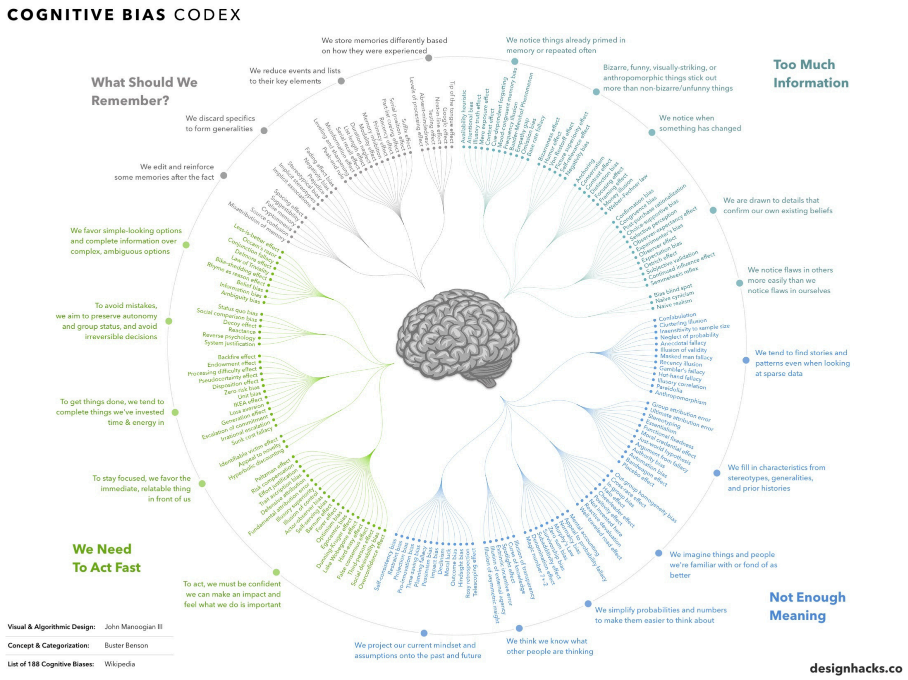

Modeling non-trading behavior

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Abstract

We present an application of a discrete choice modeling framework with heterogeneous decision rules to a Swiss mode choice case study. The proposed framework formally accommodates the heterogeneity of people with respect to the decision strategies they follow when making choices. It draws insights from the fields of cognitive and mathematical psychology, marketing and consumer research, economics and behavioral decision theory, and embeds normative as well as heuristic decision rules in the formulation of finite mixture models.

In this simple application, we present a model that accounts for non-trading behavior, as to heuristic rules, and distinguishes it from compensatory behavior that is represented by the normative rule of *utility maximization*. The specification includes a class-membership model that depends on the socio-economic characteristics of the respondent and the influence of important context variables, the latter being accumulated in a relative advantage (RA) component. The preliminary results demonstrate the presence of non-trading behavior in the sample and an improvement in the model fit —in comparison with the simple multinomial logit model— when accounting for it.

Keywords

Decision-making processes; Discrete choice modeling; Heterogeneity in decision-making processes; Heuristics

1 Background and context

As well argued by Balbontin *et al.* (2017), the outcome of a decision process —i.e. the choice itself— is equally important to the underlying process adopted by the individual in order to make the decision. The former has nevertheless received undoubtedly more attention than the latter in the context of discrete choice modeling (DCM) for demand analysis. While numerous studies have analyzed demand accounting for taste/preference heterogeneity, less studies have tackled the inter- and intra-personal heterogeneity in the decision-making processes (DMPs).

A common distinction of the DMPs within the DCM framework is between: (i) the optimal or normative decision rules and (ii) the suboptimal decision rules or heuristics[1] . Optimal decision rules entail the use of some optimality criterion that is usually associated with higher complexity, while heuristic rules connote the omission of part of the information by the individual in order to make decisions faster and simpler. The underlying assumption of the former has its foundations in economics; individuals are rational, have almost complete information and sufficient capacity to process it and make trade-offs in order to arrive at an optimal choice. The underlying assumption of the latter is that individuals have cognitive constraints and cannot/do not process the full information contained in the choice tasks.

Generally, optimal decision rules are associated with *compensatory* choice behavior, while heuristic rules with *non-compensatory* choice behavior. Individual choice behavior within the DCM framework is mostly assumed to be optimal/fully compensatory. Individuals are commonly treated as utility maximizers or, less often, regret minimizers in a linear-in-parameters and additive-in-attributes approach. Evidence about which type of rules people use is mixed though (Shen and Ma, 2016) and combinations or coexistence of both types are possible, prompting *semi-compensatory* modeling approaches. One example is the two-stage choice paradigm (Manski, 1977), where individuals are assumed to use a simple screening rule (heuristic) at a first stage in order to reduce the choice set (first-stage elimination), followed by a second stage compensatory choice process (Cantillo and de Dios Ortúzar, 2005).

Recently, following works that have investigated alternative rules as competing to each other (e.g. Collins, 2012, Chorus *et al.*, 2014, Hess *et al.*, 2014, Belgiawan *et al.*, 2019), more and more studies identify the need to integrate more than one decision process in the formulation of DCMs, in order to explain diverse behavior in subgroups of the population (see e.g. Elrod *et al.*, 2004, Hensher and Greene, 2010, Zhu and Timmermans, 2010, Hess *et al.*, 2012, Leong and Hensher, 2012, McNair *et al.*, 2012, Hess and Stathopoulos, 2013, Hensher *et al.*, 2013, Boeri

[1]The terms decision process, decision strategy and decision rule are used interchangeably in this paper.

et al., 2014, Balbontin *et al.,* 2017, Hensher *et al.,* 2018, Dey *et al.,* 2018, Balbontin *et al.,* 2019). Yet, there is still broad scope for work towards an integrated framework that systematically considers various decision rules.

> "*We must continue to find ways to embed more realistic processing heuristics or rules in ways that will, in time, make it easy and become standard practice in real world applications. It would be interesting to test this form in other datasets to see if there is a common pattern with the process strategies.*" (Hensher *et al.,* 2018)

We aim at contributing in the current literature by operationally combining traditional microeconomics with behavioral economics and quantitative psychology to better explain the variations in the demand formation by modeling the distribution of the decision rules in a population. Our goal is to develop a unified discrete choice modeling framework that formally accommodates the heterogeneity of the individuals with respect to the underlying decision-making processes, in the formulation of *finite mixture models*. We are currently conducting a comprehensive literature review in the areas relating to decision-making processes. The objective is to identify and summarize the prominent (i) optimal and (ii) heuristic decision processes, with a particular focus on (a) how they are currently modeled and (b) how they are applied in practice to derive elasticities and willingness-to-pay measures within the DCM framework. In general, the framework has a keen eye for practical real world applications and deliberates the importance of *context dependence* in the relevance of the decision rules, as pointed out by Hensher (2019). For the purposes of the study, we adopt the classification of the DPMs and the modeling approaches into (a) compensatory, (b) non-compensatory (c) and semi-compensatory.

In this paper, we present a first, simple application of the framework to a Swiss stated preference (SP) mode choice dataset. It integrates compensatory and non-compensatory decision rules and tests for contextual effects on the selection of the decision strategy by the individual. Evidence from the data suggests the presence of two types of respondents, manifesting trading and non-trading choice behavior, respectively. Non-trading behavior refers to the case where a respondent always chooses the same alternative across choice situations (Hess *et al.,* 2010). Hess *et al.* (2010) discuss the possible drivers behind such behavior. These include: (i) strong preference towards a particular alternative, albeit utility maximizing respondent, (ii) non-trading heuristic employed by a non-utility maximizing respondent due to fatigue, boredom etc., and (iii) some sort of political or strategic behavior, such as never choosing a tolled road alternative. The authors argue that respondents in the first category, i.e. utility maximizers with strong preference towards a specific alternative should not be excluded from a utility maximizing model, while those in the other two categories should ideally be identified and excluded from the model in order to avoid biases in the estimation of measures such as willingness to pay. They acknowledge the fact though that, in the majority of cases, it is not possible to distinguish the different types of non-traders among each other.

The proposed framework treats non-trading behavior as the outcome of a non-compensatory decision strategy and accommodates it appropriately in the formulation of the model, rather than excluding it from the model estimation. Here, we present a mixture model that involves two classes of respondents, accordingly denoted as traders and non-traders. A relative advantage (RA) component (Leong and Hensher, 2014) is incorporated in the specification of the class-membership model (CMM) —along with socio-economic characteristics of the respondent— assuming that the manifestation of non-trading behavior may be driven by the context, and more specifically the RA of one's preferred mode in the experiment with respect to the remaining alternatives.

The remainder of the paper is organized as follows. Section 2 discusses the conceptual framework. Section 3 presents an application of the framework to a Swiss case study. Section 4 summarizes the first findings of the work.

2 Probabilistic decision process model

Some of the works that provide the theoretical background for the conceptual framework include Payne *et al.* (1993), who provide a typology of decision-making processes and Hensher *et al.* (2015), who present an extended review of decision heuristics in the context of preferences. A comprehensive review of decision heuristics within the DCM framework with SP data is presented by Leong and Hensher (2012). After discussing the contribution of decision heuristics and contextual effects in explaining choice behavior, the authors suggest that a logical way forward would be to *"consider the use of mixture models, where multiple heuristics are weighted in a utility function, using weighting functions that depend on the socio-economic characteristics of the respondent and other choice context variables, including individual-specific perceptions data, where available."* This work adopts such an approach.

The operational framework builds upon the state-of-the-art finite probabilistic mixture models, under the assumption that each sub-population is associated with a specific underlying decision process. This assumption gives rise to a probabilistic decision process (PDP) modeling approach[2] (see e.g. McNair *et al.,* 2012). The probability that an individual n choses alternative i given the

[2]This is essentially a latent class modeling approach, where each class is characterized by different preference measures, as a result of the differences in the underlying decision process.

choice set of alternatives C_n and the set of possible decision processes $\mathcal{D}$ is defined as

$$P(i \mid C_n) = \sum_{d=1}^{D} P(d) \cdot P(i \mid d), \tag{1}$$

where $P(d)$ denotes the probability that n adopts decision rule d to make a choice, $P(i \mid d)$ the probability that n chooses i given that she follows decision rule d and D the number of decision processes. $P(d)$ can be modeled as a function of decision-maker's characteristics, choice context variables, as well as (depending on availability) individual-specific attitudinal/perceptual data (see e.g. Hess and Stathopoulos, 2013).

3 Playground

We use data from a SP survey for mode and route choice behavior that was conducted in Switzerland in 2015[3]. We focus on the mode choice experiments of the survey. Each respondent was presented with a choice set of 2-3 alternatives, depending on her availability of transport means and her reported (last) trip for a specific trip purpose. In total, four modes appear in the experiments: (i) walking, (ii) bike, (iii) car and (iv) public transport. The data about the RP choice for the trip in question is also available, along with the socio-economic characteristics of the respondent and her indications about which attributes of the alternatives she considered *unimportant* for making a choice. [4].

The sample concerns 1522 respondents generating $1522 \times 8 = 12176$ observations —after excluding (i) the observations from the pre-tests, (ii) respondents who did not report their household income and (iii) those who did not answer all 8 experiments in the design.

3.1 Context

Approximately 55% of the retained respondents systematically chose their RP choice across all 8 experiments. The data exhibits some sort of *non-trading* behavior, where respondents tend to chose the mode of transport that corresponds to their recent experience (Hess *et al.,* 2010) or

[3] *Data source*: Stated preferences surveys for transport behavior 2015, Federal Office for Spatial Development ARE, Bern, 2017, http://www.are.admin.ch/statedpreference. We refer the reader to Weis *et al.* (2016) for more details regarding the survey design and the dataset.

[4] This study uses the socio-economic characteristics of the respondents. The rest of the available data may be used in the future for further developments of the model.

to their habitual mode. For each individual in the sample we compute the level of persistence of choosing her RP choice across the SP experiments; that is if n chooses her RP choice four times out of the 8 experiments, her persistence is 50%. Individuals with high persistence could belong to the first category of non-trading behavior, identified in Hess *et al.* (2010); these are utility maximizers with strong preference towards one alternative. The rationale is that those individuals would tend to choose their preferred alternative unless another alternative is much more attractive with respect to important attributes (e.g. time and cost) or possibly all of the attributes (fully compensatory behavior). The same may hold for some, or all, of the individuals with 100% persistence to their preferred alternative that strike as strong non-traders. Subsequently, we assume that non-trading behavior may not be merely inherent but likely to be triggered by the context. In order to test this assumption, we incorporate a RA component —capturing the context dependence— in the class-membership model, along with the socio-economic characteristics of the respondent —reflecting the inherent tendency for non-trading behavior. This is contrary to the traditional use of the RA model, where the RA component is included in the utility functions of the alternatives to capture the context dependence of preferences. Here, we evaluate the influence of the context on the choice of a decision rule.

3.2 Modeling set-up

The base model is a multinomial logit model (MNL). It assumes that the utility maximization rule and compensatory behavior holds for all respondents:

0. MNL

Its first extension concerns the inclusion of the two latent classes (i) traders and (ii) non-traders with equal probabilities w_d for all n to belong to a class (Model 1) —w_d a parameter to be estimated:

1. LC model with equal weights w_d for all n in the sample

$$P(i \mid C_n) = \sum_{d=1}^{D} \boldsymbol{w_d} \cdot P(i \mid d),$$

where $P(i \mid d)$ is the class-specific model (CSM) specified as a MNL. The utility functions of the alternatives for the *traders* are defined on the basis of attributes of the alternatives x_{in}. For *non-traders*, $V_i = 0$ if i is the preferred alternative p of n, i.e. if i corresponds to the reported chosen alternative for the specific trip in the RP data, and $V_i = -\infty$, otherwise.

The next extensions concern the specification of class-membership models (CMMs) starting with the inclusion of the socio-economic characteristics of the respondent and followed by the specification and inclusion of the RA component:

2. LC model with CMM specified as a binary logit model based on the socio-economic characteristics z_n

$$P(i \mid C_n) = \sum_{d=1}^{D} \boldsymbol{P(d)} \cdot P(i \mid d), \text{ where } P(d) \text{ is given by a logit model with } V_{\text{trader}} = 0 \text{ and } V_{\text{non-trader}} \sim z_n$$

3. LC model with CMM based on z_n and the RA component

$$P(i \mid C_n) = \sum_{d=1}^{D} \boldsymbol{P(d)} \cdot P(i \mid d), \text{ where } P(d) \text{ is given by a logit model with } V_{\text{trader}} = 0 \text{ and } V_{\text{non-trader}} \sim z_n + RA$$

and $P(i \mid d)$ same as before.

For the definition of the RA component we adopt the formulation described by Leong and Hensher (2014)[5]. We define the relative advantage RA of the preferred alternative p with respect to each alternative $j \neq p$ in the choice context as

$$RA(p, j) = \frac{A(p, j)}{A(p, j) + D(p, j)}, \tag{2}$$

where $A(p, j) = \sum_k A_k(p, j)$ and $D(p, j) = \sum_k D_k(p, j)$ are, respectively, the overall advantage and disadvantage of p over j over all relevant attributes k. The advantage of p over j with respect to k is defined as $A_k(p, j) = D_k(j, p) = \ln[1 + \exp(\beta_{pk}X_{pk} - \beta_{jk}X_{jk})]$, if $v_k(X_{pk}) \geq v_k(X_{jk})$, and zero otherwise, with $v_k(X_{jk})$ being the utility of attribute k for alternative j. Finally, the overall RA of p over all $j \neq p$ is $\sum_j RA(p, j)$.

The CMM model is then

$$V_{\text{trader}} = 0, \tag{3}$$

$$V_{\text{non-trader}} = \beta_0 + \sum_{z_n} \beta_{z_n} z_n + \boldsymbol{\theta} \sum_{j \neq p} RA(p, j), \tag{4}$$

where the parameter θ captures the weight/importance given to the RA component (see Tversky and Simonson, 1993).

[5]Earlier formulations of the RA model can be found in Tversky and Simonson (1993) and Kivetz *et al.* (2004)

3.3 Model specifications

Table A1 shows the four model specifications. The CS specification is the same across all models. Alternative specific parameters are specified for all attributes. We define a piecewise transformation of the walking time attribute, with a threshold value at 30 minutes. Furthermore, the in-vehicle time of public transport is specified as

$$\left(\beta_{\text{inVehTime}} + \beta^{\text{high/overloaded}}_{\text{crowd}\times\text{inVehTime}} \times \text{high/overloaded}\right) \times \text{inVehTime}$$

to account for the additional effect of discomfort due to crowdedness on the perception of travel time. Finally, we have defined two dummy variables for headways of maximum 10 minutes (high frequency) and more than one transfers for the public transport alternative.

The CMM assumes that high-income, senior males and owners of driving license and public transport subscriptions are more likely to be non-traders. The RA component in this study is computed based on the *total time* and *total cost* of the alternatives[6]. Generic parameters are specified for these two attributes ($\beta_{pk} = \beta_{jk}$).

3.4 Estimation results

The four model specifications are first estimated ignoring the panel nature of the data. Panel effects are then added to all model specifications, accounting for the necessary normalizations. The models are eventually estimated with 500 Halton draws, using the parameters of the first estimation as starting values. The output of Models 0 to 2 is shown in Tables 1 and 2, presenting the goodness of fit and the estimated parameters, respectively. We are currently facing numerical issues in the estimation of the most advanced specification (Model 3) with the RA component.

Models 1 and 2 demonstrate significant improvement in the goodness of fit in comparison with the MNL model, while Model 2 with the specification of the CMM further outperforms Model 1. All the estimated parameters in Table 2 exhibit the expected signs. With the exception of some constants, and the parameter associated with the high frequency for public transport in Model 2, all parameters of the CSMs are significant. We have chosen to keep all the socio-economic characteristics of the respondent in the CMM of Model 2, despite the fact that the parameters associated with the gender, high income and the driving license are not significant at the 95% confidence level (they are significant at 90%). The reason is that we want to have a complete

[6]Remark: The attribute values of p are taken from the experiment, not from the RP data.

segmentation of our sample with respect to important characteristics in the final model (Model 3) so that we are able to comment on it (once the numerical issues are solved).

It is interesting to observe the fluctuation of the non-trading component. Obviously, the MNL assumes that all individuals are trading. Model 1 suggests that each individual is by 75% trading and by 25% non-trading (equal for all individuals in the sample). Model 2 increases the non-trading component to 49% on average —in this case each individual has a different probability to belong to each component due to the specification of the CMM. This percent is lower than the percent of respondents that appear to be strong non-traders (55%) based on their persistence of choosing their RP choice in all 8 experiments. We are awaiting the result of Model 3 to be able to comment on how much this persistence can be attributed to an underlying non-trading behavior or could possibly be affected bythe experimental setup.

4 Summary

We have presented a discrete choice modeling framework of heterogeneous decision rules that accounts for non-trading behavior and distinguishes it from compensatory behavior that is represented by the utility maximization decision rule. The approach is applied to a Swiss SP mode choice case study. It employs a CMM specification that depends on the socio-economic characteristics of the respondents and the effect of important context variables that are accumulated in a RA component. The first results demonstrate the presence of non-trading behavior in the sample and an improvement in the model fit when accounting for it.

We are currently working on solving the numerical issues in the estimation of the model with

Table 1: Summary of goodness of fit

	Model 0	Model 1	Model 2	Model 3
description	MNL	LC with equal w_d $\forall n$	LC with CMM	LC with CMM and RA
# of draws	500	500	500	500
# of parameters	20	24	30	33
# of observations	12176	12176	12176	12176
# of individuals	1522	1522	1522	1522
$\mathcal{L}(\hat{\beta})$	**−4583.13**	**−4408.70**	**−4164.50**	×

Table 2: Estimation results

	parameter*	Model 0	Model 1	Model 2	Model 3
class-specific	$ASC_{WALK_{trader}}$	6.64 (6.50)	6.51 (4.13)	1.13 (1.14)	×
	$ASC_{BIKE_{trader}}$	−0.02 (−0.03)	5.70 (5.27)	1.93 (1.81)	×
	$ASC_{CAR_{trader}}$	2.29 (6.46)	2.75 (3.22)	0.45 (1.09)	×
	$ASC_{PT_{trader}}$	0	0	0	×
	$\beta_{fuelCost_{trader}}$	−0.36 (−7.96)	−1.00 (−3.69)	−0.46 (−4.38)	×
	$\beta_{parkingCost_{trader}}$	−0.51 (−16.21)	−1.38 (−9.04)	−0.77 (−9.92)	×
	$\beta_{toll_{trader}}$	−0.28 (−5.73)	−0.97 (−4.59)	−0.42 (−4.32)	×
	$\beta_{ticketCost_{trader}}$	−0.27 (−6.60)	−1.06 (−3.59)	−0.42 (−6.50)	×
	$\beta_{walkTime^{\leq 30min}_{trader}}$	−0.34 (−7.67)	−0.49 (−6.95)	−0.20 (−4.29)	×
	$\beta_{walkTime^{>30min}_{trader}}$	−0.10 (−4.19)	−0.49 (−9.28)	−0.26 (−4.75)	×
	$\beta_{cycleTime_{trader}}$	−0.20 (−12.20)	−0.94 (−11.59)	−0.41 (−8.35)	×
	$\beta_{drivingTime_{trader}}$	−0.14 (−10.33)	−0.49 (−8.24)	−0.24 (−8.79)	×
	$\beta_{parkingTime_{trader}}$	−0.20 (−5.91)	−0.52 (−5.22)	−0.26 (−4.90)	×
	$\beta_{inVehTime_{trader}}$	−0.13 (−14.62)	−0.41 (−11.09)	−0.21 (−8.65)	×
	$\beta^{high/overloaded}_{crowd \times inVehTime_{trader}}$	−0.09 (−7.83)	−0.09 (−4.83)	−0.05 (−4.72)	×
	$\beta_{accessTime_{trader}}$	−0.17 (−8.24)	−0.55 (−9.63)	−0.26 (−7.03)	×
	$\beta_{highFreq^{\leq 10min}_{trader}}$	1.13 (3.75)	1.33 (2.10)	1.57 (1.17)	×
	$\beta_{numTranfers^{\geq 2}_{trader}}$	−0.72 (−4.56)	−2.17 (−3.57)	−0.96 (−3.67)	×
panel effect	$\omega_{WALK_{trader}}$	0	0	0	×
	$\omega_{BIKE_{trader}}$	8.11 (10.79)	14.8 (10.56)	5.87 (6.62)	×
	$\omega_{CAR_{trader}}$	−3.69 (−13.99)	7.37 (9.50)	1.55 (4.45)	×
	$\omega_{PT_{trader}}$	2.79 (12.15)	7.05 (31.44)	2.58 (7.00)	×
	$\omega_{WALK_{non\text{-}trader}}$	-	0	0	×
	$\omega_{BIKE_{non\text{-}trader}}$	-	2.21 (5.31)	−2.43 (−1.57)	×
	$\omega_{CAR_{non\text{-}trader}}$	-	12.00 (22.04)	10.5 (9.88)	×
	$\omega_{PT_{non\text{-}trader}}$	-	−0.78 (−2.73)	−1.76 (−1.95)	×

⋆ Value of estimated parameter (robust t-test)

the RA component. We are also interested in the effect that the deviation of the choice context attributes from the real trip attributes may have on the manifestation of non-trading behavior. This can be done once again by means of a RA component specification. Finally, a critical aspect of the probabilistic decision process modeling approaches concerns the computation of policy indicators, such as the value of time. We are going to investigate the implications that the

Table 2: Estimation results (continued)

	parameter⋆	Model 0	Model 1	Model 2	Model 3
class-membership	w_{trader}	1	**0.75**	**0.51** (average)	×
	$w_{\text{non-trader}}$	0	**0.25**	**0.49** (average)	×
	$\text{ASC}_{\text{trader}}$	-	-	0	×
	$\text{ASC}_{\text{non-trader}}$	-	-	−0.42 (−0.48)	×
	$\beta_{\text{male}_{\text{non-trader}}}$	-	-	−0.32 (−0.58)	×
	$\beta_{\text{highINC}_{\text{non-trader}}}$	-	-	1.57 (1.84)	×
	$\beta_{\text{senior}^{\geq 55}_{\text{non-trader}}}$	-	-	1.32 (2.28)	×
	$\beta_{\text{driver}_{\text{non-trader}}}$	-	-	1.30 (1.62)	×
	$\beta_{\text{ABO}_{\text{non-trader}}}$	-	-	−2.49 (−3.30)	×
RA component	θ	-	-	-	×
	$\beta_{\text{totalCost}}$	-	-	-	×
	$\beta_{\text{totalTime}}$	-	-	-	×
panel effect	ω_{trader}	-	-	0	×
	$\omega_{\text{non-trader}}$	-	-	6.39 (7.12)	×

⋆ Value of estimated parameter (robust t-test)

deviation from the standard random utility model entail for the derivation of such indicators.

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A Model specifications

Table A1: Specification table

	parameter	Model 0	Model 1	Model 2	Model 3
class-specific	$\text{ASC}_{\text{WALK}_{\text{trader}}}$	1	1	1	1
	$\text{ASC}_{\text{BIKE}_{\text{trader}}}$	1	1	1	1
	$\text{ASC}_{\text{CAR}_{\text{trader}}}$	1	1	1	1
	$\text{ASC}_{\text{PT}_{\text{trader}}}$	0	0	0	0
	$\beta_{\text{fuelCost}_{\text{trader}}}$	1	1	1	1
	$\beta_{\text{parkingCost}_{\text{trader}}}$	1	1	1	1
	$\beta_{\text{toll}_{\text{trader}}}$	1	1	1	1
	$\beta_{\text{ticketCost}_{\text{trader}}}$	1	1	1	1
	$\beta_{\text{walkTime}^{\leq 30\text{min}}_{\text{trader}}}$	1	1	1	1
	$\beta_{\text{walkTime}^{>30\text{min}}_{\text{trader}}}$	1	1	1	1
	$\beta_{\text{cycleTime}_{\text{trader}}}$	1	1	1	1
	$\beta_{\text{drivingTime}_{\text{trader}}}$	1	1	1	1
	$\beta_{\text{parkingTime}_{\text{trader}}}$	1	1	1	1
	$\beta_{\text{inVehTime}_{\text{trader}}}$	1	1	1	1
	$\beta^{\text{high/overloaded}}_{\text{crowd}\times\text{inVehTime}_{\text{trader}}}$	1	1	1	1
	$\beta_{\text{accessTime}_{\text{trader}}}$	1	1	1	1
	$\beta_{\text{highFreq}^{\leq 10\text{min}}_{\text{trader}}}$	1	1	1	1
	$\beta_{\text{numTranfers}^{\geq 2}_{\text{trader}}}$	1	1	1	1
panel effect	$\omega_{\text{WALK}_{\text{trader}}}$	0	0	0	0
	$\omega_{\text{BIKE}_{\text{trader}}}$	1	1	1	1
	$\omega_{\text{CAR}_{\text{trader}}}$	1	1	1	1
	$\omega_{\text{PT}_{\text{trader}}}$	1	1	1	1
	$\omega_{\text{WALK}_{\text{non-trader}}}$	0	0	0	0
	$\omega_{\text{BIKE}_{\text{non-trader}}}$	0	1	1	1
	$\omega_{\text{CAR}_{\text{non-trader}}}$	0	1	1	1
	$\omega_{\text{PT}_{\text{non-trader}}}$	0	1	1	1
class-membership	w_{trader}	-	✓	✓	✓
	$w_{\text{non-trader}}$	-	✓	✓	✓
	$\text{ASC}_{\text{trader}}$	-	-	0	0
	$\text{ASC}_{\text{non-trader}}$	-	-	1	1
	$\beta_{\text{male}_{\text{non-trader}}}$	-	-	1	1
	$\beta_{\text{highINC}_{\text{non-trader}}}$	-	-	1	1
	$\beta_{\text{senior}^{\geq 55}_{\text{non-trader}}}$	-	-	1	1
	$\beta_{\text{driver}_{\text{non-trader}}}$	-	-	1	1
	$\beta_{\text{ABO}_{\text{non-trader}}}$	-	-	1	1
RA component	θ	-	-	-	1
	$\beta_{\text{totalCost}}$	-	-	-	1
	$\beta_{\text{totalTime}}$	-	-	-	1
panel effect	ω_{trader}	-	-	0	0
	$\omega_{\text{non-trader}}$	-	-	1	1