In-store vs. online shopping of search and experience goods: A Hybrid Choice approach

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ICMC Conference Paper **March 2017**

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March 2017

Abstract

This paper aims at explaining the choice between online and in-store shopping for experience (groceries) and search (standard electronic appliances) goods in Zurich, Switzerland, within an experimental setting assuming no privately owned vehicles, applying an integrated choice and latent variable (ICLV) approach to model choice behavior: In a stated preference survey 466 respondents were requested to trade-off different attributes related to their choice between online and in-store shopping, together with a separate questionnaire asking for their attitudes towards online shopping and the pleasure of shopping.
Respondents with more positive attitudes towards online shopping exhibit a higher shopping cost sensitivity, which can be explained by the larger choice set when effectively considering both purchasing channels, while shopping time sensitivity differs by the product category and the pleasure of shopping. The strongest socio-economic factor explaining choice behavior is education: Well-educated people tend to have a better access to ICT in general and make use of that technology, thus exhibit a higher choice probability of online shopping that is mainly mediated via the pro-online shopping attitudes.
Results reveal further potential for online shopping services, given the relatively high value of travel time savings (VTTS) of about 75 CHF/h for experience and 45 CHF/h for search goods, compared to the value of delivery time savings (VDTS) ranging between 6 CHF/day for experience and 2.50 CHF/day for search goods: Especially for search goods, avoiding a shopping trip produces more benefits than waiting for the delivery of the ordered products.

Keywords

Online shopping, in-store shopping, attitudes towards online shopping, pleasure of shopping, integrated choice and latent variable (ICLV), value of delivery time, value of travel time, maximum simulated likelihood (MSL)

1 Introduction

Information and communication technologies (ICT) have experienced a persistent increase in usage over the last 25 years, which, in the context of e-commerce, allow for a more flexible spatial and temporal accomplishment of shopping activities (Mokhtarian, 2004). A shift from traditional store towards online shopping has been ongoing for some time, and has become more and more important in terms of market shares and individual behavior, as discussd in Rudolph et al. (2015) for the case of Switzerland. Regarding the interdependencies with travel behavior, Mokhtarian et al. (2006) argue that apart from expanding individuals' choice sets, the potential effects of ICT are ambiguous and require further empirical investigations (see also e.g. Farag et al. (2007) and Cao (2009), for an extended literature review on the topic). But what are the key attributes in individual decision making for either visiting a store or shopping online? Identifying the main factors that affect the choice between in-store and online shopping is not only important for developing effective retailing strategies, but also for predicting the responsiveness to specific attributes of heterogeneous consumer segments in travel demand modeling: How do people value travel, delivery and shopping/ordering time when directly facing the trade-offs between these two alternative shopping channels? Is there a difference between product categories, and how do income, time budget and soft factors, such as attitudes towards shopping and ICT related aspects, affect these trade-offs?

The data analyzed in this paper was collected as part of an interdisciplinary project between the Eidgenössische Technische Hochschule Zürich (ETHZ), the École Polytechnique Fédérale de Lausanne (EPFL) and the Università della Svizzera Italiana (USI), Lugano, investigating how a world with restricted car ownership would affect choice, travel and scheduling behavior (*Post-Car World*, abbrev. PCW; see also http://postcarworld.epfl.ch/). Importantly, for the in-store alternative, the absence of private cars was justified to the respondents by car-reducing policy developments, suggested by an increased public support of carpooling and free-floating car sharing systems, leaving public transport as the only traditional reference mode for longer distances. The main objective of the project is to investigate how today's people behave in a possible future situation where private cars were no longer part of their daily travel (Schmid et al., 2016a). In the context of shopping, the main motivation is to explore how under such conditions, the choice behavior between in-store and online shopping and the heterogeneity in taste parameters by using soft factors, such as attitudes and perceptions, can be explained.

We present an innovative survey design and sophisticated modeling approach by investigating the relative importance of attributes related to the choice between in-store and online shopping for two product categories: Search and experience goods. Typically, the key characteristics of search goods can more easily be evaluated from externally provided information, while experience goods need to be physically inspected or tried (Peterson et al., 1997). Results provide new insights on purchasing channel preferences by allowing attribute sensitivities to differ by product type (shopping purpose): Search goods (in our example, standard electronic appliances) typically are more often purchased online, while the main product characteristics of experience goods (in our example, groceries) are mainly obtained in-store. Importantly, multi-channel shopping, i.e. explicitly distinguishing between pre-purchase and purchase channels as e.g. discussed in Mokhtarian and Tang (2013), was ruled out to break down the experimental design to a manageable level of complexity. Nevertheless, in-store shopping/ordering time - including product search time - was presented as an alternative-specific attribute, which has to be seen as a simplifying though not always realistic assumption, especially in the case of electronic appliances.

To provide deeper behavioral insights, we estimate a Hybrid Choice model (HCM) with alternative-specific attributes applying an integrated choice and latent variable (ICLV) approach (Ben-Akiva et al., 2002): Two latent variables (LVs) that are hypothesized to affect the choice of the purchasing channel are included, capturing the acceptance level of ICT and online shopping and the pleasure of shopping. This approach enables the simultaneous estimation of attitudes based on socio-economic indicators: Knowing some basic characteristics of a target consumer segment, the potential market shares and responsiveness to specific attributes can be predicted via the LVs. An interaction term of the pro-online shopping LV and income with shopping costs was included to measure the heterogeneity in price sensitivity. In addition, we tested for heterogeneity in shopping time sensitivity by including an interaction term with the pleasure of shopping LV and working hours.

This paper builds on an earlier version by the authors, refining the modeling framework to better explain choice behavior: While in Schmid et al. (2016b) we used a cross-sectional and closed-form estimation approach for essentially the same but smaller data set (at that point in time, the study was still ongoing), this paper explicitly accounts for the panel structure of the data and unobserved preference heterogeneity using a flexible parametric approach (Greene et al., 2006) as discussed in Section 4, which was found to increase estimation complexity substantially. However, neglecting the panel structure would impose a strong violation of model assumptions, typically leading to biased estimates and too small standard errors. Apart from the attitudes towards online shopping and the pleasure of shopping, other soft factors and their effects on choice behavior have been tested, and a simulation approach was used to approximate the multi-dimensional integral of the likelihood function (Train, 2009). The main contribution of this paper is the application of these advanced econometric methods to model and better understand individual preferences in the context of shopping channel choice, which, to our best knowledge, is the first alternative-specific Hybrid choice model using stated preference data in the field of shopping behavior research.

The structure of the paper is organized as follows: Section 2 presents a short literature review on the factors affecting the choice between in-store and online shopping. Section 3 gives an overview of the recruitment and survey process, describes the methods used, compares descriptive figures of the recruited sample's characteristics and explains how the attitudes towards online shopping and the pleasure of shopping were assessed. Section 4 provides a overview on the modeling framework, including a short motivation, literature review and the mathematical formulation of the structural and measurement equations of the ICLV modeling approach. Section 5 presents the results of four models with increasing complexity and discusses the implications on choice behavior, attribute elasticities and valuation indicators. Section 6 provides a discussion of results, some concluding remarks and limitations of the study.

2 Literature review

Salomon and Koppelman (1988) discuss the underlying factors affecting the choice between in-store and online shopping. They define shopping as a process of collecting information on product attributes until the final purchase decision. Alternative-specific attributes (service, delivery, travel, etc.) and personal characteristics (socio-economic background) are hypothesized to affect the perceptions of shopping alternatives (being among people, pleasure, time use, etc.), while attitudes towards shopping alternatives (perceptions and feelings, risks, etc.) are mainly determined by personal characteristics. The ultimate factors affecting shopping behavior are the perceptions of alternatives and the attitudes. Dijst et al. (2008) present a model for online and in-store shopping of media products, in which attitudes play a major role in explaining shopping channel preferences. Farag et al. (2005) show that positive attitudes towards online shopping increase the frequency of online shopping, with more positive attitudes among young and single males with high education and income living in urban residential locations, a similar user profile that has been revealed in many other related studies (Cao, 2009; Chocarro et al., 2013) and in the case of Switzerland (Rudolph et al., 2004). Bellman et al. (1999) also mention the potential importance of a lower time budget - measured the amount of household working hours - on the propensity to shop online.

Several studies have shown substantial product-specific heterogeneity in factors affecting choice between in-store and online shopping. E.g. Peterson et al. (1997), Chiang and Dholakia (2003), Rotem-Mindali and Salomon (2007) and Chocarro et al. (2013) argue that the intention to shop online is much higher for search (e.g. electronic appliances, books or other media products) than experience goods (e.g. fresh food, perfume or cars), as online shopping reduces search costs substantially while the dominant product attributes of experience goods cannot be obtained online. Another main criteria to shop online often referred to is the (lower) price in combination with facilitated price comparisons (Farag et al., 2007), one of the main driving forces when considering online shopping in Switzerland (Rudolph et al., 2015). Also, the general product risk, which is typically higher for expensive and experience goods, may lead to a decreasing propensity for online shopping. However, especially expensive electronics, soft- and hardware may partially compensate these risks by offering a high level of shopping convenience. Chocarro et al. (2013) argue that high involvement goods - expensive goods with low purchase frequency - increase the risks for consumers, and conditional on the distance to the store, exhibit a higher probability of in-store shopping. For search goods, the authors show that a higher travel time has a positive effect on online shopping. While most of the aforementioned studies used revealed preference (RP) data, our approach is comparable to Hsiao (2009): The author conducted a stated preference (SP) experiment on book purchasing behavior in Taiwan by assessing channel-specific effects including the product price, travel time, travel cost and delivery time. He concludes that avoiding a shopping trip produces more benefits in terms of monetary values than waiting for the delivery of an online purchased book, highlighting the potentials of ICT services in the context of a typical search good. Given these findings, we tried to incorporate those different key facets to explain shopping channel preferences - product and channel-specific, socio-economic and psychological factors - in the subsequent analyses.

3 Survey methods and data

3.1 Survey administration and response rates

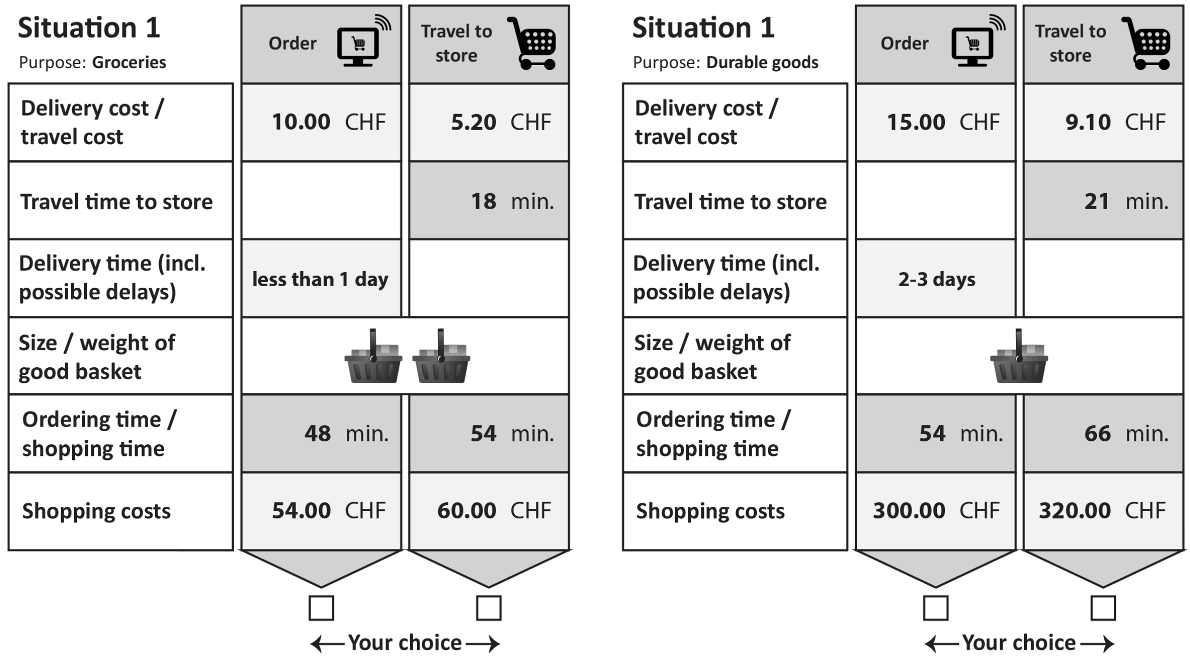
No former studies are known to serve as example for this survey as a whole. Apart from a multi-day reporting period to capture respondents' travel, expenditure and online behavior, stated preference experiments were conducted, including computer-based stated adaptation interviews for daily scheduling and mobility tool ownership (Schmid and Axhausen, 2015). The sample was drawn from a commercially available address data base, covering the metropolitan area of Zurich, Switzerland. The comprehensive and burdensome survey process was organized in three stages. The questionnaires for stage I (empirical basis) were sent to 509 households that agreed to participate during the telephonic recruitment interviews, of which 311 returned the complete questionnaires. The data analyzed for this paper was collected during stage II (stated choice and attitudinal questionnaires). 301 households (467 respondents) sent back these questionnaires. Each full participant received an incentive of 50 CHF ≈ 50 US$ after completion of the personal interview in stage III. Data was collected in four waves between January 2015 and July 2016, with an average response rate - corresponding to the *COOP4* cooperation rate (The American Association for Public Opinion Research, 2015) - of about 55%.

3.2 Online vs. in-store shopping choice experiment

The empirical basis is an enriched one-week travel diary based on the *MOBIDrive* protocol (Axhausen et al., 2002) that was required to explore the individual patterns in activity-based travel and shopping behavior and to obtain the individual reference values for the personalized choice experiments, including questionnaires asking for detailed household, vehicle and person characteristics. The choice experiment requested participants to trade-off different attributes related to their ICT (online shopping/ordering) and out-of-home (personal procurement) shopping activities for either search (standard electronic appliances) or experience goods (groceries). The aim of the experiment is to reveal how sensitive individuals react to changes in alternative-specific attributes for a given shopping purpose, using a pivot design approach to calculate the personalized attribute levels based on revealed preference (RP) data from the first stage of the survey (Rose et al., 2008). Reference values of shopping time, shopping cost, travel time and travel cost attributes were calculated based on reported shopping trips and average expenditures for groceries.[1] A *D*-efficient design with 24 choice situations blocked in three parts was calculated using *Ngene* (ChoiceMetrics, 2014), including weak parameter priors and assigning eight choice situations to each participant. More details on the experimental design, data collection and survey administration can be found in Schmid et al. (2016b) and Schmid and Axhausen (2015).

[1] Durable goods expenditures, including electronic household appliances, were part of a separate questionnaire on an aggregated yearly basis and not used for reverence value calculation. If a respondent did not report any shopping trip during the multi-day reporting period, a potential shopping location was chosen offering a high variety of goods and high level of accessibility, assigning this respondent to the standard electronic appliances experiment as from a behavioral aspect it might be more problematic to postulate a travel distance to a grocery store. In addition, reference travel time and travel cost to the store were calculated for either carsharing/carpooling or public transport. To avoid anchoring effects with respect to transport modes, a specific mode for the in-store alternative was never explicitly mentioned.

Figure 1: Example choice situations.



The experiments were introduced to frame the choice environment for the participants and place them in a coherent choice situation: Shopping trips are often chained with other activities (Adler and Ben-Akiva, 1979), which was ruled out by outlining that respondents should imagine a home-based round trip for the in-store alternative. To eliminate social motives and shopping trips as pure leisure activities (Hsiao, 2009), respondents were told that buying the specific goods is the one and only purpose of doing this shopping task. To account for this issue, purchases have been explicitly defined as either daily or weekly grocery (i.e. food, tobacco, drinks, cosmetics, detergent, etc.) or as durable goods shopping (i.e. multimedia, HiFi or electronic household appliances), respectively. Depending on reported shopping trips, respondents were assigned to one of these two experiments. Transaction security, information asymmetries and delivery uncertainties are difficult to include as explicit attributes in the choice experiment, though respondents were asked in the attitudinal questionnaire about their perception and feelings of such issues. The attributes presented below and summarized in Table 1 were included in the choice experiment:

- **Shopping cost**: If assigned to the groceries experiment, respondents were assigned to one out of three reference expenditure categories based on average shopping expenditures for groceries: 40 CHF, 80 CHF and 120 CHF. If assigned to the durable goods experiment, respondents were randomly assigned to one out of three reference expenditure categories: 150 CHF, 300 CHF and 600 CHF.
- **Time spent for in-store/online shopping**: Based on average shopping duration

Table 1: Attribute levels of online vs. in-store shopping choice experiment.

Attributes	Online	In-store	Levels	μ	σ	ν
Shopping cost [CHF]	√	–	−10%, −5%, 0%	237.8	184.4	0.7
Shopping cost [CHF]	–	√	−5%, 0%, +5%	250.5	193.7	0.7
Time for shop. [min]	√	–	−20%, −10%, +5%	38.5	14.8	1.2
Time for shop. [min]	–	√	−10%, 0%, +10%	42.2	16.3	1.3
Del. cost & duty [CHF]	√	–	0, 5, 10, 15 CHF	7.6	5.6	0.0
Travel cost [CHF]	–	√	−20%, +10%, +40%	5.3	3.3	3.0
Del. time groceries [d]	√	–	< 1 day, 1-2 days, > 2 days	1.6	0.6	0.5
Del. time electronics [d]	√	–	2-3 days, 4-7 days, > 1 week	5.4	2.5	0.0
Travel time [min]	–	√	−30%, 0%, +30%	23.6	16.6	2.2
Size/weight of the good basket	√	√	Low (1), medium (2), high (3) (same for both alternatives)	1.9	0.8	0.1

μ = mean, σ = standard deviation, ν = skewness.

Note: Summary statistics for delivery time are based on a attribute level mid-point approximation.

for either groceries or durable goods, respondents were assigned to one out of three reference shopping duration categories (groceries: 15 min, 30 min and 50 min; durable goods: 25 min, 40 min and 60 min).

- **Delivery cost** including duty: 0 CHF / 5 CHF / 10 CHF / 15 CHF
- **Travel cost**[2] depend on the reported mode in the travel diary and the distance to the store for the reference shopping trip. If the reported mode was ...
  (1) car or motorbike: Average of carpooling and carsharing travel costs
  (2) public transport: Personalized PT travel costs
- **Delivery time** groceries: Within one day / 1-2 days / more than 2 days; standard electronic appliances: 2-4 days / 4-7 days / more than 1 week
- **Travel time** depends on the reported mode in the travel diary and the distance to the store for the reference shopping trip. If the reported mode was ...
  (1) car or motorbike: Car travel time, including an additional detour factor of 10 % assuming that the driver spends some time to find a parking space
  (2) public transport: PT door-to-door travel time
- **Size/weight of the good basket**: This environmental attribute (i.e. the same value for both alternatives) is included in the choice experiments, indicating how convenient it is to do a specific shopping task

[2] Travel costs were calculated based on current Swiss market prices for carsharing, carpooling and public transport (PT). Details on underlying assumptions, the routing and cost calculations would go beyond the scope of this paper but can be found in Schmid and Axhausen (2015).

3.3 Descriptive analysis of the sample

Descriptive figures of the recruited sample's characteristics (PCW sample; 301 households, 467 respondents) are shown in Table 2 and compared with data from the Mikrozensus 2010 (Swiss National Household Travel Survey, MZ2010, Swiss Federal Statistical Office ARE, 2010), a weighted, representative sample of the population. Although the PCW sample size is small to draw clear conclusions about representativeness, it highlights potential sampling biases, which one should keep in mind when interpreting the results[3]. While the residential location area, gender and car availability of the household members lie in the expected range, older, larger and more public transport affine households with high income and education are clearly overrepresented. Note that season tickets on a national level in Switzerland are the half-fare card (175 CHF per year) providing a 50 % discount on almost all public transport services, while the full-discount pass (GA; 3650 CHF per year) is a flat rate card for the whole Swiss transit network. The comparisons indicate the usual sample selectivity problems of other studies conducted at the IVT.

3.4 Attitudes and socio-demographic characteristics

A broad range of attitudinal traits were assessed together with the stated choice experiments in stage II of the survey. The implemented attitudinal questionnaires are based on the *MOBIDrive* protocol (Axhausen et al., 2002) and a survey by Rieser-Schüssler and Axhausen (2012). To focus on items reflecting the attitudes towards online shopping and the pleasure of shopping, twelve 4-point-Likert scale items were considered for the subsequent analyses. Note that additional LVs were tested to better explain choice behavior: The three top candidates that were also available in the data and hypothesized to have a potential effect on shopping channel choice - "general risk aversion", "environmental sensitivity" and "love of variety" according to Rieser-Schüssler and Axhausen (2012) - did not show a substantial or significant effect, thus were excluded for the subsequent analysis.

According to our hypotheses and the factor structure of a previously conducted exploratory factor analysis, two latent constructs are defined, measured by the following items $I_{w,n}$ (see also Eq. (9) and Eq. (10)): The first set of items measures the attitudes regarding the general risks and perceptions of online shopping, and if respondent make use and are aware of this technology (onl1-onl9), while the second set mainly covers the pleasure of

[3] A re-weighting of willingness-to-pay estimates to correctly compute the population level valuation indicators was not done in this paper, but will be reconsidered.

Table 2: Descriptive statistics: MZ2010 (Canton of Zürich) vs. PCW sample.

Variable	Value	MZ2010 (%)	PCW (%)
Household members	1	31.6	18.4
	2	37.4	29.1
	≥ 3	30.0	42.4
Household income	Not reported	24.1	4.9
	$\leq$ 12'000 CHF	57.5	34.7
	$>$ 12'000 CHF	18.4	60.4
Personal income (after imputation)	0 CHF	–	4.9
	$\leq$ 6'000 CHF	–	44.5
	$>$ 6'000 CHF	–	50.6
Household type	Single-person household	31.6	18.4
	Couple without kids	33.0	23.6
	Couple with kids	26.6	50.0
	Single-parent household	5.8	4.6
	Living community	3.1	3.4
Residential location area	City centre	38.9	41.4
	Agglomeration	54.8	42.3
	Rural	6.3	16.3
Sex	Female	54.3	50.4
	Male	45.7	49.6
Age	18 - 35 years	20.7	10.8
	36 - 50 years	29.4	38.4
	51 - 65 years	27.4	46.5
	66 - 80 years	22.5	4.3
Education	Low	21.0	13.3
	Medium	54.9	22.6
	High	24.1	64.2
Season tickets	None	37.3	11.1
	Half-fare card	51.8	73.5
	GA	10.9	15.4
Car availability	Always	74.6	59.1
	Sometimes	18.0	27.1
	Never	7.3	13.8
Married	Yes	46.4	58.7
	No	53.6	41.3
Shopping accessibility	Next shop $\leq$ 10 min. of walk	–	90.1
	Next shop $>$ 10 min. of walk	–	9.9
Working hours	Weekly working hours $\leq$ 5 h	–	10.7
	Weekly working hours $>$ 5 h	–	89.3

in-store shopping and the desire to physically examine the product(s) (ple1-ple3):

- **onl1:** I often order products on the internet
- **onl2:** Online shopping is associated with risks
- **onl3:** Credit card fraud is one of the reasons why I don't like online shopping
- **onl4:** The internet has more cons than pros
- **onl5:** Online shopping facilitates the comparison of prices and products
- **onl6:** The risk of receiving a wrong product is one of the main reasons why I don't like online shopping
- **onl7:** I like to follow the new developments in the tech industry
- **onl8:** All what I need, I find in the shops
- **onl9:** Number of different IT gadgets in possession

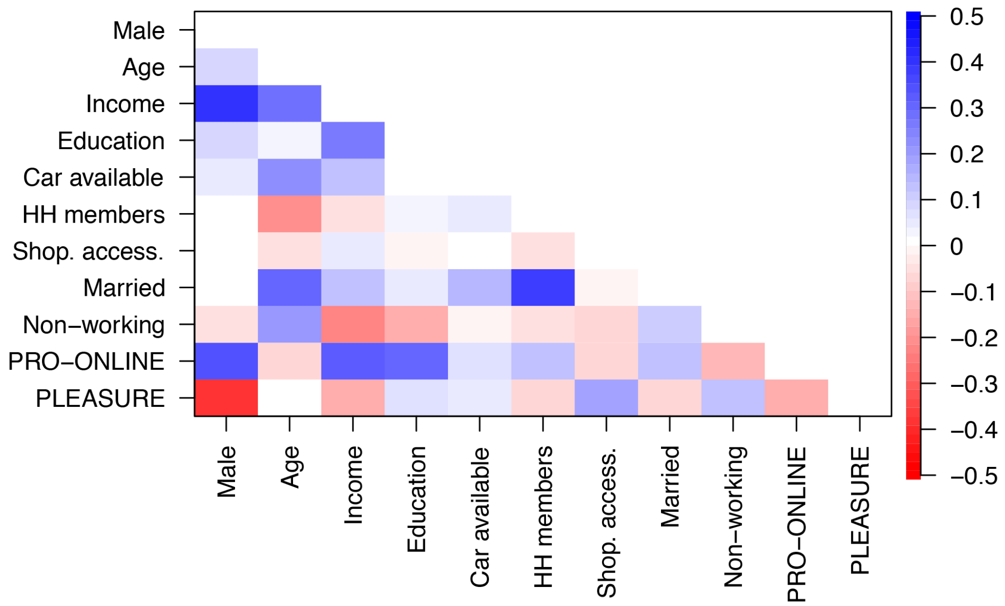
- **ple1**: I like to visit shops, even if I don't want to buy something, just for looking around
- **ple2:** A disadvantage of online shopping is that I cannot physically examine the products
- **ple3**: Shopping usually is an annoying duty

For getting a better understanding on how attitudes are defined by various exogenous socio-demographic characteristics $Z_{z,n}$, the key variables which were found to describe the two latent variables best are (see also Eq. (8) and Table 2 for some basic summary statistics):

- **Male** (dummy)
- **Age** (continuous)
- Personal **income** (continuous; mean normalized)
- Higher **education** (dummy for high-school degree or higher)
- **Car** always **available** (dummy)
- **Household members** (continuous)
- **Shopping accessibility** (dummy; supermarket within 10 minutes of walk from residential location)
- **Married** (dummy)
- **Non-working** (dummy; weekly regular payed job working hours $\leq$ 5 hours)

Fig. 2 gives a first overview on how attitudes (i.e. the predictions of an Ordered Logit MIMIC model described in Section 4.1) and socio-economic characteristics are linked to each other, and also gives some idea about potential multi-collinearity issues in the structural model. Regarding the two soft factors, besides a moderate negative correlation between each other, it shows that pro-online shopping attitudes are more pronounced for men with higher education and income, while the pleasure of shopping is higher for non-working women living nearby a supermarket.

Figure 2: Correlation patterns of socio-demographic characteristics and attitudes.



4 Modeling framework

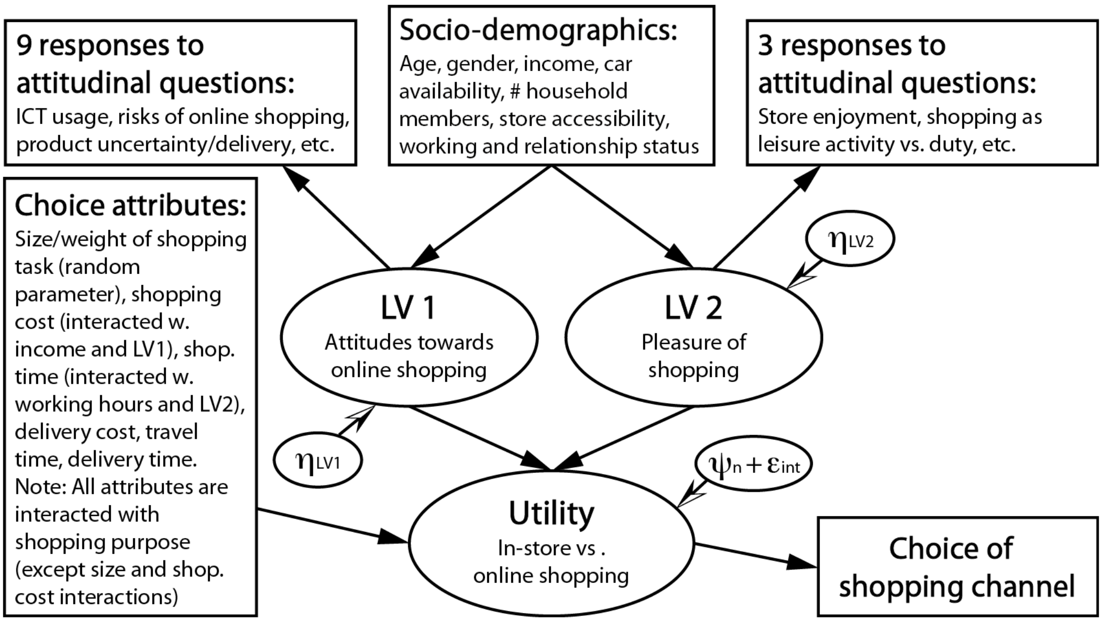
The hybrid choice modeling (HCM) approach described by Ben-Akiva et al. (2002) is an integration of the random utility-maximization (RUM) framework and functionalities such as error heterogeneity, random parameters and latent variables (Walker and Ben-Akiva, 2002). The integration of latent variables (LVs) into RUM models is an example of the general HCM framework which addresses the problem of attitudes and perceptions of individuals, which are at the same time relevant to the choice process and hard to observe directly. The RUM model is therefore extended by latent variables as part of the utility formulation. The LVs are defined in the structural models by measurable socio-economic variables, and can be seen as a type of interaction between variables in the utility formulation with a dedicated type of disturbance. A measurement model links the LVs with indicators assumed to be affected by the latent constructs. The attitudinal part of the integrated choice and latent variable (ICLV) model with the measured "indicator variables - LV" relationships is therefore often represented by a multiple-indicator multiple-cause (MIMIC) model (Jöreskog and Goldberger, 1975).

There are essentially two ways how to include attitudes in a choice model: Raveau et al. (2010) compared a sequential (two-step procedure, first estimating a MIMIC model and predicting the distribution of attitudes, which then are included in the choice model) and a simultaneous (maximizing the joint probability given the observed choices and indicators) estimation method. Although the sequential estimation approach is consistent, they emphasize the advantages of the simultaneous method in terms of bias and efficiency, which, in the former case, can have implications on valuation indicators. Apart from a better representation of the decision process (all available information is used jointly) and more efficient and consistent estimation properties (Daziano and Bolduc, 2013), the simultaneous approach can be better applied to predict the distribution of attitudes and/or market shares for specific consumer segments based on socio-economic characteristics. In this paper, we also estimate a sequential model as a first benchmark to compare the results with the more dedicated simultaneous approach. Also, while LVs estimated in a sequential approach are usually zero-centered, this is not necessarily the case in the simultaneous approach. We argue that a normalization of the LVs should be considered such that the mean is always zero, which is a practical concern when working with interaction terms, as part of the mean effect of an interacted choice attribute would otherwise be "mediated" via the LVs.

Further considerations of ICLV models arise when dealing with repeated within-group observations, in our case multiple choices of one and the same individual, which, even in advanced literature, was often not taken into account (see e.g. Kim et al. (2014), for an overview of previous research applying HCMs in travel behavior research). Besides a substantial increase in estimation complexity when accounting for the panel structure and unobserved heterogeneity in HCMs (as we believe, mainly regarding runtime, parameter instability when using simulation methods and the non-availability even in advanced standard software packages), one issue is the appropriate weighting of the LVs: Choices in a SP survey are usually observed several times, but the responses to attitudinal questions only once. Since the literature has, to our best knowledge, no clear advise in this topic, the normalization applied here was to reweigh the product of the conditional indicator probabilities by the number of choice tasks each respondent did complete.

Panel data usually comes along with an unobserved component in the utility function that is correlated within, but uncorrelated across individuals, violating the assumptions of independent and identically distributed (IID) error terms, as e.g. in simple multinomial Logit (MNL) models. In the case of HCMs, Daziano and Bolduc (2013) showed that LVs already induce correlation among choices of the same individual similar to a Mixed Logit model (Train, 2009; Greene et al., 2006), as the same value of a LV - partly defined by an individual-specific random component - is shared by multiple observations, thus relaxing

Figure 3: Hybrid Choice modeling framework.



the IID assumptions of pure RUM models[4]. However, often there is still a substantial amount of remaining unobserved heterogeneity, which we partly accounted for by using two additional random components in the utility function. Although it can be shown that such a specification substantially weakens the effects of LVs, the remaining contributions of attitudes to the likelihood are rectified by the "pure" within-group correlations otherwise captured by the LVs only, thus can be seen as a more conservative approach.

Fig. 3 gives an overview of the HCM framework developed to model the choice between online and in-store shopping, including two LVs for the attitudes towards online shopping and the pleasure of shopping. The structural model includes the specification of the alternative-specific utility equations and the relationship between attitudes (LVs) and socio-economic characteristics, while the measurement model captures the relationship between the online, ICT use and pleasure of shopping indicators and the LVs as well as the relationship between alternative-specific utilities and observed choices. Each model component is described in the following subsections.

[4]Daziano and Bolduc (2013) also argue that, in the case of more than 2 choice alternatives, the independence of irrelevant alternatives (IIA) assumption is also relaxed when distinct alternatives share the same LVs, thus inducing correlations among alternatives.

4.1 Structural model

The utility equations for shopping channel $i \in \{\mathrm{O}, \mathrm{IS}\}$ and individual $n \in \{1, 2, .., N\}$ in choice scenario $t \in \{1, 2, .., T_n\}$[5] with choice attributes $X_{i,n,t}$ and the latent variables $LV_{z,n}$ with $z \in \{\text{online shopping attitudes, pleasure of shopping}\}$ are given by

$$U_{O,n,t} = X_{O,n,t}\beta_O + \sum_z \mu_{LV_z}\widetilde{LV}_{z,n} + f_{1,O,n,t} + f_{2,O,n,t} + f_{4,n,t} + \psi_{O,n} + \epsilon_{O,n,t} \tag{1}$$

$$U_{IS,n,t} = X_{IS,n,t}\beta_{IS} + f_{1,IS,n,t} + f_{2,IS,n,t} + f_{3,n,t} + \epsilon_{IS,n,t} \tag{2}$$

where

$$f_{1,i,n,t} = \beta_{cost} \cdot cost_{i,n,t} \cdot \left(\frac{inc_n}{\overline{inc}}\right)^{\lambda_{inc}} + \varphi_{LV_{online},cost} \cdot \widetilde{LV}_{online,n} \cdot cost_{i,n,t} \tag{3}$$

$$f_{2,i,n,t} = \beta_{time} \cdot time_{i,n,t} \cdot \left(\frac{workhours_n}{\overline{workhours}}\right)^{\lambda_{work}} \tag{4}$$

$$f_{3,n,t} = \varphi_{LV_{pleasure},IS-time} \cdot \widetilde{LV}_{pleasure,n} \cdot time_{IS,n,t} \tag{5}$$

$$f_{4,n,t} = size_{n,t} \cdot \exp(\alpha_{size} + \alpha_{male} \cdot male_n + \alpha_{age} \cdot age_n + \psi_{size,n}) \tag{6}$$

$$\widetilde{LV}_{z,n} = LV_{z,n} - \overline{LV_z} \tag{7}$$

$X_{i,n,t}$ is a $(1 \times J_i)$ vector of alternative-specific choice attributes and β_i is a $(J_i \times 1)$ alternative-specific coefficient vector. Both LVs are directly affecting the constant of the online alternative (note that for identification of the parameters, in-store shopping is always defined as the reference alternative) and are interacted with shopping cost and time to reveal heterogeneity in respective attribute sensitivities: $\widetilde{LV}_{z,n}$ is a zero-centered[6] latent variable z (invariant in t), μ_{LV_z} is the coefficient of latent variable z for the utility of online shopping, $\varphi_{LV_{online},cost}$ and $\varphi_{LV_{pleasure},IS-time}$ are the coefficients of the interaction terms between the two LVs and some selected choice attributes (i.e. shopping cost $\times$ pro-online shopping attitudes; in-store shopping time $\times$ pleasure of shopping). A higher pleasure of shopping is hypothesized to reduce shopping time sensitivity, while more positive attitudes towards online shopping are assumed to increase cost sensitivity.

[5] Subscript n indicates that some respondents did not complete all eight choice scenarios.
[6] The sample mean $\overline{LV_z}$ is subtracted from $LV_{z,n}$.

All choice attributes were interacted with the shopping purpose, with grocery shopping as a reference, to allow for heterogeneity in attribute sensitivities, except for the size/weight of the shopping basket and the interaction of shopping cost $\times$ online shopping attitudes. This increases estimation efficiency compared to a segmented estimation approach by product category (shopping purpose), mainly regarding the estimation of only one measurement model. Also, one scale parameter (Train, 2009) was tested to correct for unequal variances between the two shopping purposes, with grocery shopping as a reference, but was not included in the final model specifications.[7]

For shopping cost and time, continuous interaction terms according to Mackie et al. (2003) were included: β_{cost} is a generic cost coefficient of shopping cost, $cost_{i,n,t}$. inc_n is the individual gross income with sample mean $\overline{inc}$ and corresponding elasticity of shopping costs λ_{inc}. β_{time} is a generic time coefficient of shopping time, $time_{i,n,t}$. $workhours_n$ are the individual effective work hours per week with sample mean $\overline{workhours}$ and corresponding elasticity of shopping time λ_{work}. Scarcity typically leads to a higher sensitivity in related resource consumption: High-income respondents are hypothesized to have a lower cost sensitivity, while hard-working respondents are assumed to have a higher time sensitivity, which would be the case for $\lambda_{inc} < 0$ and $\lambda_{work} > 0$.

To account for the correlation across choices within individuals and unobserved coefficient heterogeneity (Greene et al., 2006), two additional components were added to the utility function which vary across individuals but are constant over choice situations. $\psi_{O,n} \sim N(0, \sigma_O^2)$ is an individual-specific random error component with mean zero and standard deviation σ_O, for each individual shifting the intercept of the online alternative by the respective amount. The log-normal random coefficient for the size/weight of the shopping basket attribute[8] is defined by the constant effect α_{size} and an individual-specific random effect $\psi_{size,n} \sim N(0, \sigma_{size}^2)$ with mean zero and standard deviation σ_{size}. Also, the heterogeneity in the size/weight attribute sensitivity regarding gender and age was explicitly taken into account. Given the strong and positive effect of this choice attribute on the probability of online shopping - for some respondents showing an almost deterministic pattern - a log-normal specification was found to fit the data best. This specification allows for (observed) preference heterogeneity in varying levels of shopping inconvenience regarding physical conditions and random (unobserved) preferences/shopping habits captured by the random component. Finally, $\epsilon_{i,n,t}$ is the remaining alternative-specific IID extreme value type I disturbance vector.

[7] Independent of the model specification, the estimated scale parameter was roughly about 1.1, indicating a slightly lower variance in the standard electronic appliances experiment, but was always highly insignificant. This is not surprising, as most variables are interacted with the shopping purpose.

[8] Note that a dummy specification for the size/weight attribute was tested, but indeed a linear specification was found to be appropriate.

The LV equations (LV structural model) for latent variable z are linear functions of observed socio-economic characteristics $Z_{z,n}$ for individual n:

$$\begin{aligned} LV_{z,n} &= \overline{LV_z} + Z_{z,n}\rho_z + \eta_{LV_{z,n}}, \\ \eta_{LV_{z,n}} &\sim N(0, \sigma^2_{LV_z}) \end{aligned} \tag{8}$$

where $Z_{z,n}$ is a $(1 \times Q_z)$ vector of socio-economic characteristics (invariant in t) to define $LV_{z,n}$ (note that each LV is defined by a partially different set of socio-economic characteristics), ρ_z is a $(Q_z \times 1)$ coefficient vector and $\overline{LV_z}$ is the constant of latent variable z.

4.2 Measurement model

The latent variable measurement equations with responses to the attitudinal questions (indicators) $I_{w,n}$ with $w \in \{\text{onl1}, \text{onl2}, .., \text{ple3}\}$ discussed in Section 3.4 are given by

$$\begin{aligned} I_{w,n} &= \overline{I_w} + \tau_{I_w} LV_{z,n} + \nu_{w,n}, \\ \nu_{w,n} &\sim N(0, \sigma^2_{I_w}) \end{aligned} \tag{9}$$

in the linear case, where $\overline{I_w}$ are the mean ratings of the 4-point-Likert scales of each indicator w calculated beforehand (Hess and Beharry-Borg, 2012), avoiding the estimation of unnecessary parameters, or - when using an Ordered Logit (OL) link function by accounting for the discrete nature of the items as proposed in Daly et al. (2012b) - by

$$I_{w,n} = \begin{cases} 1 \text{ if } -\infty < I^*_{w,n} \leq \kappa_{1,I_w} \\ 2 \text{ if } \kappa_{1,I_w} < I^*_{w,n} \leq \kappa_{2,I_w} \\ 3 \text{ if } \kappa_{2,I_w} < I^*_{w,n} \leq \kappa_{3,I_w} \\ 4 \text{ if } \kappa_{3,I_w} < I^*_{w,n} \leq \infty \end{cases} \tag{10}$$

$$I^*_{w,n} = \tau_{I_w} LV_{z,n} + \nu^*_{w,n} \tag{11}$$

$I_{w,n}$ are the observed indicators for individual n, $LV_{z,n}$ is latent variable z (invariant in t), τ_{I_w} is the LV measurement coefficient for each indicator w, σ_{I_w} are the standard deviation coefficients in the linear case and κ_{I_w} are the threshold coefficients in the Ordered Logit case. Finally, the choice of shopping channel i is modeled by maximizing the alternative-specific utility $U_{i,n,t}$ for each individual n and choice scenario t:

$$choice_{i,n,t} = \begin{cases} \text{Online shopping if } U_{O,n,t} > U_{IS,n,t} \\ \text{In-store shopping if } U_{O,n,t} \leq U_{IS,n,t} \end{cases} \tag{12}$$

4.3 Estimation

Assuming that the random components ψ_n and the latent variables $LV_{z,n}$ are mutually independent and $\epsilon_{i,n,t}$ is IID extreme value type I, the unconditional joint probability $L_n(.)$ - the expected value over all possible values of ψ_n and $LV_{z,n}$ that individual n chooses alternative i among a sequence of choices T_n, and, simultaneously, stating his/her attitudes via indicators $I_{w,n}$ only once - is defined by the integral of the product of conditional choice (Mixed Logit) and indicator probabilities over the distributions of ψ_n and $LV_{z,n}$ (Ben-Akiva et al., 2002; Walker and Ben-Akiva, 2002; Bolduc and Daziano, 2010):

$$\begin{aligned} L_n(choice_{i,n,t}, I_{w,n}|X_{i,n,t}, Z_{z,n}, \Omega) = \int_{\psi_n}\int_{LV_{z,n}} & \prod_{t=1}^{T_n} P(choice_{i,n,t}|X_{i,n,t}, LV_{z,n}, \theta, \psi_n) \\ & \times u(I_{w,n}|LV_{z,n}, \tau_{I_w}, \zeta)^{1/T_n}\; g(LV_{z,n}|Z_{z,n}, \rho_z, \eta_{LV_z}) \\ & \times h(\psi_n|R)\; dLV_{z,n}\; d\psi_n \end{aligned} \tag{13}$$

where

$$\Omega = \{\alpha, \beta, \kappa, \lambda, \mu, \rho, \sigma, \tau, \varphi\} \;\text{ with }\; \theta = \{\alpha, \beta, \lambda, \mu, \sigma, \varphi\} \in \Omega \tag{14}$$

is the vector of parameters to be estimated (depending on the measurement model),

$$P(choice_{i,n,t}|X_{i,n,t}, LV_{z,n}, \theta, \psi_n) = \frac{\exp(U_{i,n,t})}{\exp(U_{O,n,t}) + \exp(U_{IS,n,t})} \tag{15}$$

is the conditional choice probability and, for the linear measurement model,

$$u(I_{w,n}|LV_{z,n}, \tau_{I_w}, \sigma_{I_w}) = \prod_{I_w}\left(\frac{1}{\exp(\sigma_{I_w})}\phi\left(\frac{I_{w,n} - \overline{I_w} - \tau_{I_w} LV_{z,n}}{\exp(\sigma_{I_w})}\right)\right) \tag{16}$$

with ϕ as the standard normal density function, or, for the OL measurement model,

$$u(I_{w,n}|LV_{z,n}, \tau_{I_w}, \kappa_{I_w}) = \prod_{I_w}\left(\frac{\exp(\kappa_{j,I_w} - \tau_{I_w} LV_{z,n})}{1 + \exp(\kappa_{j,I_w} - \tau_{I_w} LV_{z,n})} - \frac{\exp(\kappa_{j-1,I_w} - \tau_{I_w} LV_{z,n})}{1 + \exp(\kappa_{j-1,I_w} - \tau_{I_w} LV_{z,n})}\right) \tag{17}$$

and, finally,

$$g(LV_{z,n}|Z_{z,n}, \rho_z, \eta_{LV_z}) \sim N(Z_{z,n}\rho_z, \sigma^2_{LV_z}) \qquad h(\psi_n|R) \sim N(0, \sigma^2_{\psi}) \tag{18}$$

corresponds to independent normal distributions of the LVs and random components. Due to identification issues (Vij and Walker, 2014), the first τ_{I_w} of each LV was fixed to 1. Also, in the OL measurement model, the corresponding κ_{2,I_w} was fixed to 0. This approach worked slightly better in terms of robustness in parameter estimates than the one used in Daly et al. (2012b) (i.e. fixing all κ_{1,I_w} to 0, but including additional constants).

The estimation of HCMs is computationally demanding, and gets cumbersome with increasing number of LVs and/or random coefficients, as simulation or Bayesian techniques are required to solve the multi-dimensional integrals that have no closed-form expression. Using the former approach, the maximum simulated likelihood estimator (MSLE) of Eq. (13) is derived by approximating the joint probability for any given value of ψ_n and $LV_{z,n}$ using a smooth simulator that is consistent and asymptotically normal (Train, 2009): (1) Draw a value from ψ_n and $LV_{z,n}$ from the $g(LV_{z,n}|Z_{z,n}, \rho_z, \eta_{LV_{z,n}})$ and $h(\psi_n|R)$ distributions, and label it ψ_n^r and $LV_{z,n}^r$ with superscript $r = 1$ referring to the first draw of $r \in R$. (2) Calculate the joint choice probability for this draw. (3) Repeat steps (1) and (2) many times. (4) With panel data, take the product over the sequence of individual choices T_n of the joint choice probability for each draw, and normalize indicator probability $u(I_{w,n}|LV_{z,n}, \tau_{I_w}, \zeta)$ of individual n by T_n. (5) Take the average over all R draws: $\widetilde{L_n}(.)$ shown in Eq. (20) is the simulated likelihood for individual n, and the MSLE is the value of $\widehat{\boldsymbol{\Omega}}$ that maximizes $\widetilde{LL}(\boldsymbol{\Omega})$: The sum of individual contributions to the log-likelihood.

$$\max \widetilde{LL}(\Omega) = \sum_{n=1}^{N} \log\left(\widetilde{L_n}(choice_{i,n,t}, I_{w,n}|X_{i,n,t}, Z_{z,n}, \Omega)\right) \tag{19}$$

$$\begin{aligned}\widetilde{L_n}(choice_{i,n,t}, I_{w,n}|X_{i,n,t}, Z_{z,n}, \Omega) = \frac{1}{R}\sum_{r=1}^{R}\prod_{t=1}^{T_n} & P(choice_{i,n,t}|X_{i,n,t}, LV_{z,n}^r, \theta, \psi_n^r) \\ & \times u(I_{w,n}|LV_{z,n}^r, \tau_{I_w}, \zeta)^{1/T_n}\end{aligned} \tag{20}$$

Models were estimated in R version 3.2. The R-code builds on the *maxLik* package, using the BFGS algorithm to efficiently calculate the approximate Hessian (Train, 2009). To reduce the almost intractable runtime of several weeks to a few days, the calculation of the likelihood was parallelized using the *dopar* package and estimation was executed on a 16-core cluster. Robust standard errors were calculated using the Eicker-Huber-White sandwich estimator (Zeileis, 2006). Quasi-random draws for the simulation of the likelihood were generated using Modified Latin Hypercube Sampling (MLHS) methods. MLHS was found to avoid undesirable correlation patterns especially - as discussed in Hess et al. (2006) - when dealing with higher-order integrals: Model stability substantially improved compared to Halton draws. Also, the main criteria regarding identifiability and simulation bias as discussed in Vij and Walker (2014) were investigated. Importantly, even for a very large number of Halton draws, the LV structural model including the effects of socio-demographics on the two latent variables did not reach stability (within $+/-1$ standard errors) in the coefficient estimates. After 2000 MLHS draws, estimates were carefully considered to be robust and stable.

5 Results

5.1 Descriptive analysis of choice behavior

The analyzed sample comprises 3722 choice observations for 466 respondents[9]: 37% were assigned to the groceries (G) and 63% to the standard electronic appliances (E) experiment. The market shares of online and in-store shopping choices depend on the shopping purpose: In the G experiment, 66% chose the in-store and 34% the online alternative, while in the E experiment, 38% chose the in-store and 62% the online alternative. Although the total market share of online shopping is remarkably high for both shopping purposes partly resulting from the assumptions made to frame the respondents (most important, assuming that no private cars would be available for the in-store alternative; see also Section 3.2), it clearly shows the tendency that for G, people prefer shopping in a store. This is also reflected by the non-negligible share of respondents always choosing the same alternative within all choice situations, also referred to as "non-traders": While the overall share of non-traders is about 24 %, the share of non-traders in the E experiment is substantially lower compared to the G experiment (19% and 31%, respectively; $p_\Delta < 0.01$). Almost 30% of participants that were assigned to the G experiment always chose the in-store alternative, whereas 14% that were assigned to the E experiment always chose the online alternative. Although providing limited trade-off information, non-trading behavior can still be consistent with random utility theory. In a "labeled" choice experiment, this can occur when offering too small trade-off variations with respect to these respondents' underlying preferences. Part of these non-trading patterns should be captured by the attitudes towards online shopping and the pleasure of shopping.

5.2 Estimation results

Four different models with increasing complexity are presented which were found to represent best the different aspects of shopping channel choice.[10] The base model in Table 3 (MIXL) explains choices with attributes specific to each shopping channel, including a non-linear interaction term for the income elasticity of shopping cost and the two

[9] One respondent was excluded as he refused to complete the attitudinal questionnaire.

[10] Note that several model specifications (e.g. direct effects of socio-demographic characteristics on utility, and other interaction terms with latent variables) have been tested, but have been rejected due to insignificance of parameters and/or interpretation issues. Starting point was a simple MNL model using a two-stage approach without any random components (but accounting for the panel structure), in which most of the currently reported coefficients were significant at the 5% level.

components for the random intercept and the random size/weight coefficient. The sequential model (SM) adds the online shopping and the pleasure of shopping attitudes based on the first-stage predictions[11] of a combined Ordered Logit (OL) MIMIC model shown in Eq. (10) and a LV structural model shown in Eq. (8), while the hybrid models simultaneously estimate the structural and measurement models as explained in Section 4, comparing a linear (HCMLIN) and an OL (HCMOL) measurement modeling approach. Results in Table 3 are organized in blocks: The choice model is presented first, followed by the direct/interaction effects of LVs on utility, the two LV structural models and the two LV measurement models.

Regarding AICc, for finite sample size corrected Akaike Information Criterion for assessing the goodness of fit of a model, the improvement from the base to the sequential model is highly significant, with an increase in log-likelihood by 58 units.[12] This suggests that a substantial part of otherwise unobserved heterogeneity is captured by the two LVs (i.e. the 7 additional parameters in the utility function). The final log-likelihood of the hybrid models is not directly comparable to the first two models, as it is jointly determined over the whole set of parameters. Thus, what is decisive for model comparison is the log-likelihood of the choice model only (Walker and Ben-Akiva, 2002), which is also reported in Table 3 and given by

$$\widetilde{LL}_{choice}(\widetilde{\boldsymbol{\Omega}}) = \sum_{n=1}^{N} \log \frac{1}{R} \sum_{r=1}^{R} \prod_{t=1}^{T_n} P(choice_{i,n,t} | X_{i,n,t}, LV_{z,n}^{r}, \theta, \psi_n^r) \tag{21}$$

This approach is representing a forecasting methodology based on a restricted set of parameters $\widetilde{\boldsymbol{\Omega}}$, in which the (unknown) indicators of the measurement model are not used for assessing the goodness of fit. Interestingly, similar to the work of Daly et al. (2012b), both hybrid models show a similar fit, meaning that the HCMOL does not outperform the HCMLIN in explaining the choice of the shopping channel. However, the former shows a much better overall model fit than the latter of more than 500 log-likelihood units, meaning that the OL specification has much more power in measuring the two LVs than the linear approach. Also, while both hybrid models show a better fit than the base model of about 30 log-likelihood units, they perform significantly worse than the sequential model, as it wrongly treats the LVs as exogenous variables rather than jointly determined, endogenous constructs.

[11] The MIMIC model was estimated in STATA 14.2. Thus, the SDs of the LV structural model reported in Table 3 are in fact variances, and the constants were fixed to zero. Note that no correction factors for the second-stage standard errors were used as e.g. suggested by Raveau et al. (2010).

[12] Note that without the two random components, the MIXL and SM would have a log-likelihood of −2077 and −1931, respectively. Thus, the increase in log-likelihood would be much higher (146 units). This clearly shows that the random components capture the main source of heterogeneity which otherwise would be (partly) explained by the LVs.

The choice attributes shopping cost, delivery cost, travel time and delivery time[13] all exhibit the expected negative effect. However, respondents did not react on travel costs, but were anchoring behavior with respect to shopping costs, which was not the case for delivery costs: Shopping costs were perceived as much less unpleasant than delivery costs, which one would also expect. On the other hand, travel time was perceived as much more unpleasant than the time spent for online/in-store shopping, with the latter showing, on average, no significant and substantial effect. Most choice attributes were interacted with the shopping purpose, with grocery shopping (G) as a reference: While shopping costs, shopping time and travel cost exhibit no significant difference between G and electronic household appliances (E), it is interesting to see that travel time, delivery time and delivery cost show much less strong negative effects on utility for E than for G (but are still significantly smaller than zero; $p < 0.05$)[14]. There are several psychological mechanisms in force that can explain these findings: Buying E is usually done on a much more irregular basis, it exhibits a longer planning horizon and goods are non-perishable, thus leading to both a lower disutility of delivery and travel time. The effect of delivery cost is almost four times as large for G than for E. Possible explanations are that 1) delivery costs are at fixed levels, and their share of total shopping costs is substantially larger for G than for E (see also Table 1), thus are perceived as more negative and 2) people could more easily avoid high delivery costs for G by just visiting a nearby grocery store.

A larger size/weight of the shopping basket strongly increases the choice probability of online shopping, exhibiting a highly significant amount of preference heterogeneity captured by standard deviation (SD) of the corresponding random component, as visualized in Fig. 4(a) and Fig. 4(b) for the HCMLIN and HCMOL specification, respectively. Note that Fig. 4 presents the posterior distributions of individual-level parameters or LVs (Train, 2009; Hess, 2007). Given the observed sequence of choices $choice_{i,n,t}$ and indicators $I_{w,n}$ of respondent n, $\widetilde{L_n}(choice_{i,n,t}, I_{w,n}|X_{i,n,t}, Z_{z,n}, \widehat{\mathbf{\Omega}}, \xi^r)$ is the respective simulated probability for a specific value of ξ^r, given the estimates of $\mathbf{\Omega}$, $\widehat{\mathbf{\Omega}}$. $\widehat{\xi_n}$ is the most likely mean value of the random coefficient or LV of that same respondent and given by

$$\widehat{\xi_n} = \frac{\sum_{r=1}^{R} \widetilde{L_n}(choice_{i,n,t}, I_{w,n}|X_{i,n,t}, Z_{z,n}, \widehat{\mathbf{\Omega}}, \xi^r)\xi^r}{\sum_{r=1}^{R} \widetilde{L_n}(choice_{i,n,t}, I_{w,n}|X_{i,n,t}, Z_{z,n}, \widehat{\mathbf{\Omega}}, \xi^r)} \tag{22}$$

where ξ^r are independent multi-dimensional draws from the normal distributions of the random coefficient or LVs. Results in Table 3 show that female ($p < 0.01$) and older

[13]Note that in Schmid et al. (2016b), delivery time was (correctly) treated as a dummy specification due to the unequal time spacing. However, for interpretation issues, its more convenient to treat it as a continuous variable, mainly to calculate valuation indicators (i.e. CHF/day) similar to Hsiao (2009). We used attribute level mid-points to approximate delivery time for both shopping purposes.

[14]Robust standard errors were calculated using the delta method (Daly et al., 2012a).

($p \approx 0.1$) respondents' choice probability of online shopping increases stronger with a larger size/weight of the shopping basket. Although this choice attribute is not of primary interest in this analysis, it was found to be an important control variable, especially to detect some sort of "conditional non-trading behavior" with respect to the respondents' physical conditions and unobserved preference heterogeneity in varying levels of shopping inconvenience.

The robustness of parameter estimates is constituted by the results of the four choice models: Choice attribute coefficients and standard errors only change marginally between the different model specifications. However, there are some notable differences for the effects of LVs and their interactions with choice attributes. The sequential model (SM) and the HCM with an OL measurement model (HCMOL) show very similar coefficient magnitudes, as the LVs are measured by using essentially the same methodology. Still, there are some important differences: While the SM reveals a significant and positive interaction effect of in-store shopping time and the pleasure of shopping[15], this is not the case for the HCMOL and the HCM with a linear measurement model (HCMLIN). Also, the HCMLIN exhibits much larger coefficient magnitudes, as the variance of the LVs undergo a different scaling than in the SM and HCMOL (i.e. LVs in HCMLIN have a much smaller standard deviation; see also Fig. 4(c) - Fig. 4(f) for the posterior distributions of LVs). Together with highly asymmetric threshold coefficients (not reported), findings justify the application of an OL measurement specification, given the large increase in estimation complexity (e.g. increase in runtime by factor 3; see also Table 3 at the bottom). However, the differences between the two HCM specifications are small: All correlations between the individual-level parameter and LV posteriors (see also Fig. 4) are very high (> 0.99). While the pro-online shopping LV coefficients would essentially lead to the same conclusions in all model specifications, the HCMLIN shows slightly stronger effects ($p < 0.1$) of the pleasure of shopping LV than the HCMOL.

The pro-online shopping LV shows, not surprisingly, a strong and positive effect on the choice of online shopping independent of the shopping purpose. More interesting is the significant interaction term of shopping cost and the pro-online shopping LV, meaning that participants with more positive attitudes towards online shopping exhibit a substantially higher shopping cost sensitivity. This can be explained by the expanded alternative set when not considering in-store shopping as the dominant purchase channel, leading to a stronger price-driven trade-off behavior than for "traditional" shoppers.

[15]Importantly, different specifications for the pleasure of shopping $\times$ shopping time interactions were tested. They were highly insignificant for online shopping time or when using a generic in-store/online shopping time specification and sometimes resulted in not estimable standard errors.

Table 3: Estimation results: In-store vs. online shopping (hybrid) models.

Base category: In-store (IS) shopping	MIXL Coef./(SE)	SM Coef./(SE)	HCMLIN Coef./(SE)	HCMOL Coef./(SE)
Alternative-specific constant (O)	−3.66***	−3.55***	−3.61***	−3.62***
	(0.38)	(0.37)	(0.37)	(0.38)
Shopping cost	−0.06**	−0.06**	−0.06**	−0.06**
	(0.02)	(0.02)	(0.02)	(0.02)
Shopping cost × electronics	0.01	0.01	0.01	0.01
	(0.02)	(0.02)	(0.02)	(0.02)
Income elasticity of shopping cost	0.00	−0.01	−0.01	−0.01
	(0.03)	(0.02)	(0.02)	(0.03)
Shopping time	0.01	0.01	0.01	0.01
	(0.02)	(0.02)	(0.02)	(0.02)
Shopping time × electronics	−0.03	−0.03	−0.03	−0.03
	(0.03)	(0.03)	(0.03)	(0.03)
Delivery cost (O)	−0.19***	−0.19***	−0.19***	−0.19***
	(0.02)	(0.02)	(0.02)	(0.02)
Delivery cost × electronics (O)	0.14***	0.14***	0.14***	0.14***
	(0.02)	(0.02)	(0.02)	(0.02)
Travel cost (IS)	−0.01	−0.00	−0.00	−0.00
	(0.05)	(0.05)	(0.05)	(0.05)
Travel cost × electronics (IS)	0.01	0.00	0.00	0.00
	(0.06)	(0.06)	(0.06)	(0.06)
Delivery time (O)	−1.24***	−1.17***	−1.18***	−1.18***
	(0.17)	(0.17)	(0.17)	(0.17)
Delivery time × electronics (O)	1.10***	1.03***	1.04***	1.04***
	(0.17)	(0.17)	(0.17)	(0.17)
Travel time (IS)	−0.06***	−0.07***	−0.07***	−0.07***
	(0.01)	(0.01)	(0.01)	(0.01)
Travel time × electronics (IS)	0.03*	0.03**	0.03**	0.04**
	(0.02)	(0.02)	(0.02)	(0.01)
Size/weight (O)	0.52***	0.54***	0.53***	0.57***
	(0.15)	(0.14)	(0.15)	(0.14)
Size/weight × age (O)	0.00	0.00*	0.01*	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Size/weight × male (O)	−0.06	−0.24***	−0.23***	−0.23***
	(0.07)	(0.07)	(0.07)	(0.07)
SD of random size component (O)	0.48***	0.41***	0.42***	0.42***
	(0.04)	(0.04)	(0.04)	(0.04)
SD of random panel effect (O)	1.99***	1.70***	1.57***	1.57***
	(0.18)	(0.16)	(0.17)	(0.17)
Pro-online-shopping LV (O)	–	0.63***	2.04***	0.61***
		(0.12)	(0.37)	(0.12)

Continued on next page

Table 3 – *Continued from previous page*

Base category: In-store (IS) shopping	MIXL Coef./(SE)	SM Coef./(SE)	HCMLIN Coef./(SE)	HCMOL Coef./(SE)
Pro-online LV × electronics (O)	–	−0.11	−0.45	−0.13
		(0.14)	(0.47)	(0.13)
Pro-online LV × shopping cost	–	−0.00**	−0.03***	−0.01***
		(0.00)	(0.01)	(0.00)
Pleasure of shopping LV (O)	–	0.41	1.84	0.33
		(0.31)	(1.27)	(0.39)
Pleasure LV × electronics (O)	–	−0.56	−2.81*	−0.53
		(0.40)	(1.55)	(0.47)
Pleasure LV × in-store shop. time	–	0.02**	0.06*	0.01
		(0.01)	(0.03)	(0.01)
Pleasure LV × in-store shop. time × electronics	–	−0.02	−0.07*	−0.01
		(0.01)	(0.04)	(0.01)
Pro-online-shopping LV: Const.	–	0	−0.13	−1.30*
		–	(0.20)	(0.72)
Age	–	−0.02**	−0.01***	−0.03**
		(0.01)	(0.00)	(0.01)
Male	–	1.03***	0.31***	1.11***
		(0.24)	(0.07)	(0.24)
Income	–	0.07***	0.13***	0.48***
		0.02	(0.04)	(0.17)
Higher education	–	1.13***	0.34***	1.17***
		(0.29)	(0.09)	(0.32)
Supermarket accessibility	–	−0.59*	−0.18	−0.62
		(0.35)	(0.11)	(0.43)
Household members	–	0.16*	0.04	0.19**
		(0.09)	(0.03)	(0.09)
SD of pro-online-shopping LV	–	3.96***	0.58***	2.07***
		(0.78)	(0.03)	(0.21)
Pleasure of shopping LV: Const.	–	0	−0.32**	−0.34
		–	(0.16)	(0.56)
Male	–	−1.37***	−0.45***	−1.41***
		(0.34)	(0.08)	(0.35)
Higher education	–	0.62**	0.22**	0.66**
		(0.31)	(0.10)	(0.34)
Supermarket accessibility	–	1.21***	0.36***	1.27***
		(0.42)	(0.13)	(0.45)
Car availability	–	0.29*	0.10**	0.27*
		(0.15)	(0.04)	(0.16)
Married	–	−0.42*	−0.16**	−0.42
		(0.25)	(0.08)	(0.26)

Continued on next page

Table 3 – *Continued from previous page*

Base category: In-store (IS) shopping	MIXL Coef./(SE)	SM Coef./(SE)	HCMLIN Coef./(SE)	HCMOL Coef./(SE)
Nonworking	–	0.80**	0.30***	0.77**
		(0.39)	(0.11)	(0.38)
SD of pleasure of shopping LV	–	3.79***	0.62***	1.99***
		(1.46)	(0.06)	(0.39)
Pro-online-shopping LV: onl1	–	1	1	1
onl2	–	−0.53***	−0.55***	−0.49***
		(0.08)	(0.07)	(0.08)
onl3	–	−0.89***	−1.04***	−0.80***
		(0.12)	(0.08)	(0.12)
onl4	–	−0.65***	−0.60***	−0.61***
		(0.09)	(0.06)	(0.10)
onl5	–	0.57***	0.78***	0.57***
		(0.08)	(0.06)	(0.07)
onl6	–	−0.59***	−0.71***	−0.53***
		(0.08)	(0.07)	(0.08)
onl7	–	0.53***	0.74***	0.50***
		(0.07)	(0.07)	(0.07)
onl8	–	−0.80***	−0.72***	−0.78***
		(0.11)	(0.05)	(0.10)
onl9	–	0.46***	0.70***	0.44***
		0.07	(0.07)	(0.07)
Pleasure of shopping LV: ple1	–	1	1	1
ple2	–	0.14**	0.17**	0.15**
		(0.06)	(0.07)	(0.06)
ple3	–	−1.02***	−0.82***	−0.95***
		(0.35)	(0.11)	(0.30)
# estimated parameters	19	26	64	81
# respondents / choice observations	466/3722			
# MLHS draws	2000			
Runtime [hours]	1.7	3.8	33.6	94.5
LL_{final}	−1671.31	−1613.53	−7999.20	−7448.95
$LL_{choicemodel}$	−1671.31	−1613.53	−1643.53	−1643.38
AICc	3382.32	3282.25	16147.15	15094.49

SM: # estimated parameters refers to the choice model only.

HCMOL: Measurement indicator levels with <10% of total observations were pooled together with the next level.

This was done in 6 cases to increase estimation stability, leading to 6 fewer cut-off values to estimate.

Indicator SD's from the linear and cut-off values from the OL measurement model are not reported in the table.

Robust standard errors: *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.1$

Interestingly, the income elasticity of shopping cost is not significantly different from zero, which stands in contrast to the expectations and results of Swiss mode or destination choice surveys (Axhausen et al., 2007; Erath et al., 2007). The main explanation can be found in the LV structural model: People with high income have more positive attitudes towards online shopping ($p < 0.01$), which implies a higher cost sensitivity, thus diluting the interaction effect between income and shopping cost.

The pleasure of shopping LV and the interactions with in-store shopping time shows no substantial effects. Although there is a weak "trend" observable that people who enjoy shopping also like visiting a store to purchase E relative to G (the net effect almost cancels out), but only have a positive utility of in-store shopping time when purchasing G, the data does not fully support this argumentation ($p \approx 0.1$). Also, similar to the income elasticity, the working hours elasticity of shopping time is essentially zero.[16] However, the effect of "working less than 5 hours per week" on the pleasure of shopping is highly significant and positive. Thus, it can be concluded that non-working respondents do not exhibit a lower shopping time sensitivity, but a higher pleasure of shopping, which then leads to a slightly more positive valuation of in-store shopping time for G. Supporting our intuition and confirming the findings in Fig. 2, there is a small negative correlation of about -0.15 between the two LVs: People with pro-online shopping attitudes tend to have a lower pleasure of shopping.

The LV structural model describes the LVs in term of observable socio-economic characteristics (as already discussed above for income and working hours), revealing or confirming interesting relationships between attitudes and respondent profiles: Younger and male respondents with high income and education living in larger households exhibit a significantly ($p < 0.05$) higher pro-online shopping attitude, characterizing a technology-oriented generation of younger and well-educated men. On the other hand, female and non-working respondents with high education and supermarket accessibility exhibit a significantly ($p < 0.05$) higher pleasure of shopping, supporting the often encountered picture of well educated upper-class housewives who enjoy visiting a (nearby) store. Finally, the coefficients of the measurement models (i.e. the effects of LVs on the indicators) are all highly significant and show the expected signs, confirming the results of a previously conducted factor analysis regarding the interpretation of the two LVs.

[16]Note that the working hours elasticity of shopping time as shown in Eq. (4) often resulted in highly insignificant and often not even estimable standard errors, and thus is not included in the final model specifications. Also, a simple dummy interaction of shopping time with "working less than 5 hours per week" resulted in a zero effect.

5.3 Demand and valuation indicators

Policy implications derived from choice models mainly comprise the responsiveness to changes in different attribute levels, i.e. the elasticities of choices with respect to certain attributes, and the marginal rates of substitution between these attributes, with e.g. the value of travel time savings as a main valuation indicator in transportation science (Louviere et al., 2000). Although predicted changes in real-world market shares are not reliable when using SP data alone (Glerum et al., 2013), results give insights in how people trade-off travel, delivery and shopping/ordering time when directly facing the attributes of these two alternative shopping channels under well-defined experimental conditions.

The direct and cross arc-elasticities presented in Table 4 show the responsiveness of choice probabilities to changes in significant ($p < 0.05$) attributes at their means (mean values reported in Table 1). Direct elasticities measure the percentage change in the probability of choosing either the in-store or online alternative given the percentage change in an attribute of that same alternative, while cross elasticities (in brackets) measure the percentage change in the probability of choosing either the in-store or online alternative given the percentage change in an attribute of the competing alternative.

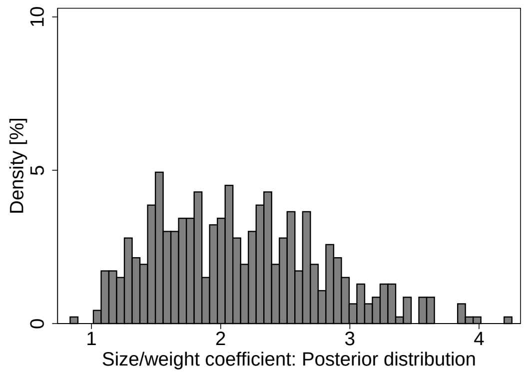
Table 4: Average direct and cross (in brackets) arc-elasticities in the HCMOL specification.

Choice attribute (+ 1%)	Online [% change]	In-store [% change]
Shopping cost	−2.22 (2.29)	−2.35 (2.27)
Shopping cost (pro-online shopping LV + 2 SD)	−3.00 (3.47)	−3.51 (3.04)
Shopping cost (pro-online shopping LV − 2 SD)	−1.15 (1.04)	−1.08 (1.19)
Travel time groceries	–	−0.23 (0.40)
Travel time electronics	–	−0.21 (0.14)
Delivery time groceries	−0.47 (0.27)	–
Delivery time electronics	−0.14 (0.20)	–
Delivery cost groceries	−0.32 (0.18)	–
Delivery cost durables	−0.07 (0.10)	–
Higher education (dummy)	2.25	−2.18
Non-working (dummy)	−1.67	1.73
Supermarket accessibility (dummy)	−1.06	1.09
Age (+ 1%)	0.01	−0.01
Male (dummy)	−0.07	0.07
Income (+ 1%)	0.06	−0.06

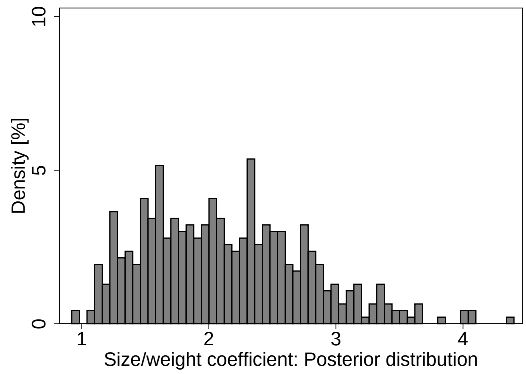
Focusing on shopping costs, the relatively high direct and cross elasticities shown in Table 4 are independent of the shopping purpose, as no substantial interaction effect was

Figure 4: Posterior distributions of random coefficients and latent variables.

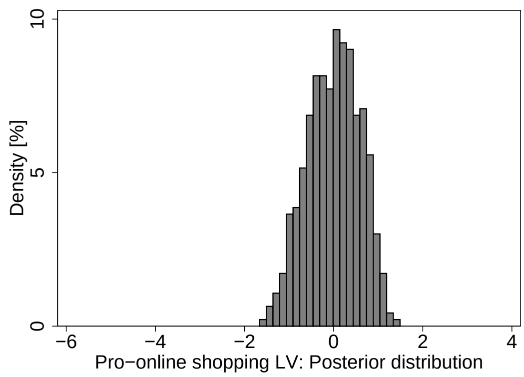
(a) Size/weight (HCMLIN).



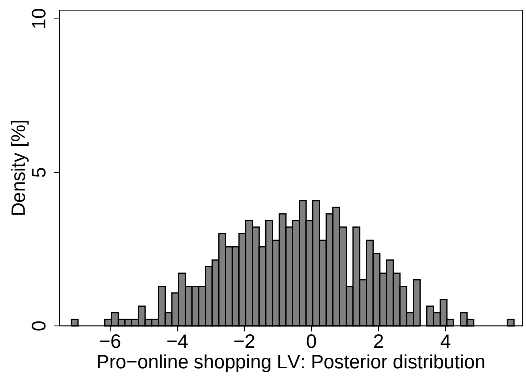
(b) Size/weight (HCMOL).



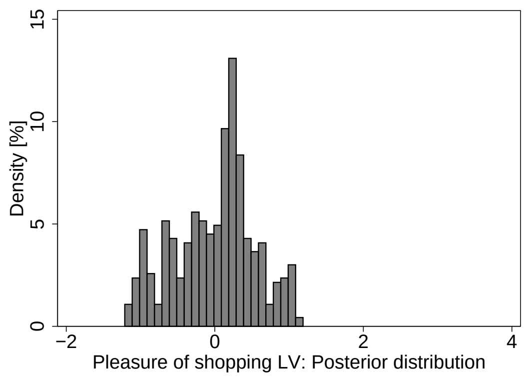
(c) Pro-online shopping LV (HCMLIN).



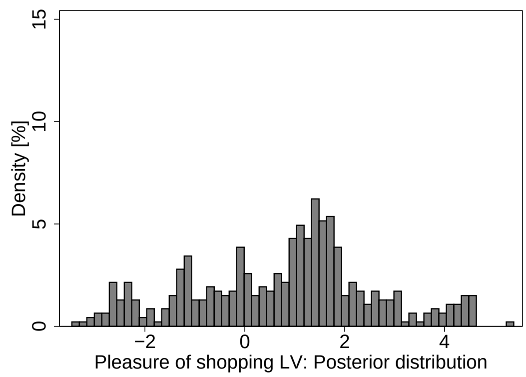
(d) Pro-online shopping LV (HCMOL).



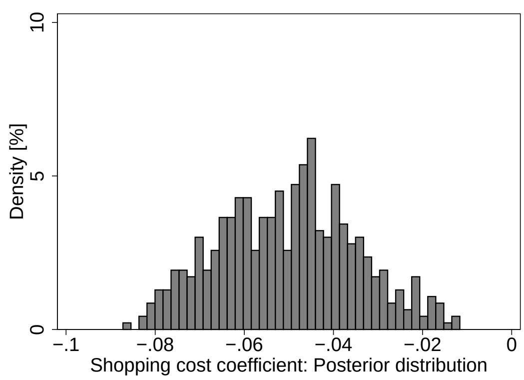
(e) Pleasure of shopping LV (HCMLIN).



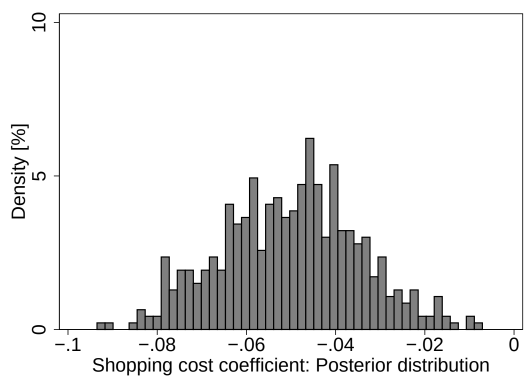
(f) Pleasure of shopping LV (HCMOL).



(g) Shopping cost (HCMLIN).



(h) Shopping cost (HCMOL).



found: Ceteris paribus, on average, a 1% increase in in-store shopping cost decreases the predicted choice probability of in-store shopping by 2.4% and increases the predicted market share of online shopping by 2.3%. These elasticities follow the distribution of the pro-online shopping LV due to the interaction term: The direct elasticity varies from a decrease in the in-store market share of 1.08% for extreme anti-online shoppers (−2 SD) to a decrease of 3.51% for extreme pro-online shoppers (+2 SD). Thus, given the results of the LV structural model and by knowing some basic socio-economic characteristics of a target consumer segment, one can get an idea about the responsiveness to shopping costs and based on that, develop an effective pricing strategy for store and/or online retailers. Regarding the effects of socio-demographic characteristics on market shares - mediated via the two LVs - the key factors are education, working hours and supermarket accessibility: Ceteris paribus, respondents with a high-school degree or higher exhibit a 2.25% higher probability of choosing the online alternative, while non-working respondents exhibit a 1.67% lower probability. The effects of gender and age are diffuse: Young and male respondents care less about the size/weight of the shopping basket, decreasing the probability of choosing the online alternative, while at the same time they exhibit increased pro-online shopping attitudes. Thus, the net effects tend to cancel out.

Table 5 shows the key valuation indicators, focusing on the value of travel time (VTTS) and delivery time savings (VDTS). The current study reveals relatively high[17] VTTS of about 75 CHF/hour for groceries (G) and 45 CHF/hours for standard electronic appliances (E) when considering the shopping cost coefficient as a reference (the travel cost coefficient was highly insignificant), which was also used in Erath et al. (2007), leading there to rather high VTTS of up to 160 CHF/hour. However, the standard error of average VTTS, especially for G, is large, indicating a substantial amount of estimation unreliability. Note that VTTS are calculated using directly the point estimates in Table 3 and are not based on the shopping cost posteriors, thus neglecting the interaction with the pro-online shopping LV, as the simulation of coefficient ratios across the conditional distributions involved the occurrence of some extreme outliers (Hess, 2007). Results show that when not including attitudes in the choice model, valuation indicators remarkably change due to some sort of omitted variable bias, confirming the findings in Raveau et al. (2010) that not using attitudes at all (MIXL) is worse than the sequential approach (SM), with the latter being much closer to the preferred simultaneous approach (HCMLIN and HCMOL). E.g. VTTS for G increases by up to 14% when comparing HCMOL with MIXL. Importantly, this difference mainly results from a more negative utility of travel time when purchasing G in the HCMOL specification, while the shopping cost coefficient almost remains unchanged.

[17] An interaction between travel time and distance was tested, but did not indicate a marginal decrease in travel time dis-utility for longer shopping trips.

Table 5: Average valuation indicators.

Coefficient ratios	MIXL Value/(SE)	SM Value/(SE)	HCMLIN Value/(SE)	HCMOL Value/(SE)
VTTS shopping trips groceries [CHF/h]	64.90	70.08	71.44	75.05
	(30.13)	(30.77)	(33.25)	(30.07)
VTTS shopping trips electronics [CHF/h]	47.05	45.75	44.76	44.70
	(12.11)	(17.09)	(12.15)	(11.21)
VDTS delivery time groceries [CHF/day]	6.44	6.14	6.17	6.10
	(1.06)	(1.06)	(0.91)	(1.07)
VDTS delivery time electronics [CHF/day]	2.56	2.58	2.62	2.60
	(0.56)	(0.56)	(0.57)	(0.58)
Delivery cost groceries / shop. cost [-]	3.24	3.33	3.31	3.38
Delivery cost electronics / shop. cost [-]	1.19	1.21	1.18	1.17

Robust standard errors calculated using the delta method: *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.1$

VTTS heterogeneity is captured by the interaction of the pro-online shopping LV and shopping cost (see also Fig. 4(g) and Fig. 4(h)). This interaction basically implies that respondents with pro-online shopping attitudes tend to have a lower VTTS, as their cost sensitivity is higher while sharing an identical (non-distributed) travel time coefficient. Important to note, an interaction of pro-online shopping attitudes and travel time was tested, but was found to be highly insignificant and small. However, results have to be interpreted with caution: First, the methodology to calculate VTTS based on point estimates of an actually distributed coefficient is not fully appropriate (Bliemer and Rose, 2013). Second, it remains unclear whether shopping cost is the correct reference for calculating VTTS, only because the travel cost coefficient is highly insignificant and small. From a behavioral perspective, an explicit trade-off between travel time to a store and shopping cost under the given experimental assumptions has to be challenged.

Findings indicate a potential for online retailers when comparing VTTS to the relatively low VDTS (with delivery cost coefficient as a reference): VDTS for G is around 6 CHF/day and for E around 2.50 CHF/day. Therefore, delivery time savings of 9 days are still valued less than the average travel time savings of one grocery shopping round trip[18], also resulting from the high delivery cost sensitivity. Online retailers should take note of the relative valuation of delivery compared to shopping costs, especially for groceries, as shown in Table 5: From a behavioral perspective, incorporating delivery costs in shopping costs would increase consumers' utilities and therefore the market shares, thus should be considered as an effective pricing strategy as e.g. Amazon has been doing for years.

[18]Note that average total travel time savings of 47 minutes for a home-based grocery shopping trip corresponds to a monetary value of about 55 CHF, for electronics its about 35 CHF.

Hsiao (2009) conducted a similar choice experiment in Taiwan on 300 respondents' preferences between in-store and online shopping of books, revealing an average VDTS of 0.53 US$/day and arguing that in terms of monetary value, avoiding a shopping trip with an average VTTS of about 5.30 US$/hour produces more benefits than waiting for the delivery of an ordered book, observing a comparable relative magnitude between VTTS and VDTS as in the current study. With VTTS for shopping trips in Switzerland being highly transport mode, shopper-type and study dependent (Erath et al., 2007; VSS norm, 2009; Weis et al., 2014), ranging between 6 CHF/hour for public transport and 160 CHF/hour for weekly grocery shopping trips, the current analysis contributes new evidence for large potentials of ICT shopping services from a travel behavior perspective.

6 Conclusions

This paper presents the first alternative-specific Hybrid choice model using stated preference data in the field of shopping behavior research, presenting a sophisticated modeling approach to explore the trade-offs individuals face when choosing between online and in-store shopping for two distinctly different types of products: Search (i.e. standard electronic appliances; E) and experience (i.e. groceries; G) goods.

The simultaneous maximization of joint probabilities and the dedicated treatment of the panel structure comes along with an enhanced behavioral richness, estimation efficiency and consistency in parameter estimates, leading to a more realistic representation of individual decision making. However, the price in terms of estimation complexity is high, which is often infeasible for practitioners without the presupposed computational infrastructure. We show that the sequential model - which is relatively easy to implement - almost tells the same story as the hybrid approach, but in terms of prediction the latter obviously has a clear advantage. By including two latent variables (LVs) reflecting the attitudes towards online shopping and the pleasure of shopping - apart from other soft factors that were tested, such as general risk aversion, love of variety or environmental sensitivity, which were found to exhibit no substantial effects on choice behavior - the LV structural model reveals a posterior sample distribution of attitudes conditional on basic socio-demographic characteristics: Given a specific target consumer segment, one can predict alternative-specific market shares or heterogeneity in attribute sensitivities and based on that, develop an effective operating strategy for store and/or online retailers.

Supporting the findings by Rudolph et al. (2015) that price advantages are a key factor for doing online shopping in Switzerland, respondents with more positive attitudes towards online shopping exhibit a higher cost sensitivity, which can be explained by the larger choice set when effectively considering both purchasing channels. Interestingly, the income elasticity of shopping cost is not significantly different from zero, which stands in contrast to the expectations. The main explanation is that people with high income have more positive attitudes towards online shopping, implying a higher price-driven trade-off behavior while diluting the income elasticity of shopping costs. Furthermore, results from the LV structural model indicate that the strongest socio-economic factor explaining choice behavior is education: Well-educated people tend to have a better access to ICT in general, thus exhibit a higher choice probability of online shopping that is mainly mediated via the pro-online shopping LV. Another important factor is the working status, indicating that respondents with a less constrained time budget exhibit a higher probability of in-store shopping mediated via the pleasure of shopping LV.

Results show a clear pattern of purpose-specific shopping channel preferences, supporting the hypothesis for experience goods that grocery shopping is mainly conducted in stores, and that people with positive attitudes towards online shopping choose the online alternative more often independent of the product category. On the one hand, a higher pleasure of shopping shows a weak negative effect ($p \approx 0.1$) on choosing the online alternative for purchasing E relative to G, with a net effect that is positive for G and basically zero for E: While for G, also people who do not enjoy shopping still prefer visiting a store given the nature of experience goods, in-store shopping of search goods can better be avoided, while people who enjoy shopping do also consider the online alternative when purchasing G. On the other hand, especially for experience goods, going to a store is more attractive in terms of shopping enjoyment than for search goods: Respondents exhibiting a high pleasure of shopping value the time of in-store shopping for G more positive relative to E (for E, the net effect is essentially zero). Note, however, that the effects of the pleasure of shopping LV are small and not robust between the different model specifications, and would need further investigations. To summarize, heterogeneity in cost sensitivity is mainly captured by differences in acceptance levels of online shopping, while shopping time sensitivity differs by the shopping purpose and the pleasure of shopping.

From a travel behavior perspective, results reveal a high potential for online shopping services, given the relatively high value of travel time savings (VTTS) of about 75 CHF/h for G and 45 CHF/h for E compared to the value of delivery time savings (VDTS) ranging between 6 CHF/day for G and 2.50 CHF/day for E. For longer distances, avoiding a shopping trip thus produces more benefits than waiting for the delivery of the products, especially when purchasing E. However, as the experimental framing explicitly assumes home-based round trips, an assumption that might be plausible for weekly grocery shopping, VTTS is possibly overestimated as the dis-utility of travel time may fade away for shopping trips chained with other activities (Adler and Ben-Akiva, 1979). In addition, shopping costs are perceived as less unpleasant relative to delivery costs. Online retailers should take note of that when designing an effective pricing strategy: From a behavioral perspective, incorporating delivery in shopping costs would increase customers' utilities and therefore the market shares of online shopping.

The main limitations of this study result from the general nature of stated preference experiments. First, the reader has to be aware that results are not easily generalizable to other scenarios than the ones presented to the respondents. Especially in terms of travel time, delivery time and cost, the current analysis shows a significant heterogeneity in attribute sensitivities between groceries and electronic appliances. Other product categories might also ask for more differentiated choice attributes, as e.g. clothing, furniture or entertainment, which would require further investigations. Also the term "groceries" remains vague and might need further refinements. Second, by assuming home-based round trips, abstracting from social motives and excluding private vehicles for the in-store alternative - although important for the coherence of choice situations and the overall project guidelines - might have affected behavior in an unpredictable way. Third, a general limitation of stated preference surveys one should always be aware of is the difficulty of respondents to decide exclusively based on the presented choice attributes and to abstract from any hidden factors in their decision making process. And finally, the causality of the reported effects regarding the LVs on choice behavior should be interpreted with caution. Apart from the cross-sectional nature (i.e. attitudes were not observed over time) of the model assumptions to derive direct policy implications for *changes* in the attitudes (Chorus and Kroesen, 2014), it is not clear if e.g. positive attitudes towards online shopping lead to an increased cost sensitivity, or if respondents with an increased cost sensitivity have more positive attitudes towards online shopping.

7 Acknowledgments

The authors gratefully thank to the SNSF (Swiss National Science Foundation) for funding the *Post-Car World* project. Also, we give thanks to Simon Schmutz, former research assistant at the IVT, for his outstanding contributions to the project. Furthermore, we acknowledge the work of Stephane Hess, Professor in Choice Modelling at the University of Leeds, and his team for developing and making available the basis of the R-code we used for model estimation. Last but not least, we give thanks to Michiel Bliemer, Professor in Transport Network Modeling at the University of Sydney, for his more than helpful comments and suggestions.

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