascetta and Papola (2001) introduce an inclusion function in the utility functions discounting the utility of alternatives perceived to be unconsidered. The unobserved degree of consideration is modelled as a function of the attributes of the alternatives and/or of the individual (see also Martinez et al., 2009).

More recently, authors started collecting supplementary information on thresholds on attributes (Swait, 2001a; Hensher and Rose, 2012), and/or acceptability of the alternatives (Hensher and Rose, 2012; Hensher and Ho, 2015) during SC surveys. This information has been used to account for possible heteroscedasticity and/or introduce penalties in the utilities. Swait (2001a) tested the direct use of self-reported thresholds on attributes to identify consideration. In a way, this might be seen as a means to avoid possible confounding between the two stages, i.e. consideration and choice.

In this paper, we also use additional information on individuals' processing strategies provided during a SC experiment (namely *stated consideration* of alternatives and *stated thresholds*). While in a traditional multinomial logit model, choices are only explained by preferences, the Manski model allows for additional flexibility, but this does not ensure that consideration effects are captured. Therefore, a better approach to measure consideration within this model might be to collect (and use) indicators of this stage.

We propose two models accounting for probabilistic consideration of a subset of alternatives. In the first model, information on *stated consideration* is directly used to identify consideration probabilities. In the second model, a binding function assigns a probability of consideration at each choice occasion comparing the presented attribute levels with the *stated thresholds*. The two proposed approaches are then contrasted against a more traditional formulation which instead assumes full consideration of all alternatives.

3. The case study

3.1. The Rome-Milan Corridor

The Rome-Milan corridor represents an interesting case study to investigate consideration effects among medium-long distance passengers. Seven alternatives (i.e. transport modes) are available: high-speed and inter-city trains, full-service and low-cost flights, bus and car-pooling services, and private car. These alternatives are not homogeneous in terms of core (e.g. travel time and cost), and soft attributes (e.g. Wi-Fi availability and comfort). Hence, it is reasonable to assume that travellers might not consider all the alternatives in their mode choice decisions.

In the high-speed rail (HSR) market, *Trenitalia* and *Nuovo Trasporto Viaggiatori* offer together 65 daily services in both directions, which take less than 3 hours. *Trenitalia* also offers 3 Inter-City (IC) trains. These are slower and can take up to 7 hours. In the air market, the full-service carrier (FSC) *Alitalia* offers 25 services to/from Rome and Milan city airports (Fiumicino and Linate) and 3 to/from Milan Malpensa airport. At the latter airport, *Alitalia* competes with the low-cost carrier (LCC) *EasyJet* (2 services). A dozen of scheduled coach services are also offered by *Stagecoach-Megabus*, *Flixbus*, and *Baltour*, including over-night services. At the time of the data collection (April-May 2016), these coach services were characterised by cheap fares (from €1 with *Stagecoach-Megabus*), and travel times ranging between 7 and 11 hours.[1] Finally, the car alternative on this corridor is available as a private or a shared mode of transport. The car-pooling network *Bla-bla-car* connects riders and passengers willing to share the cost of a 6-hour trip.

The Italian Authority for Transport Regulation (ART, 2015) provides the official figures with respect to modal shares on this corridor. In 2014, 24% of passengers travelled by air, 65% by train, and the remaining 11% by bus and car.

[1] In June, 2016, the Italian branch of *Stagecoach-Megabus* was sold to *Flixbus*, and €1 fares are no longer available.

3.2. Survey design and descriptive statistics

In the absence of an online journey planner where all alternatives are available for simultaneous comparison, an individual physically needs to: 1) decide which alternatives to consider from those s/he is aware of, and search on the respective websites; 2) process the information available regarding price and non-price attributes of the considered alternatives; 3) end the process by choosing the preferred alternative or decide to consider more alternatives and repeat steps 1-3 until s/he has made the choice. In light of this, some relevant options might be left out due to unawareness or searching costs.

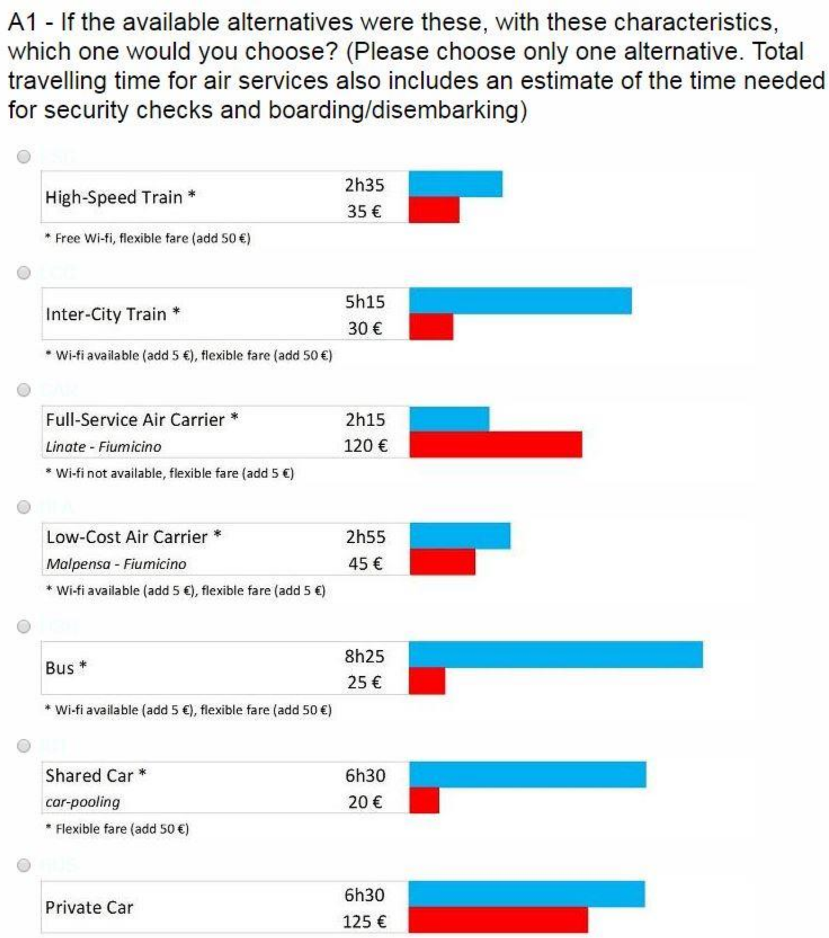
The advent of the Internet has substantially lowered searching costs. Websites such as www.goeuro.com and www.rome2rio.com allow users to compare services for all available modes on a specific route according to travel time, cost etc., and offer the opportunity to purchase tickets. At the same time, alternatives that consumers were previously unaware of might now be chosen. Transport operators report increasing shares of tickets being purchased online on their official websites[2] and for some the internet is the only available marketplace.

Given these premises, we designed a SC survey mimicking a real purchasing decision through an online journey planner. The experiment was conducted in Rome and Milan between April and May, 2016.[3] A total of 209 on-site face-to-face TAPI (Tablet Assisted Personal Interview) surveys were administered to travellers going from Rome to Milan (and *vice versa*) while waiting at the platform for their train (57%), at the bus terminals (17%), or in the proximity of the airports (12%). We also administered a smaller portion of surveys online (8%), and in two service stations on the A1/E35 highway, located around half way between Rome and Milan, in the proximity of Bologna (6%).[4]

[2] The HSR operator Trenitalia reports that more than 50% of tickets are purchased online (2017).
[3] Prior to final administration to travellers on the corridor, the survey has been individually discussed with international Masters' and PhD students in the transport discipline.
[4] The response rate was higher at bus and train stations (≈ 50%) than at airports and service stations (≈ 20%).

Each respondent completed 6 choice tasks, and we used a layout similar to the one displayed by the website www.goeuro.com (Figure 2). To avoid possible ordering effects, we randomised the order of the presented alternatives across respondents.

Figure 2. The layout of the choice tasks.



The attributes of the alternatives were travel time[5], travel cost, ticket flexibility, and level of connectivity on-board (Wi-Fi). The attributes all referred to a standard one-way trip between Rome and Milan. In Table 1, we report the ranges for travel time and cost for all

[5] We acknowledge that access/egress time in large cities might play an important role in situations like the one modelled in this experiment. However, due to software restrictions it was not possible to customise the experiment depending on respondents' departure/arrival place. However, we collected information on respondents' distance (in minutes from/to departure/arrival place) and HSR stations, principal and secondary airports, and bus terminals. This information was accordingly used as a respondent-specific explanatory variable in the choice model.

alternatives on this particular route at the time of the SC survey (*current ranges*, i.e. as displayed on operators' websites), as well as those used in the survey design. The latter were designed around the former, or around values which are expected to be feasible in the near future. For example, the HSR operator *Trenitalia* has already announced it will reduce travel time between the two cities to 2h20 in the upcoming months by increasing speed up to 400km/h. With respect to ticket flexibility, we used three levels, i.e. the possibility of changing the ticket for free, or to do it with a fee of €5 or €50. Wi-Fi availability was also presented in three levels, namely not available, available for free, or available at a fee of €5. We set the choice tasks using a Bayesian D-efficient experimental design, with *priors* drawn from the literature or based on our expectations (Rose et al., 2008). Finally, we decided not to remove strictly dominant alternatives because the independent usage of price discrimination strategies by transport operators sometimes allows for some alternatives to be cheaper and faster than others.

Table 1. Current ranges and survey attribute levels.

	Current ranges				**Attribute levels**	
	Travel time		*Travel cost (€)*		*Travel time (h/min)*	*Travel cost (€)*
Alternatives	*min*	*max*	*min*	*max*		
HSR	2h55	4h28	19.9	209	2h15, 2h35, 2h55, 3h20, 3h40	20, 35, 50, 90, 120
IC	6h27	6h50	9	79	5h15, 6h, 6h45, 7h30, 8h15	10, 30, 45, 60, 80
FSC	2h20[1]		55.71	244.71	1h45, 2h, 2h15, 2h30, 2h50	50, 80, 120, 180, 280
LCC	2h25[1]		44.73	267.23	1h50, 2h05, 2h20, 2h35, 2h55	30, 45, 75, 110, 220
Bus	7h25	10h45	1	29	6h15, 7h20, 8h25, 9h30, 10h35	1, 10, 15, 20, 25
Car-pooling[2]	5h41		25	45	5h, 5h45, 6h30, 7h15, 8h	15, 20, 25, 30, 40
Private car[3]	6h22		99 (41 toll/58 fuel)		5h, 6h, 6h30, 7h15, 8h	60, 80, 100, 125, 150

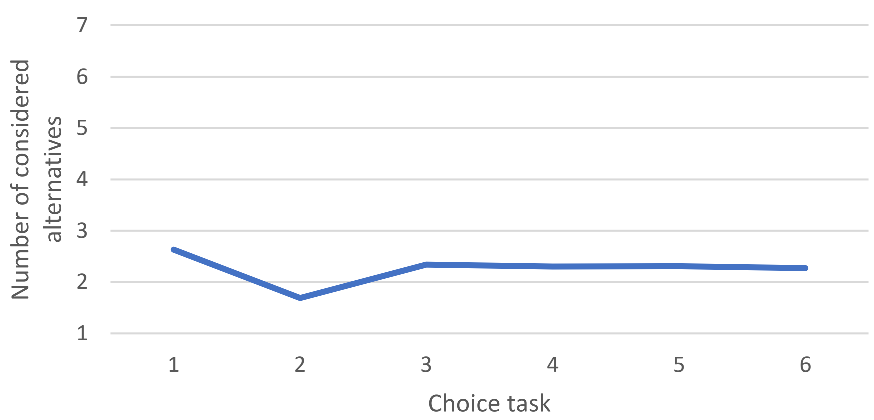
Note: 1 - includes an estimate of in-flight and boarding time as reported by www.goeuro.com; 2 - www.blablacar.it; 3 - www.viamichelin.com.

At the end of each choice task we asked respondents to state which non-chosen alternatives they had considered. The following question format was used:

"*Which other alternatives did you consider? (Please select all the other considered alternatives)*"

In Figure 3, we show a plot of the average number of considered alternatives (including the chosen one) across choice tasks. Overall, the average number of considered alternatives is 2.26; this number is slightly larger for the first choice task (2.63), and lower for the second choice task (1.69). For the sake of completeness, in around half of the choices (49%), respondents stated to only have considered 2 alternatives. Respondents stated to have considered just one and three alternatives in respectively 22% and 19% of the choices. Only in 2% of the choices respondents stated to have considered all seven alternatives.

Figure 3. The average number of considered alternatives.



Prior to collecting socio-economic information, but after presenting the choice tasks, we asked respondents to provide their self-imposed thresholds on total travel time and cost. Moser and Raffaelli (2014) argue such thresholds should be based on previous experience and not on the information contained in the experiment. This suggests collecting thresholds right at the beginning of the experiment. However, we believe that prior elicitation can similarly condition answers to the choice tasks. Given that there is evidence that the positioning of threshold elicitation questions has no significant influence on parameter estimates (Bush, 2008), we decided to collect this information after the SC tasks.

4. Methodology

Mode choice is modelled using RUM (McFadden, 1974), where the utility of alternative *i* for individual *n* in choice task *t* is given by (Equation 1):

$$U_{i,n,t} = V_{i,n,t} + \varepsilon_{i,n,t} \quad (1)$$

$V_{i,n,t}$ is a function of an alternative specific constant, of the attributes of the alternative (e.g. travel time, travel cost, Wi-Fi availability, and ticket flexibility), of individual characteristics in relation to the alternative (e.g. access/egress time to/from rail and bus stations and airports), and of individual socio-economic and context-specific characteristics, while $\varepsilon_{i,n,t}$ is the random component. We define the probability of choosing alternative *i* from the *J* available alternatives individual's comprised in choice set $C_{n,t}$ by (Equation 2):

$$P_{i,n,t} = P\left(U_{i,n,t} \geq U_{j,n,t}, \forall\, j \neq i \in C_{n,t}\right) \quad (2)$$

For an alternative to be chosen, alternative *i* should provide the highest overall utility over all available alternatives in the choice set. Assuming that the error terms are *iid* type I extreme value distributed, this probability can be represented by the multinomial logit model (MNL, Equation 3):

$$P_{i,n,t} = \frac{exp(V_{i,n,t})}{\sum_{j \in C_{n,t}} exp(V_{j,n,t})} \quad (3)$$

Besides accounting for unavailable alternatives from the universal set (e.g. due to not owning a car), we allow individuals to consider only a subset of the available alternatives.

Hence, choices are made over $C^*_{n,t} \subseteq C_{n,t}$. As a result, the choice probability for considered alternatives increases relative to the MNL model in Equation 3, given that the number of alternatives included in the denominator decreases.

Manski (1977) proposed a probabilistic model averaging consideration set specific conditional choice probabilities $P_{i,n,t}(C^*_{n,t})$, where the probability of using a particular consideration set $\pi_{n,t}\left(C^*_{n,t}\right)$ is used as a weight in the averaging process (Equation 4):

$$P_{i,n,t} = \sum_{C^*_{n,t} \subseteq C_{n,t}} \pi_{n,t}\left(C^*_{n,t}\right) P_{i,n,t}(C^*_{n,t}) \tag{4}$$

We compare two model formulations using supplementary information on stated consideration of the alternatives and stated thresholds on attributes, respectively. This information is used to derive the consideration probability of each alternative. In both models, we assume that probabilistic consideration only applies to a subset of alternatives - rather than to all the available alternatives-, and, at the choice-level, we define the probability of observing consideration set, $\pi_{n,t}\left(C^*_{n,t}\right)$, by (Equation 5):

$$\pi_{n,t}\left(C^*_{n,t}\right) = \prod_{n,t,j \in C^*_{n,t}} W_{j,n,t} * \prod_{n,t,j \notin C^*_{n,t}} \left(1 - W_{j,n,t}\right) \tag{5}$$

The consideration probability for alternative $j, W_{j,n,t}$, is independent of the consideration probability of the other alternatives. The two model specifications differ in the way $W_{j,n,t}$ is defined. In the first model specification, the predicted consideration probability, $\widehat{W_{J,n,t}}$, is estimated separately from the choice model using a binary logit model on stated consideration (Equation 6):

$$\widehat{W_{j,n,t}} = \frac{1}{1+\exp\left(\alpha_{j,n}+Z_{j,n,t}\right)}, \tag{6}$$

where $\alpha_{j,n}$ is a constant and $Z_{j,n,t}$ is a function of the attributes of alternatives j, and of individual socio-economic and context characteristics.

In the second model, we identify $W_{j,n,t}$ using information on thresholds on attributes. In particular, we specify a binding function (Equation 7), which accounts for the level of adherence of an attribute k (e.g. travel time) of that alternative to the respective predicted threshold, $\widehat{max_{k,n}}$, which is derived after applying a linear regression on the stated threshold.

$$W_{j,n,t} = \frac{1}{1+\exp\left(\alpha_{j,n}+\beta_{i,n,t}\left(k_{i,n,t}-\widehat{max_{k,n}}\right)\right)} \tag{7}$$

The use of a probabilistic binding function based on the predicted thresholds to identify consideration probabilities deviates from the approach taken by Swait (2001a), who employed stated thresholds. Hess and Hensher (2013) recommend not to directly employ stated indicators, such as ours for stated consideration and thresholds, for two reasons. First, these might be highly dependent on the phrasing of the survey and not correspond to an actual behaviour (i.e. there is potential for measurement error). Second, indicators of processing strategies are likely to be correlated with the error of the choice model, and therefore potentially subject to endogeneity bias.

Finally, we account for the presence of unobserved preference heterogeneity in the choice model, which might be due to unobserved characteristics of the individual or the alternatives. Therefore, we estimate a mixed logit model (MMNL) with random alternative specific constants. The MMNL models are estimated using maximum simulated likelihood and 500 Halton draws. Accounting for the role of consideration introduces additional flexibility in the model specification and if we do not also take into account unobserved preference heterogeneity, we might end up putting too much emphasis on the role of consideration.

5. Results and discussion

5.1 Stated consideration of alternatives and thresholds on the travel time attribute

We assume that respondents always consider the *faster* alternatives, i.e. HSR, FSC, and LCC, which are also more expensive. For the *slower* modes, i.e. IC, bus, and car-pooling, consideration will be modelled probabilistically. These assumptions are supported by the self-reported consideration data as well as choice data. On average, the self-reported level of consideration for faster modes is higher than that for slower ones (HSR: 74%; LCC: 37%; FSC: 31%; bus: 25%; IC: 24%; car-pooling: 21%; private car: 14%). At the same time, we observe that a large share of respondents (94%) chose at least once one the faster alternatives, while slightly more than half of them (52%) chose at least once one of the remaining, slower, alternatives.

Moreover, we further assume that the private car alternative is always considered when stated to be available. As a result of modelling consideration probabilistically on only three alternatives, the number of possible consideration sets is reduced to eight, and we are therefore less exposed to the first problem associated with Manski's framework as discussed in Section 2.

Table 2a presents the results of three binary logit models explaining stated consideration for the three modes associated with consideration effects. The longer the travel time on a mode, the less likely it is to be considered. Indeed, travel time is found to be a less important driver of consideration for busses (i.e. the slowest mode) compared to IC and car-pooling. Similar effects are found in relation to travel cost. Bus is the cheapest alternative, which might explain why travel cost was found to be not significant in explaining its stated consideration. Stated consideration for IC increases when Wi-Fi is available on-board; and providing ticket flexibility increases the probability of considering bus. The probability of considering car-pooling is higher amongst higher educated travellers, but is lower for females. The former result can be explained by the fact that car-pooling has a high ICT component, where seats can only be booked online. The latter result is most likely due to a lower perception of safety.[6] Finally, the probability of consideration for all three slow modes decreases with age and income level, and if the trip is paid by the employer or family members and (or) friends.

Table 2a. Logistic regressions of stated consideration - Results.

	Inter-City Train		**Bus**		**Car-Pooling**	
Regressors	*est.*	*t-stat(0)*	*est.*	*t-stat(0)*	*est.*	*t-stat(0)*
Constant	2.256	2.07	2.929	3.28	0.973	0.65
Travel time	-0.008	-2.92	-0.004	-2.54	-0.009	-3.60
Travel cost	-0.040	-5.08			-0.042	-1.91
Wi-fi free (vs not available)	1.505	4.37				
Wi-fi 5 € (vs not available)	1.009	2.47				
Flexible ticket free (vs 50 €)			0.920	2.35		
Flexible ticket 5 € (vs 50 €)			0.921	2.56		
Female	0.590	1.94			-1.595	-4.66
Age (18-24) - base						
Age (25-34)			-1.282	-3.36		
Age (35-49)			-1.747	-2.84	-1.197	-2.25
Age (50+)			-0.774	-0.95	-1.973	-1.87
Income (0-500 €/month) - base						
Income (500-1.000 €/month)	-1.056	-1.70	-1.060	-1.84		
Income (1.000-2.000 €/month)	-1.050	-1.72	-0.729	-1.28		
Income (2.000-4.000 €/month)	-1.124	-3.00	-2.667	-6.06	-1.753	-4.41
Income (4.000+ €/month)	-4.034	-6.98	-4.965	-5.75	-3.080	-4.25
Income (not declared)	-4.127	-6.60	-3.899	-5.33	-4.752	-5.11
Education (years)					0.259	3.71
Paid employer (vs paid her/himself)			-2.834	-4.88	-2.087	-3.90
Paid family/friends (vs paid her/himself)	-0.812	-1.87	-2.089	-4.58	-0.772	-1.78
Predicted consideration (mean)	0.24		0.25		0.21	
Predicted consideration (min)	0.02		0.01		0.00	
Predicted consideration (max)	0.67		0.77		0.77	
Log-Likelihood (null)			-856.73			
Log-Likelihood (final)	-604.77		-547.35		-529.69	

Note: for all models: observations = 1254, respondents = 209

[6] The car-pooling network *Bla-bla-car* already offers the possibility for female travellers of sharing the ride exclusively with other female travellers, opting for the so-called "pink ride". However, in the design of this study we did not include the pink-ride as a separate attribute for car-pooling.

In Table 2b, we present the results of a linear regression (OLS) of the stated thresholds on travel time (in the logarithm form) over respondents' socio-economic characteristics and trip purpose. This closely matches the approach taken in the models explaining stated consideration for the slower modes. Consideration for these slow modes is now explained by the presence of self-imposed thresholds on travel time. Results shows that, ceteris paribus, female respondents have a lower self-imposed threshold on travel time relative to male respondents. Moreover, the time threshold is also lower for those aged 50 and over, with more years of education, travelling for business purposes, whom the trip was for paid by the employer and having a monthly income higher than 2,000 €/month.

Table 2b. Regressions of stated thresholds on travel time - Results.

Regressors	*est.*	*t-stat(0)*
Constant	6.517	77.93
Female	-0.120	-4.74
Age (50+)	-0.179	-4.28
Education (years)	-0.026	-5.02
Income (2,000-4,000 €/month)	-0.211	-6.62
Income (4,000+ €/month)	-0.287	-6.89
Income (not declared)	-0.233	-5.14
Paid employer	-0.121	-3.34
Trip purpose (business)	-0.139	-4.11
Predicted thresholds (mean)	328.4	
Predicted thresholds (min)	182.2	
Predicted thresholds (max)	483.3	
Adjusted R-squared	0.25	

Note: observations = 1254, respondents = 209.

5.2 Consideration of alternatives and choice

We present the results for three choice models in Table 3. Model 1 represents a mixed logit model (MMNL) with normally distributed alternative specific constants (ASC). This model does not account for the role of consideration in mode choice. It assumes that all alternatives are fully considered. Models 2 and 3 probabilistically account for consideration of the slower alternatives. The latter two models are compared against Model 1 in terms of parameter estimates and goodness of fit. In addition, we explore the implications of accounting for consideration effects on willingness-to-pay indicators and forecasted aggregate market shares.

For Model 1, car-pooling was found to be the minimum variance alternative, and therefore used as baseline alternative to prevent over-identification of the model (Walker et al., 2007). The ASCs reveal a strong preference for FSC over car-pooling, while the opposite occurs for private car. Indeed, private car was chosen in only very few occasions (21 out of 1254 choices).

Table 3. Estimated models - Results.

	Model 1		Model 2		Model 3	
Regressors	*est.*	*t-stat(0)*	*est.*	*t-stat(0)*	*est.*	*t-stat(0)*
ASC choice HSR	1.510	2.07	-0.588	-0.60	1.449	1.81
ASC choice IC	0.708	1.53	1.447	1.19	0.465	0.62
ASC choice FSC	3.843	3.78	1.915	1.67	4.744	4.69
ASC choice LCC	1.536	1.46	-1.125	-0.92	1.837	1.71
ASC choice Bus	-0.629	-1.25	-1.231	-1.40	-1.696	-2.09
ASC choice Private Car	-3.431	-1.32	-5.302	-1.76	-2.707	-1.08
Travel time alone HSR	-0.010	-3.88	-0.010	-3.30	-0.008	-3.15
Travel time alone IC	-0.010	-6.67	-0.015	-4.22	-0.009	-4.04
Travel time alone FSC	-0.021	-4.94	-0.017	-3.94	-0.017	-4.450
Travel time alone LCC	-0.011	-2.84	-0.008	-2.89	-0.008	-2.34
Travel time alone Bus	-0.008	-7.06	-0.010	-4.83	-0.007	-3.81
Travel time alone Car-Pooling	-0.010	-6.00	-0.012	-4.71	-0.007	-3.01
Travel time alone Private Car	0.002	0.57	0.003	0.59	0.002	0.42
Travel time with others	1.363	1.70*	1.263	1.29*	1.524	1.59*
Travel cost paid themselves	-0.052	-9.24	-0.057	-6.92	-0.057	-7.47
Travel cost paid themselves, income na	-0.038	-4.38	-0.044	-3.67	-0.040	-4.04
Lambda income	-0.220	-3.66	-0.266	-3.70	-0.287	-3.71
Travel cost paid employer	0.414	-6.99*	0.357	-7.89*	0.373	-7.84*
Travel cost paid family/friends	0.735	-1.97*	0.804	-1.14*	0.693	-2.05*
Wi-fi (free)	0.242	1.54	0.280	1.30	0.284	1.58
Wi-fi (€5)	0.102	0.78	0.098	0.56	0.089	0.61
Flexible ticket (free)	0.353	2.72	0.574	3.07	0.439	2.86
Flexible ticket (€5)	0.354	2.93	0.523	3.23	0.445	3.23
Access/egress time main airports	-0.037	-4.12	-0.035	-4.38	-0.033	-4.08
Access/egress time secondary airports	-0.017	-2.38	-0.018	-2.61	-0.018	-2.57
Female FSC	0.738	1.70				
Fidelity card (FSC)	2.105	3.94	1.947	4.37	1.960	4.28
Business (HSR)	1.144	3.24	0.824	2.62	0.808	2.66
Business (Private car)			-3.011	-2.65	-3.371	-3.15
Higher-education (all but HSR)	-0.788	-2.76			-0.880	-2.86
Higher-education (car)			-2.457	-2.28		
Age 25-34 (FSC)	1.061	1.76				
Age 25-34 (LCC)	1.191	2.37	0.656	1.84	0.674	1.96
Age 35+ (HSR)	1.173	2.41				
Age 35+ (IC)	0.896	2.08				
Age 35+ (FSC)	2.453	3.43				
Age 35+ (LCC)	1.743	2.86				
Sigma parameters (random coefficients)						
ASC choice HSR (sigma)	1.752	6.76	1.538	6.51	1.602	6.84
ASC choice IC (sigma)	0.857	2.37	-1.434	-2.06	-1.447	-3.11
ASC choice FSC (sigma)	1.494	2.75	0.836	1.50	-1.087	-2.54
ASC choice LCC (sigma)	-1.484	-4.90	-1.311	-4.41	-1.364	-4.80
ASC choice Bus (sigma)	1.542	3.70	2.928	3.57	2.207	5.14
ASC choice Private Car (sigma)	-3.056	-2.82	-3.335	-5.99	-3.105	-5.52
Consideration component						
ASC consideration IC					1.371	1.57
ASC consideration Bus					3.510	2.59
ASC consideration Car-pooling					0.001	0.00
Binding function IC					-2.453	-0.89
Binding function Bus					-5.470	-2.53
Binding function Car-pooling					-6.481	-5.01
LL(0)	-2319.01		-2063.49		-2188.27	
LL(final)	-1211.47		-1223.74		-1199.96	
AIC	2504.93		2519.47		2483.93	
BIC	2714.43		2704.3		2699.56	
Prob. chosen alternative (100 holdout samples)	41.04%		40.90%		41.31%	
Number of parameters	41		36		42	

Note: for all models: observations = 1254, respondents = 209; *t-stat (1), see footnotes 7-8.

The mode specific travel time coefficients - which assume respondents are travelling alone (base) - have the expected negative sign and are statistically different from zero, with the exception of travel time for private car. The latter result can be explained by the fact that this alternative was chosen in very few occasions and our feeling is that those respondents would have chosen to travel by car anyway, regardless of its characteristics and those of the other alternatives. Surprisingly, the interaction term accounting for respondents travelling with others is significantly different from (larger than) unity, which means that those travellers place a higher value on travel time than those travelling alone.[7] We do not have an intuitive explanation for this finding.

Travel cost has been interacted with income in a non-linear way.[8] The negative value for the estimated elasticity (*Lambda Income*) implies that the (absolute) sensitivity to travel cost decreases with increases in income. Similarly, travellers who did not pay for the trip themselves also place a lower importance on the cost attribute. Results also show that respondents are more likely to select a particular mode when they can get a flexible ticket at a reasonable price (i.e. free or up to 5€) instead of having to pay a larger fee of 50€ for this option. The latter value is more in line with current airlines' fees. The presence of Wi-Fi seems, surprisingly, not to affect mode choice. We have two possible explanations. First, Wi-Fi connections are currently available only on-board HSR and busses. In the SC experiment, it was also assumed available on-board IC and flights, which will be realistic in the near future. Second, travellers currently experience low levels of connectivity on this corridor due to the large amount of tunnels.

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[7] The specification for the travel time coefficient is the following:

$$\beta_{travel\_time_{i,n}} = \beta_{travel\_time\_alone_{i,n}} * (travel\_alone\_dummy_n + \beta_{travel\_time\_with\_others_n} * (1 - travel\_alone\_dummy_n)).$$

[8] Given that the income information was collected using income classes, we used class-midpoints for those respondents who stated in which income class they belonged to, acknowledging the obvious averaging error this involves. Moreover, we estimated a separate travel cost coefficient for those respondents who preferred not to disclose this information, and we interacted both coefficients with information on who paid for the trip. Therefore, the specification for the travel cost coefficient is the following:

$$\beta_{travel\_cost_n} = ((\beta_{travel\_cost\_paid\_themselves\_income\_yes_n} * ((\frac{income_n}{average\_income})^{lambda\_income_n}) * (income\_yes\_dummy_n)) +$$

$$+ (\beta_{travel\_cost\_paid\_themselves\_income\_na_n} * (1 - income\_yes\_dummy_n)) *$$

$$* (paid\_themselves\_dummy_n + \beta_{paid\_employer_n} * paid\_employer\_dummy_n + \beta_{paid\_family_n} * paid\_family\_dummy_n)$$

Coefficients for access/egress time are, as expected, negative and significant for airports. The airports in Rome and Milan are located quite far from the city centres. For train stations and bus terminals, access and egress time were not found to be significant due to being located in more central areas. Finally, we discuss the influence of socio-economic and context-specific characteristics on mode choice, and reflect on the degree of random heterogeneity associated with the ASCs. With respect to the former, we notice that, ceteris paribus, car-pooling gains appeal over other modes amongst more educated travellers (university level) and very young travellers. With respect to the latter, standard deviations (*sigma parameters*) are highly significant; we particularly observe that the standard deviation for the bus constant is larger than its mean value.

In Model 2, we account for consideration effects using *stated consideration*. We do not estimate any additional parameters relative to Model 1: predicted consideration probabilities, derived from Table 2a, are directly implemented in the Manski model (see Equation 6 in Section 4). Accounting for consideration effects on slower alternatives should increase the probability for faster alternatives with respect to Model 1, and therefore the sum of the probabilities for slower alternatives is expected to decrease. In Model 2, we interestingly observe that the marginal disutility for travel time (measured by the travel time coefficients) for faster alternatives is actually reduced with respect to Model 1, while that associated to the slower alternatives increases. These differences - which are however not statistically significant - can therefore be explained by the introduction of consideration effects, and are consistent with the expected changes in choice probabilities.

In Model 3, we instead account for consideration effects using *stated thresholds*, and consideration probabilities are calculated within the choice model. The predicted thresholds from Table 2b are included in the binding function and six additional parameters are estimated within the model to translate the binding function into consideration probabilities for the

Manski model (see Equation 7 in Section 4). The parameters for the non-linear binding functions reveal that consideration for the IC is hardly explained by the difference between the thresholds on travel time and the actual values for this attributes since the corresponding parameter for this alternative is not statistically different from zero. On the other hand, the threshold has more explanatory power for consideration of the car-pooling alternative. That is, the corresponding parameter is large and statistically significant, whilst the mode specific constant for consideration is close to zero.

In Model 3, we interestingly observe that the travel time coefficients for all modes, not only for the faster ones, are reduced. We have two possible explanations for this result. First, in Model 3, consideration effects do not act in isolation (as in Model 2 where these are exogenously introduced), but are integrated within the estimation of the choice model, which still compensates between all alternatives. This, in turn, is related to the second shortcoming of the Manski model discussed in Section 2. Second, the implicit consideration probabilities are, on average, larger in Model 3 compared to Model 2 (for IC: 70% vs 23.5%; Bus: 66.4% vs 24.9%; car-pooling: 60.5% vs 21.3%), therefore reducing the strength of consideration effects on choice. However, also in this case, differences in travel time coefficients with Model 1 are not statistically significant.

Finally, we observe two noteworthy common differences between the estimates from Models 2 and 3 relative to Model 1. First, the role of random heterogeneity, as measured by the coefficient of variation (CoV; Table 4) for the random parameters, is reduced for half of the alternatives (three in Model 2 and four in Model 3, respectively). This implies that elements previously attributed to random heterogeneity can possibly be ascribed to consideration effects. However, it is interesting that CoVs are reduced for different alternatives. This can also be explained by the differences in the consideration probabilities between the two models.

Table 4. CoV (absolute values).

	Model 1	Model 2	Model 3
HSR	1.14	2.62	1.11
IC	1.24	0.99	3.11
FSC	0.39	0.44	0.23
LCC	1.13	1.16	0.74
Bus	2.48	2.38	1.30
Private car	0.90	0.63	1.15

Second, the majority of the socio-economic and context-specific characteristics are no longer found to be statistically significant in Models 2 and 3. These variables have been used to model *stated consideration* of the alternatives and the *stated threshold* on travel time (as presented in Tables 2a and 2b), and therefore now only indirectly affect mode choice through consideration.

We now turn our attention to the goodness of fit for the three models. Given that these models are non-nested, the Likelihood ratio tests are not suitable. Similarly, a comparison over the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) would be flawed, because these indicators are based on the final Log-Likelihood. Therefore, model performance is evaluated using the average probability for the chosen alternative on 100 holdout samples.[9] This measure, reported alongside traditional measures of fit in Table 3, indicates that Model 3 is the best-performing model showing a moderate improvement over Model 1 (41.31% vs 41.04%). Previous papers accounting for probabilistic consideration using the Manski approach have obtained larger improvements in fit (e.g. Swait, 2001a; Basar and Bhat, 2004). However, differently from Swait (2001a), we do not consider supplementary information on consideration as error-free measures. Moreover, we additionally account for random heterogeneity in our choice model, while, for example, Basar and Bhat (2004)

[9] The database employed in this paper is rather small; for this reason, we randomly split individuals in the sample and their observations in five disjoint subsets, stratified on the base of the mode respondents were travelling with at the time of the survey. Then, in turn, four out of five subsets were used as the *training set* to estimate the models and we used the other subset as the *test set*. Therefore, we compared models' forecasting performance on 100 training/test sets (the procedure described has been repeated 20 times, providing 5 different combinations of training/test sets each time), as to make sure that results were robust enough to draw any conclusions from them.

estimated a multinomial logit model. With respect to the use of multinomial logit models and the Manski approach, it should be noted that the latter is similar in spirit to a *latent class* model and could thereby erroneously ascribe preference heterogeneity to consideration effects.

We also contrast the three models based on derived *willingness-to-pay* measures and forecasts for the aggregate market shares. With respect to the former, we present[10] the value of travel time savings (VTTS) for an individual who travels alone, and pays her/himself for the trip (Table 5).

Table 5. VTTS (€/hour).

	Model 1		**Model 2**			**Model 3**		
	est.	*t-stat(0)*	*est.*	*t-stat(0)*	*t-stat(Model 1)*	*est.*	*t-stat(0)*	*t-stat(Model 1)*
HSR	10.90	3.63	10.01	3.17	-0.28	8.17	3.05	-1.02
IC	11.80	5.77	16.01	3.62	0.95	9.75	3.77	-0.79
FSC	23.78	4.42	17.84	3.42	-1.14	17.53	3.98	-1.42
LCC	12.50	2.79	8.31	1.88	-0.95	8.41	2.29	-1.11
Bus	9.53	6.28	10.15	4.16	0.25	7.28	3.69	-1.14
Car-pooling	11.15	5.53	12.05	4.13	0.31	6.88	2.98	-1.85
Private car	-2.59	-0.57	-3.41	-0.59	-0.14	-1.76	-0.42	0.20

Table 5 reveals some interesting differences between Models 2 and 3 on the one hand and Model 1 on the other hand. In Model 2, we observe a reduction in the VTTS for the fully considered alternatives (i.e. HSR, FSC, and LCC), while VTTS measures for partially considered alternatives increase slightly. This result looks consistent with our expectations: when slower alternatives are poorly (or not) considered, comparisons amongst faster alternatives, which are therefore more similar in terms of travel time, should result in lower *willingness-to-pay* measures. In Model 3, instead, we observe that accounting for consideration effects reduces VTTS measures for all alternatives. In particular the VTTS for the car-pooling alternative is reduced by 38% and this value is also statistically different from the one obtained using Model 1. Given that we observe the same increase in the size for the travel cost coefficient

[10] Standard errors are calculated using the delta method for the ratio between travel time and travel cost coefficients.

in both Model 2 and 3 relative to Model 1, the differences in the VTTS measures between Model 2 and 3 are indirectly related to the differences in the travel time coefficients, which we have discussed earlier.

Forecasted aggregate market shares (Figures 4a-c) are not only affected by the alternative assumptions we make in the three models about consideration, but also by the differences in the average levels of consideration, measured by the probabilities of consideration. In general, we observe larger differences in forecasts between Model 2 relative to Models 1, than between the latter and Model 3. This result can be attributed to the average probability of consideration for slower alternatives in Model 3 being closer to unity than to zero, differently from Model 2. In a *status quo* scenario (i.e. applying the model to the choice tasks presented to the respondents, Figure 4a), Model 2 predicts slightly larger market shares for the fully considered alternatives compared to Model 1 (e.g. for HSR: 51.8% vs 50.3%), and, *vice versa,* lower market shares for partially considered ones (e.g. for IC: 7.7% vs 8.5%). This is in line with our expectations regarding choice probabilities formulated earlier in this Section. When subsequently looking at the effect of a reduction by 20% of travel time for the HSR alternative in Figure 4b, we observe similar patterns with respect to the *status quo* scenario, i.e. larger differences in prediction between Model 2 and Model 1, and more similar predictions between Model 3 and Model 1. However, in this case, we also observe that both consideration models (i.e. Models 2 and 3) predict a slightly lower increase for the HSR with respect to the *status quo* than Model 1 (+ 7.6%, + 6.8% and + 6.2% in Models 1-3, respectively). If we reduce travel time for the bus by 30%, the difference between Models 2 and Models 1 and 3 becomes more substantial (Figure 4c). Models 1 and 3 predict a larger increase over the *status quo* and larger market shares for this mode (15.6% and 15.8%, respectively) than Model 2 (13.2%), at the cost (mainly) of the HSR alternative. That is, there would a larger substitution effect between the slowest and the fastest alternative in Model 2.

Figure 4a. Predicted aggregate market shares (*status quo*).

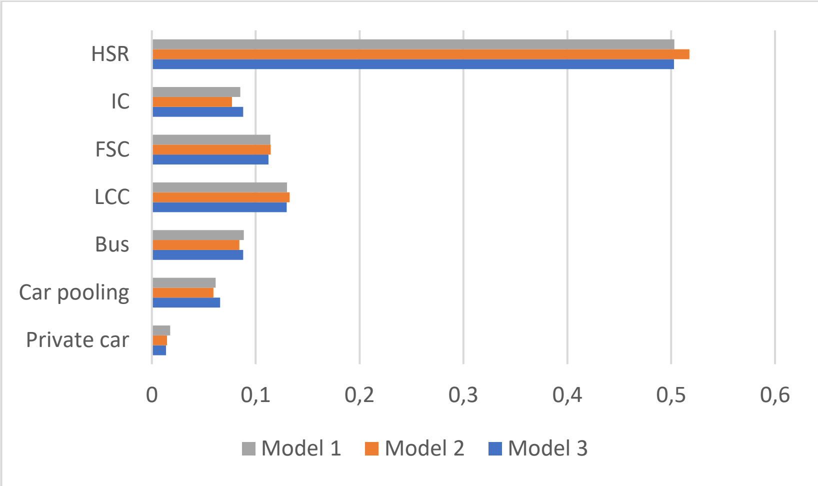


Figure 4b. Predicted aggregate market shares when travel time for HSR is reduced by 20%.

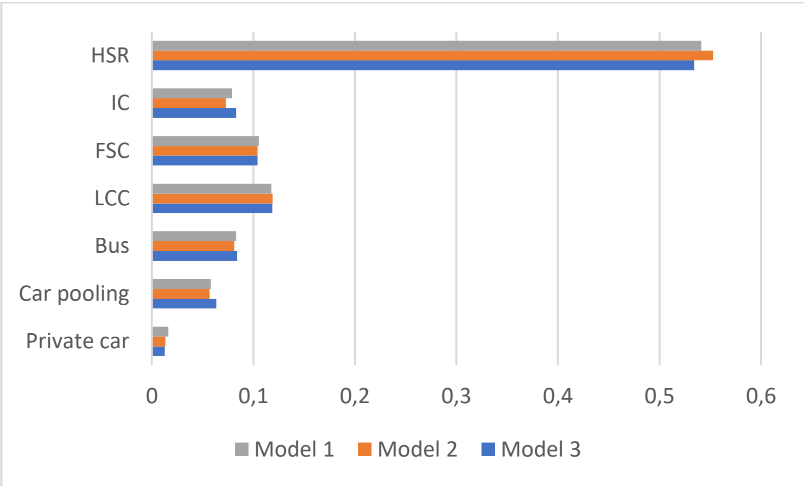
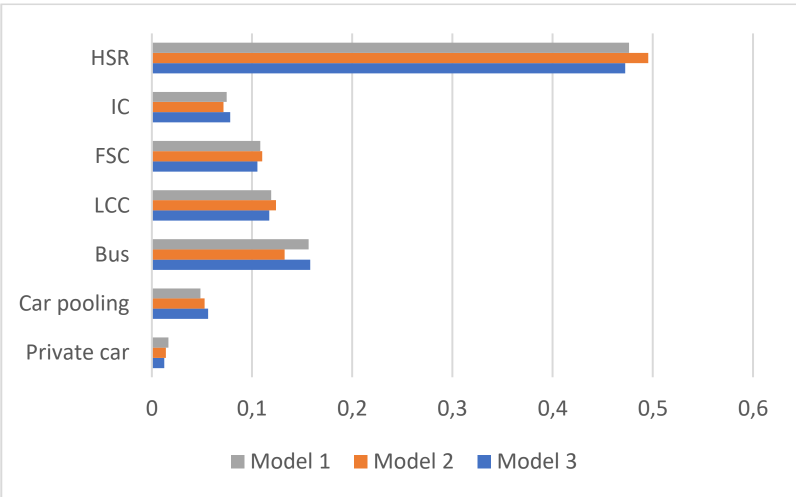


Figure 4c. Predicted aggregate market shares when travel time for bus is reduced by 30%.



To sum up, we find an indication that there are consideration effects, but at the same time we acknowledge that the use of supplementary information might not be the perfect solution to overcome the limitations of the Manski model.

We observe that elements attributed to purely random heterogeneity in the traditional approach can possibly be ascribed to consideration effects, which also have some implications in terms of parameter estimates, VTTS measures, and forecasts for aggregate market shares. However, with respect to the latter, we also observe some noticeable differences between the use of direct and indirect indicators of consideration of the alternatives.

The use of direct indicators (i.e. *stated consideration*), provides outcomes which are more consistent with our expectations relative to the use of indirect ones (i.e. *stated thresholds*). Indeed, Model 2 predicts larger choice probabilities for fully considered alternatives, and lower for probabilistically considered ones, where this has reflections on parameter estimates and VTTS measures. However, we do not actually observe a robust improvement in fit relative to the traditional approach, measured by the average probability for the chosen alternative on a series of holdout samples. This might indicate that the possible benefits in terms of predictive power might be case specific or that the mixed logit model applied in Model 1 already offers significant flexibility in terms of estimation.

In Model 3, consideration effects do not act in isolation, but these are integrated with the choice model. In addition, the probabilities of consideration are much closer to unity than to zero. On the one hand, this directly leads forecasts with this model to be more in line with those obtained with the traditional approach; on the other hand it also partially explains the observed differences (mainly in terms of estimates for travel time coefficients and VTTS measures) with respect to Model 2, where consideration effects more tightly constrain choice. In Model 3, we actually observe an improvement in fit relative to the traditional approach, which is due to the estimation of additional parameters accounting for the binding functions. However, with this approach we introduce more room for error, given that thresholds are only indirect measures for consideration.

In any case, given that the three approaches have been proven to be all valid, and estimates as well as VTTS measures are mostly not statistically different between each other's, the question on which one to rely on remains open. Therefore, we would prefer not to give any indication on the (possible) direction of bias in those indicators, which would be better defined to be within a range of values rather than as point estimates.

6. Conclusion

With this paper, we contribute to the ongoing discussion on the role of consideration of alternatives in the consumer's decision-making process. We study consideration of the available modes of transport on the Rome-Milan corridor. Here, seven alternatives (i.e. transport modes) are available, which vary substantially in terms of their core attributes, particularly travel time. We use data from a SC survey administered to travellers on this corridor and collected additional information on task-level consideration of the alternatives, and on self-imposed thresholds on the travel time attribute. Observed choice behaviour and stated levels of consideration in our survey highlight that primarily the *slower* alternatives are associated with consideration effects.

Two model specifications, embedded in the two-stage Manski framework (1977), are proposed and compared with a more traditional formulation where all alternatives are assumed to be considered. The proposed models make use of the additional information collected on consideration and thresholds, respectively. These variables are not used as error-free measures of consideration. Instead, they are specified as functions of socio-economic characteristics and/or attributes of the alternatives. The resulting functional forms are then combined with the data to derive the consideration probabilities required in Manski's model.

In the first model, the outcomes of a series of binary logit models on stated consideration are used as a direct measure of consideration probabilities. In the second model, the consideration probabilities are calculated within the choice model, using a binding function which compares the values for the travel time attribute with the predicted value for the threshold on the respective attribute. The predicted threshold levels are the outcomes of a standard regression model. Additional parameters are estimated as part of the binding function to derive the consideration probabilities.

The resulting consideration probabilities in the proposed models differ substantially. In particular, those obtained using stated consideration are, on average, lower than those obtained using the thresholds. As a result, differences with respect to the traditional approach - in terms of parameter estimates, willingness-to-pay indicators and forecasted market shares - are more evident (and more in line with expectations) in the first model than in the second. On the other hand, only the second model shows an actual improvement in fit with respect to the traditional approach, which is most likely due to the estimation of additional parameters relative to the consideration stage. In both models, we observe that elements conventionally attributed to unobserved preference heterogeneity can possibly be ascribed to consideration effects.

To conclude, we acknowledge that collecting additional information on consideration of alternatives and thresholds on attributes might be burdensome, and not always feasible. In addition, this information might be related to the desirability of the alternatives. However, it can convey additional insights into the consumer's decision-making process, including preferences. Our results suggest consideration of alternatives influences willingness-to-pay measures and forecasted market shares, and can thereby influence transport planning investment decisions. However, our findings are not as strong as those from previous studies, most likely due to the introduction of unobserved random heterogeneity.

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