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In-store or online shopping of search and experience goods: A hybrid choice approach

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ABSTRACT

This paper aims at explaining the choice between online and in-store shopping for typical search and experience goods (standard electronic appliances and groceries) within an artificial experimental setting assuming no privately owned cars. We present the first alternative-specific integrated choice and latent variable (ICLV) model using stated preference data in the field of shopping behavior research, explicitly asking respondents to trade-off attributes specific to each shopping channel.

Respondents with pro-online shopping attitudes have a higher shopping cost sensitivity, which can be explained by the expanded choice set when effectively considering both purchasing channels. They also exhibit a higher choice probability of online shopping for groceries compared to electronic appliances, given the nature of experience goods being preferably purchased in-store, while the pleasure of shopping shows no substantial effect on choice behavior.

Results reveal a user profile of pro-online shoppers that is mainly characterized by a technology-oriented generation of younger and well-educated men. Also, given the relatively high value of travel time compared to the value of delivery time, we show that especially for electronic appliances, avoiding a shopping trip produces more benefits than waiting for the delivery of ordered products.

1. Introduction

Information and communication technologies (ICT) have experienced a persistent increase in usage over the last decades, which, in the context of online shopping, 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. Salomon (1986), Farag et al. (2007) and Cao (2009), for extended literature reviews on the topic). But what are the key attributes in individual decision making for either visiting a store or shopping online? 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 socio-economic characteristics and soft factors, such as attitudes towards shopping and ICT related aspects, affect these trade-offs?

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The data analyzed in this paper was collected as part of a project[1] investigating how a world with restricted car ownership would affect choice, travel and scheduling behavior. Importantly, 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 transportation 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 and Axhausen, 2015; Schmid et al., 2016). 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 can be explained by socio-demographics, attitudes and perceptions. However, although important for the overall project guidelines, the reader has to be alerted that presented results only hold under the current hypothetical situation, and cannot be generalized to real world applications.

30 years after the first study investigating the demand for teleshopping using discrete choice analysis (Manski and Salomon, 1987), we present an innovative survey design and a sophisticated modeling approach by investigating the relative importance of attributes related to the choice between in-store and online shopping for two product categories: Groceries, a typical experience good, and standard electronic appliances, a typical search good. 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 (e.g. Peterson et al., 1997). Results provide new insights on purchasing channel preferences by allowing attribute sensitivities to differ by product type: In Switzerland, electronic appliances are often purchased online, while the main product characteristics of groceries are mainly obtained in-store (Rudolph et al., 2015). Importantly, multi-channel shopping, i.e. explicitly distinguishing between pre-purchase and purchase channels (Mokhtarian and Tang, 2013; Zhai et al., 2017), and multi-purpose shopping trips (Leszczyc et al., 2004) were ruled out to break down the experimental design to a manageable level of complexity.

Two latent variables (LVs) that are hypothesized to affect the choice of the shopping channel were tested, capturing the acceptance level of online shopping and the pleasure of shopping: We applied an integrated choice and latent variable (ICLV) modeling approach that enables the simultaneous estimation of attitudes defined by various socio-economic characteristics (Ben-Akiva et al., 2002), allows for a dedicated representation of the decision process and helps to structure respondent heterogeneity efficiently and more intuitively compared to a reduced form Mixed Logit model (Vij and Walker, 2016). Further considerations with ICLV models arise when dealing with panel data, which, even in advanced literature, was often not taken into account (see e.g. Kim et al. (2014), for an overview of hybrid choice models applied in travel behavior research). One main contribution of this paper is the application of advanced econometric methods to better understand individual decision making 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 shopping channel preferences. Section 3 describes the survey methods and explains how the attitudes towards online shopping and the pleasure of shopping were assessed. Section 4 provides a overview on the modeling framework. Section 5 presents the results and discusses the implications on behavior and valuation indicators. Section 6 provides a discussion, some concluding remarks and the main limitations of the study.

2. Literature review

As one of the first coherent studies, Salomon and Koppelman (1988) discuss the underlying factors affecting the choice between in-store and teleshopping. They define shopping as a process of collecting information on product attributes until the final purchase decision. Alternative-specific attributes (service, delivery, travel time, 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 (shopping/store enjoyment, variety seeking, perceptions, risk, service quality, etc.; see e.g. Childers et al. (2001); Rohm and Swaminathan (2004); Soopramanien and Robertson (2007); Clemes et al. (2014); Scarpi et al. (2014) and others) 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 of online shoppers that has been revealed in many other related studies (Farag et al., 2006; 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. Regarding the pleasure of shopping, e.g. Scarpi et al. (2014) found that shopping for fun is stronger associated with in-store than online shopping, although the general consensus in the literature is not clear (see also e.g. Perea y Monsuwé et al. (2004), for an extended literature review on what drives consumers to shop online).

Several studies have shown substantial product-specific heterogeneity in factors affecting the choice between in-store and online shopping (e.g. Chiang and Dholakia, 2003; Girard et al., 2003; Liu et al., 2013; Zhen et al., 2016). E.g. Peterson et al. (1997), Chiang and Dholakia (2003), Rotem-Mindali and Salomon (2007), Chocarro et al. (2013) and Zhai et al. (2017) 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 criterion to shop online often referred to is the (lower) price in combination with facilitated price comparisons (e.g. Farag et al., 2007), one of the main driving forces when considering online shopping in Switzerland (Rudolph

[1] Project website: http://postcarworld.epfl.ch/.

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 all of the aforementioned studies used revealed preference (RP) data, there has been only little research on how individuals explicitly trade-off shopping channel specific attributes. Our approach is therefore comparable to Hsiao (2009): The author conducted a simple 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. One key contribution of this paper to existing literature is to incorporate those different key facets to better explain shopping channel preferences - product and channel-specific, including socio-economic and psychological factors - in a dedicated way.

3. Survey methods and data

3.1. Survey administration and response rates

The sample was drawn from a commercially available address data base between January 2015 and July 2016, covering the metropolitan area of Zurich, Switzerland. The comprehensive 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 (466 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. More details on the data collection, survey administration and methods can be found in Schmid and Axhausen (2015).

3.2. Online versus 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, using a pivot design approach (Rose et al., 2008). The SP 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 standard electronic appliances (E) or groceries (G). The aim of the experiment is to reveal how sensitive individuals react to changes in attributes for a given shopping purpose. Reference values of shopping time, shopping cost, travel time and travel cost attributes were calculated based on reported shopping trips and average grocery shopping expenditures.[2] 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.

The experiments were introduced to frame the choice environment for the participants and place them in a coherent choice situation (see Appendix, Fig. A.1 for the main instructions respondents received for the shopping SP experiment, and Fig. A.2 for two example choice situations). Shopping trips are often chained with other activities (e.g. 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. The attributes presented below and summarized in Table 1 were included in the SP 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 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; electronic appliances: 25 min, 40 min and 60 min).
- **Delivery cost** including duty: 0 CHF/5 CHF/10 CHF/15 CHF

[2] Durable goods expenditures, including standard electronic appliances, were part of a separate questionnaire on an aggregated yearly basis and not used for reference 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 transportation. To avoid anchoring effects with respect to transportation modes, a specific mode for the in-store alternative was never explicitly mentioned.

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

Attributes	O	S	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 incl. 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

Note: Summary statistics for delivery time are based on an attribute level mid-point approximation.
O = online, S = in-store, μ = mean, σ = standard deviation, ν = skewness.

- **Travel cost** was calculated based on current Swiss market prices for carsharing, carpooling and public transportation (PT). They 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 transportation: 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 transportation: PT door-to-door travel time
- **Size/weight of the good basket**: This environmental attribute indicates how convenient it is to do a specific shopping task

3.3. *Attitudes and socio-demographic characteristics*

A broad range of attitudinal traits were assessed together with the SP experiments. The attitudinal questionnaires are based on the *MOBIDrive* protocol (Axhausen et al., 2002), a set of scales developed by Rieser-Schüssler and Axhausen (2012) and for shopping related aspects, some selected, modified items from Mokhtarian et al. (2009). To focus on attitudes that are related to online and in-store shopping, 13 four-point-Likert scale items (strongly agree to strongly disagree) were considered in subsequent analyses.[3]

According to our hypotheses and the factor structure of a previously conducted exploratory factor analysis, two latent constructs that explain the most important dimensions of variability were defined. The validity of the two latent constructs is confirmed by the Scree-plot and Eigenvalue criterion as shown in Fig. A.3 in the Appendix, clearly speaking in favor of two LVs to be retained (Hayton et al., 2004). Cronbach's α (= 0.78; measures the reliability of the latent constructs) and the Kaiser-Meyer-Olkin criterion (= 0.82; measures the degree of sampling adequacy) further confirm the validity of the constructs (in both cases, a value of 0.8 is considered as acceptable).

The first set of items (factor 1) measures the attitudes regarding the general risks and perceptions of online shopping, and if respondent make use and are aware of this technology (**pro-online shopping LV; onl1-onl10**), while the second set (factor 2) mainly covers the pleasure/enjoyment of in-store shopping (**pleasure of shopping LV; ple1-ple3**; signs of factor loadings in brackets):

- **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:** A disadvantage of online shopping is that I cannot physically examine the products (−)
- **onl6:** Online shopping facilitates the comparison of prices and products (+)
- **onl7:** The risk of receiving a wrong product is one of the main reasons why I don't like online shopping (−)
- **onl8:** I like to follow the new developments in the tech industry (+)
- **onl9:** All what I need, I find in the shops (−)
- **onl10:** 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:** Shopping is exhausting and does not make fun (−)
- **ple3**: Shopping usually is an annoying duty (−)

[3] We also tested for other latent constructs that were available in the data and may have affected the choice between in-store and online shopping, including the love of variety, risk attitudes and environmental awareness, but none of them showed a significant or substantial effect.

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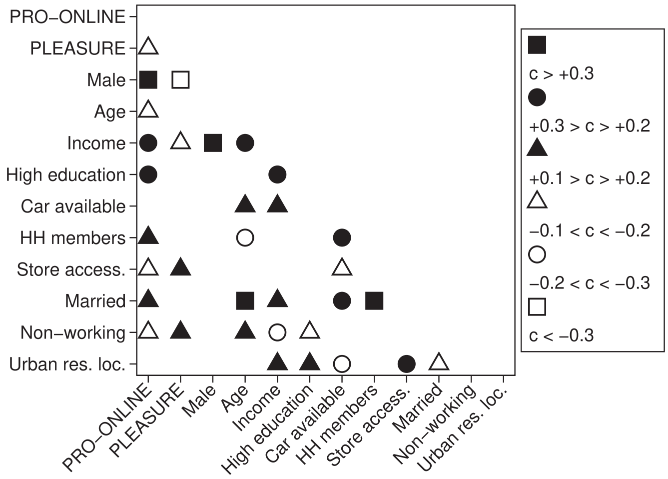

Fig. 1. Correlation patterns of socio-demographics and attitudes.

Each LV is defined by a set of socio-economic characteristics (see also Appendix, Table A.1, for some basic summary statistics). The key variables which were found to describe the two LVs best and are included in subsequent analyses are:

- **Male** (dummy)
- **Age** (continuous; scaled down by factor 100)
- Personal monthly **income** (continuous; scaled down by factor 10′000)
- **High education** (dummy for high-school degree or higher)
- **Car** always **available** (dummy)
- **Store accessibility** (dummy; store within 10 min of walk from home location)
- **Married** (dummy)
- **Non-working** (dummy; weekly regular payed job working hours ≤ 5 h)

Regarding the two soft factors, besides a moderate negative correlation between each other, Fig. 1 indicates 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.

4. Modeling framework

The hybrid choice modeling (HCM) approach described in Ben-Akiva et al. (2002) - illustrated in Fig. 2 for the current application - 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 LVs are defined in the structural models by measurable socio-economic characteristics, whereby the measurement model links the LVs with indicators assumed to be affected by the latent constructs. The attitudinal part of this 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). Each model component is described in the following subsections.

To summarize our hypotheses regarding the effects of LVs according to Fig. 2, we test if 1) pro-online attitudes increase the choice probability of online-shopping 2) this increase is lower for standard electronic appliances (E) than for groceries (G), as it may take less overcoming to purchase typical search goods than typical experience goods online 3) pro-online shopping attitudes are positively related to cost sensitivity, given the expanded alternative set such respondents may consider 4) higher pleasure of shopping attitudes decrease the choice probability of online shopping 5) this decrease is lower for E, as in-store shopping of groceries may entail more pleasure 6) higher pleasure of shopping attitudes decrease in-store shopping time sensitivity 7) this decrease is smaller when buying E, given the nature of search (E) compared to experience goods (G).

4.1. Structural model

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

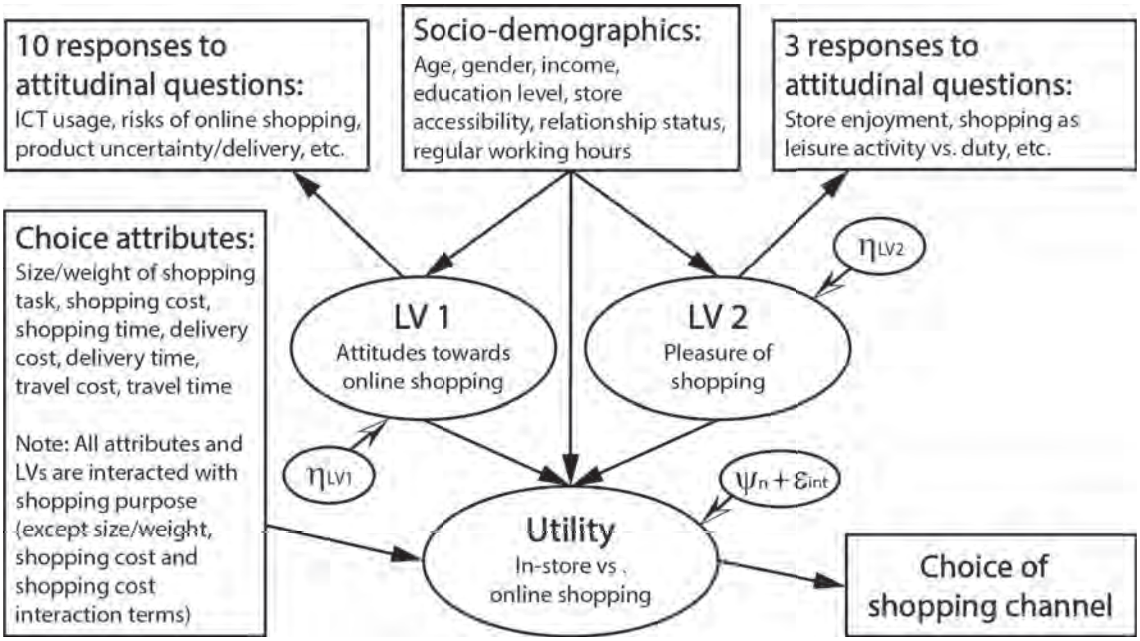

Fig. 2. Hybrid choice modeling framework.

$$U_{O,n,t} = X_{O,n,t}\beta_O + \sum_z LV_{z,n}\mu_{LV_z} + \sum_z Z_{z,n}\Theta_z + f_{1,O,n,t} + f_{3,n,t} + \psi_{O,n} + \varepsilon_{O,n,t} \quad (1)$$

$$U_{S,n,t} = X_{S,n,t}\beta_S + f_{1,S,n,t} + f_{2,n,t} + \varepsilon_{S,n,t} \quad (2)$$

where

$$f_{1,i,n,t} = \left(\beta_{cost} + Z_{online,n}\Delta_{online,cost} + \psi_{cost,n}\right)\cdot cost_{i,n,t} + \varphi_{LV_{online},cost}\cdot LV_{online,n}\cdot cost_{i,n,t} \quad (3)$$

$$f_{2,n,t} = \left(\beta_{time,S} + Z_{pleasure,n}\Delta_{pleasure,time,S} + \psi_{time,S,n}\right)\cdot time_{S,n,t} + \varphi_{LV_{pleasure},time}\cdot LV_{pleasure,n}\cdot time_{S,n,t} \quad (4)$$

$$f_{3,n,t} = \left(\alpha_{size}^{M,L} + \alpha_{male}\cdot male_n + \alpha_{age}\cdot age_n\right)\cdot size_{n,t}^{M,L} \quad (5)$$

$X_{i,n,t}$ 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 (in-store shopping is defined as the reference alternative) and are interacted with shopping cost and in-store shopping time to reveal heterogeneity in respective attribute sensitivities: $LV_{z,n}$ is a zero-centered latent variable, μ_{LV_z} is the coefficient of latent variable z shifting the intercept of the online alternative, $\varphi_{LV_{online},cost}$ and $\varphi_{LV_{pleasure},time}$ are the coefficients of the interaction terms between the two LVs and some selected choice attributes (i.e. shopping cost × pro-online shopping attitudes; in-store shopping time × pleasure of shopping).

All choice attributes and both LVs were interacted with the shopping purpose (except for the size/weight of the shopping basket and shopping costs), with grocery shopping (G) as a reference, to allow for purpose-specific taste heterogeneity. This increases estimation efficiency compared to a segmented estimation approach by product category, mainly regarding the estimation of only one measurement model.

$Z_{z,n}$ is a $(1 \times Q_z)$ vector of the same observable, socio-economic characteristics also included in the structural equations of the LVs (see also Equation (6)). To compare for the actual gains in model performance (regarding fit, behavioral insights, efficiency and forecasting) when including the LVs compared to a reduced form MIXL excluding them (Vij and Walker, 2016), $Z_{z,n}$ directly affects heterogeneity in the same parameters as the two LVs do, with Θ_z and Δ_z representing $(Q_z \times 1)$ coefficient vectors.

To account for the correlation across choices within individuals and unobserved (purely random) coefficient heterogeneity (e.g. Greene et al., 2006), three 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. $\psi_{cost,n} \sim N(0, \sigma_{cost}^2)$ and $\psi_{time,n} \sim N(0, \sigma_{time}^2)$ are two random components capturing unobserved heterogeneity in shopping cost and in-store shopping time to adequately compare the reduced form MIXL with the ICLV model (Vij and Walker, 2016): As indicated in Equation (6), each LV comprises error variance via the structural equations, which partly capture some unobserved heterogeneity in the choice model (Daziano and Bolduc, 2013a; Kløjgaard and Hess, 2014) through the constant, time and cost interaction effects.

The size/weight of the shopping basket was included using two dummy variables for medium (M) and large (L) size/weight (with small size as the reference), captured by $\alpha_{size}^{M,L}$. Including gender and age interactions allow for preference heterogeneity in varying levels of shopping inconvenience regarding physical conditions, assuming that larger shopping baskets are preferably purchased online, especially for older and female respondents. Finally, $\varepsilon_{i,n,t}$ is the remaining alternative-specific IID extreme value type I disturbance term.

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

$$\begin{aligned} LV_{z,n} &= Z_{z,n}\rho_z + \eta_{LV_{z,n}} \\ \eta_{LV_{z,n}} &\sim N\left(0, \sigma^2_{LV_z}\right) \end{aligned} \tag{6}$$

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

4.2. Measurement model

The latent variable measurement equations with responses to the attitudional questions (items) $I_{w,n}$ with $w \in \{\text{onl1}, \text{onl2}, .., \text{ple3}\}$ discussed in Section 3.3 are given by

$$\begin{aligned} I_{w,n} &= \overline{I_w} + \tau_{I_w} LV_{z,n} + \nu_{w,n} \\ \nu_{w,n} &\sim N\left(0, \sigma^2_{I_w}\right) \end{aligned} \tag{7}$$

where $\overline{I_w}$ are the mean ratings of the four-point-Likert scales of each item w calculated beforehand (Hess and Beharry-Borg, 2012; Kløjgaard and Hess, 2014), avoiding the estimation of unnecessary parameters. $I_{w,n}$ are the observed items for individual n, τ_{I_w} is the LV measurement coefficient for item w and σ_{I_w} is the corresponding standard deviation coefficient.

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:

$$choice_{i,n,t} = \begin{cases} \text{Online shopping if } U_{O,n,t} > U_{S,n,t} \\ \text{In} - \text{store shopping if } U_{O,n,t} \leq U_{S,n,t} \end{cases} \tag{8}$$

4.3. Estimation

Assuming that the random components ψ_n and the latent variables $LV_{z,n}$ are mutually independent and $\varepsilon_{i,n,t}$ is IID extreme value type I, the unconditional joint probability $L_n(\cdot)$ - 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 the items $I_{w,n}$ only once - is defined by the integral of the product of conditional choice and item probabilities over the distributions of ψ_n and $LV_{z,n}$ (e.g. Walker and Ben-Akiva, 2002):

$$L_n(choice_{i,n,t}, I_{w,n} | X_{i,n,t}, Z_{z,n}, \Omega) = \int_{\psi_n}\int_{LV_{z,n}} \prod_{t=1}^{T_n} P(choice_{i,n,t} | X_{i,n,t}, LV_{z,n}, \theta, \psi_n) u(I_{w,n} | LV_{z,n}, \tau_{I_w}, \sigma_{I_w}) g\left(LV_{z,n} | Z_{z,n}, \rho_z, \eta_{LV_z}\right) h(\psi_n | R) dLV_{z,n} d\psi_n \tag{9}$$

where

$$\Omega \equiv \{\alpha, \beta, \mu, \rho, \sigma, \tau, \varphi, \Delta, \Theta\} and\ \theta \equiv \{\alpha, \beta, \mu, \sigma_\psi, \varphi, \Delta, \Theta\} \in \Omega \tag{10}$$

is the set of parameter vectors to be estimated,

$$P(choice_{i,n,t} | X_{i,n,t}, LV_{z,n}, \theta, \psi_n) = \frac{\exp(U_{i,n,t})}{\exp(U_{O,n,t}) + \exp(U_{S,n,t})} \tag{11}$$

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

$$u(I_{w,n} | LV_{z,n}, \tau_{I_w}, \sigma_{I_w}) = \prod_{I_w}\left(\frac{1}{\sigma_{I_w}}\phi\left(\frac{I_{w,n} - \overline{I_w} - \tau_{I_w} LV_{z,n}}{\sigma_{I_w}}\right)\right) \tag{12}$$

is the item probability function with ϕ as the standard normal density function. Finally,

$$\begin{aligned} g\left(LV_{z,n} | Z_{z,n}, \rho_z, \eta_{LV_z}\right) &\sim N\left(Z_{z,n}\rho_z, \sigma^2_{LV_z}\right) \\ h(\psi_n | R) &\sim N\left(0, \sigma^2_\psi\right) \end{aligned} \tag{13}$$

correspond to independent normal distributions of the LVs and random components. Due to identification issues (e.g. Vij and Walker, 2014), the first τ_{I_w} of each LV was fixed to 1.

Using maximum simulated likelihood techniques, the integral in Equation (9) is approximated by calculating 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). This is done by drawing values from the $g(LV_{z,n} | Z_{z,n}, \rho_z, \eta_{LV_{z,n}})$ and $h(\psi_n|R)$ distributions, with superscript r referring to draw $r \in R$: $\widetilde{L_n}(\cdot)$ shown in Equation (15) is the simulated likelihood for individual n, and the maximum simulated likelihood estimator is the value of $\widehat{\Omega}$ that maximizes $\widetilde{LL}(\Omega)$:

$$\max \widetilde{LL}(\Omega) = \sum_{n=1}^{N} \log\left(\widetilde{L_n}(choice_{i,n,t}, I_{w,n} | X_{i,n,t}, Z_{z,n}, \Omega)\right) \tag{14}$$

$$\widetilde{L_n}(choice_{i,n,t}, I_{w,n} | X_{i,n,t}, Z_{z,n}, \Omega) = \frac{1}{R}\sum_{r=1}^{R}\prod_{t=1}^{T_n} P\left(choice_{i,n,t} \middle| X_{i,n,t}, LV^r_{z,n}, \theta, \psi^r_n\right) u\left(I_{w,n} \middle| LV^r_{z,n}, \tau_{I_w}, \sigma_{I_w}\right) \tag{15}$$

Models were estimated in *R* version 3.2.2 (CMC, 2017). Quasi-random draws were generated using Modified Latin Hypercube Sampling (MLHS) as proposed by Hess et al. (2006). The main criteria regarding identifiability and simulation bias as discussed in Vij and Walker (2014) were investigated: After 1000 draws, estimates were carefully considered to be robust and stable. Cluster-robust standard errors were calculated using the Eicker-Huber-White sandwich estimator (e.g. Baltagi, 2008).

5. Results

5.1. Descriptive analysis of choice behavior

The analyzed sample comprises 3722 choice observations for 466 respondents: 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. In contrast to what is observed in reality,[4] 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), it clearly shows the tendency that for G, people prefer shopping in a store.[5] 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” (which, to some extent, are also explained by individuals' attitudes): 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.

5.2. Estimation results

To have a first benchmark, to test the additional explanatory power of each LV in order to confine subsequent analyses and to compare results with the simultaneous approach, we estimate two sequential models[6] with random coefficients[7] (SM LV1; includes the pro-online shopping LV, and SM LV2; additionally adds the pleasure of shopping LV), where the predictions of a linear MIMIC model[8] are included as explanatory variables in the choice models according to the hypotheses discussed in Section 4.

These results are compared with the corresponding hybrid models (HCM LV1 and HCM LV2) with random coefficients (but without

[4] Online shopping of books and electronic gadgets accounts for roughly 25% of total retail market shares, while for food products it accounts for roughly 5% (Verband des Schweizerischen Versandhandels VSV und GfK, 2015).

[5] The imposed assumptions may have mainly led current car users to choose the online alternative more frequently. Note, however, that we tested if car availability has an effect on the choice probability of online shopping, which was not the case (the effect was positive with a t-value smaller than one).

[6] There are essentially two ways how to include LVs in a choice model: Raveau et al. (2010) compared a sequential (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 and still often used in practice (e.g. Mokhtarian and Tang, 2013; Zhai et al., 2017), 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 and more efficient estimation properties (Daziano and Bolduc, 2013a), the simultaneous approach can also be better applied to predict the distribution of taste parameters and/or market shares for specific consumer segments based on socio-economic characteristics.

[7] Including random coefficients associated with the LVs helps to get unbiased parameter estimates by partly accounting for the LV measurement error (Yáñez et al., 2010).

[8] We tested if an Ordered Logit (OL) measurement model shows different, potentially more accurate results, as suggested by Daly et al. (2012b), given the discrete nature of the items. However, the effects of the LVs in the choice models were almost identical up to a scaling factor, showing identical choice model fits, and the qualitative effects of socio-economic characteristics on the LVs were indistinguishable. Furthermore, the correlations of posterior distributions of the LVs for these two specifications were above +0.994, which is also illustrated in the Appendix, Fig. A.4. Therefore, even though the OL measurement model exhibited a much better fit, due to estimation time considerations we decided to use a linear specification. Results of the linear MIMIC model are presented in the Appendix, Table A.2.

direct effects of socio-economic characteristics; especially for the two-LV-specification, the model would become highly convoluted), as shown in the Appendix, Table A.3. The sequential approach implicitly takes into account the measurement items for assessing the goodness of fit, resulting in a choice model LL of more than 45 units higher compared to the hybrid models (which would be misleading, given that the items are typically not available for forecasting). All choice attributes with a t-value smaller than one are excluded in subsequent analyses, which include travel cost and online/in-store shopping time, as well a their interactions with the shopping purpose.

The pleasure of shopping LV does not add substantial explanatory power: A likelihood-ratio (LR) test shows an insignificant increase in model fit when comparing SM LV1 with SM LV2 ($p = 0.16$), and there is even a slightly lower choice model LL in the HCM LV2 than the HCM LV1 model (by including an "uninformative" LV and given the joint estimation of the choice and indicator data, this result is not unexpected). Based on these findings, the decision was made to 1) focus on the pro-online shopping LV and 2) also drop in-store shopping time from subsequent analyses.[9]

Four different models with increasing complexity are presented in Table 2 which were found to represent best the different aspects of shopping channel choice. The first model (REDMNL) is a reduced form MNL model that explains choices with attributes specific to each shopping channel and includes the direct (= total) effects of socio-economic characteristics: Given that the pro-online shopping LV is interacted with shopping purpose and shopping cost, the structure imposed by the ICLV model leads to a reduced form specification that has to include the same interactions for all socio-economic characteristics that are part of the LV structural model. This includes age, male, income, high education, married and store accessibility. To account for the error variance imposed by the ICLV model, the second model (REDMIX) is a reduced form MIXL model that additionally includes the random intercept and shopping cost parameter. The third model (HCMNL) is a hybrid choice model that includes the pro-online shopping LV and its interactions with shopping purpose and shopping cost. The fourth model (HCMIX) additionally adds the random intercept and shopping cost parameter. Results in Table 2 are organized in blocks: The choice model is presented first, followed by the direct/interaction effects of socio-economic characteristics, the direct/interaction effects of the pro-online shopping LV, the LV structural model and the LV measurement model.

The improvement in AICc (for finite sample size corrected Akaike Information Criterion for assessing the goodness of fit) from the REDMNL to the REDMIX model is highly significant, with an increase in LL by 370 units by including two random parameters. This demonstrates that there is a substantial amount of unobserved heterogeneity in the preference for a shopping channel and shopping cost sensitivity.

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 2 and given by

$$\widetilde{LL}_{choice}\left(\tilde{\Omega}\right) = \sum_{n=1}^{N} \log \frac{1}{R} \sum_{r=1}^{R} \prod_{t=1}^{T_n} P\left(choice_{i,n,t} \middle| X_{i,n,t}, LV^r_{online,n}, \widehat{\theta}, \psi^r_n\right) \tag{16}$$

This approach is representing a forecasting methodology based on a restricted set of parameters, in which the (unknown) indicators of the measurement model are not used for assessing the goodness of fit. Comparing the REDMNL with the HCMNL, the increase in LL of about 332 is slightly lower compared to the REDMIX. This is expected, given that the random parameters in the REDMIX are estimated on the choice data only, while in the HCMNL, the random components entering via the LV structural equation also have to incorporate the MIMIC model variance.[10] By including the two random parameters, the HCMIX model shows an identical choice LL as the REDMIX model. Clearly, in terms of model fit, this discards the benefits of a hybrid model (see also Vij and Walker (2016) for a more in-depth discussion on this topic). Nevertheless, there several advantages of the HCM approach that may justify its complexity: The inclusion of LVs allows to disentangle direct and indirect ("mediated" via the LV) effects of socio-economic characteristics, it allows to decompose heterogeneity into a purely random and attitudinal part and typically comes along with a gain in efficiency by making use of all available data (e.g. Kløjgaard and Hess, 2014). Last but not least, the REDMIX model structure would not have been considered in the absence of LVs during the process of model development, given that the majority of direct socio-economic effects are insignificant in the REDMIX model. These points are further addressed below.

The choice attributes shopping cost,[11] delivery cost, travel time and delivery time[12] all exhibit the expected negative effect. A larger size/weight of the shopping basket strongly increases the choice probability of online shopping, exhibiting a significant amount of preference heterogeneity conditional on physical conditions: Female ($p < 0.01$) and older ($p < 0.1$; only significant in the random coefficient models) respondents' choice probability of online shopping increases stronger with a larger size/weight of the shopping basket.

Most attributes were interacted with the shopping purpose, with grocery shopping (G) as a reference: While shopping costs and the size/weight attribute exhibit no significant difference between G and electronic household appliances (E), it is interesting to see that

[9] In-store shoping time would become insignificant without including the pleasure of shopping LV.

[10] The random disturbance term included in the LV structural model also contributes to the unobserved heterogeneity in shopping channel preference and shopping cost sensitivity. Given the coefficients of variation in the REDMIX model of 1.6 for the intercept ($= |2.30/-1.47|$) and 0.8 for shopping cost ($= |4.89/-5.79|$), these amounts drop in the HCMNL to 0.5 for the former ($= |0.52/-1.09|$) and 0.1 ($= |0.52/-3.70|$) for the latter, reflecting that any heterogeneity in the choice model must be perfectly correlated with the disturbance term in the LV model (Kløjgaard and Hess, 2014). In the HCMIX model, this constraint disappears by including the two additional random parameters, implying an overall amount of heterogeneity similar to the REDMIX model.

[11] Respondents did not react on travel costs, but were anchoring behavior with respect to shopping costs (given their much larger share of total costs), which was not the case for delivery costs. 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 no significant and substantial effect.

[12] For interpretation issues, its more convenient to treat delivery time 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.

Table 2
Estimation results: Reduced form models (REDMNL and REDMIX) and hybrid choice models (HCMNL and HCMIX).

Base category: In-store (S) shopping	REDMNL	REDMIX	HCMNL	HCMIX
	Coef./(SE)	Coef./(SE)	Coef./(SE)	Coef./(SE)
Alternative-specific constant (O)	−0.72***	−1.47***	−1.09***	−1.47***
	(0.17)	(0.30)	(0.23)	(0.29)
Shopping cost	−2.34***	−5.79***	−3.70***	−5.51***
	(0.27)	(0.67)	(0.42)	(0.61)
Delivery cost (O)	−0.10***	−0.18***	−0.15***	−0.18***
	(0.01)	(0.02)	(0.02)	(0.02)
Delivery cost × electronics (O)	0.07***	0.12***	0.11***	0.12***
	(0.02)	(0.02)	(0.02)	(0.02)
Delivery time (O)	−0.57***	−1.03***	−0.82***	−1.01***
	(0.09)	(0.14)	(0.13)	(0.14)
Delivery time × electronics (O)	0.50***	0.90***	0.72***	0.88***
	(0.09)	(0.14)	(0.13)	(0.14)
Travel time (S)	−2.42***	−4.71***	−4.86***	−5.60***
	(0.70)	(1.23)	(1.13)	(1.31)
Travel time × electronics (S)	0.56	1.36	2.60**	2.27*
	(0.81)	(1.34)	(1.19)	(1.37)
Size/weight small (O)	–	–	–	–
Size/weight medium (O)	1.07***	2.00***	1.52***	1.96***
	(0.10)	(0.18)	(0.15)	(0.18)
Size/weight large (O)	2.17***	3.99***	3.02***	3.94***
	(0.13)	(0.27)	(0.22)	(0.26)
Size/weight × age (O)	0.59	2.45*	1.73	2.58*
	(0.90)	(1.47)	(1.18)	(1.43)
Size/weight × male (O)	−0.58***	−0.95***	−0.87***	−0.96***
	(0.20)	(0.33)	(0.26)	(0.32)
Age (O)	−1.08	−3.33	1.70	−0.47
	(1.29)	(2.41)	(2.01)	(2.35)
Male (O)	0.13	0.22	−1.23**	−0.88
	(0.30)	(0.52)	(0.50)	(0.54)
Income (O)	0.54***	0.82***	0.41*	0.56**
	(0.17)	(0.30)	(0.23)	(0.26)
High education (O)	0.09	0.31	−0.63	−0.43
	(0.35)	(0.67)	(0.53)	(0.69)
Store accessibility (O)	−0.01	−0.04	0.44	0.37
	(0.44)	(0.79)	(0.50)	(0.64)
Married (O)	0.27	0.40	−0.32	−0.14
	(0.24)	(0.43)	(0.36)	(0.41)
Age × electronics (O)	0.44	0.64	−1.28	−0.89
	(1.37)	(2.55)	(2.06)	(2.47)
Male × electronics (O)	0.29	0.52	1.21**	1.22**
	(0.31)	(0.57)	(0.51)	(0.58)
Income × electronics (O)	−0.31	−0.41	−0.46*	−0.36
	(0.20)	(0.37)	(0.27)	(0.31)
High education × electronics (O)	−0.05	−0.22	−0.14	−0.03
	(0.42)	(0.80)	(0.61)	(0.81)
Store accessibility × electronics (O)	−0.50	−0.89	−0.56	−1.02
	(0.53)	(0.97)	(0.61)	(0.82)
Married × electronics (O)	0.17	0.35	0.51	0.69
	(0.30)	(0.56)	(0.41)	(0.51)
Age × shopping cost	7.10***	9.76**	4.77	5.72
	(2.23)	(4.11)	(3.00)	(3.85)
Male × shopping cost	−0.59	−1.55	0.06	−0.07
	(0.56)	(1.04)	(0.82)	(1.09)
Income × shopping cost	0.57	0.42	1.18**	0.92
	(0.40)	(0.77)	(0.54)	(0.67)
High education × shopping cost	−0.32	−0.74	0.27	0.20
	(0.72)	(1.37)	(0.99)	(1.38)
Store accessibility × shopping cost	0.31	−0.57	0.20	−0.55
	(0.83)	(1.50)	(1.08)	(1.41)
Married × shopping cost	−0.44	−0.96	−0.30	−0.39
	(0.56)	(1.04)	(0.73)	(1.00)
SD of random intercept (O)		2.30***		1.93***
		(0.16)		(0.15)
SD of shopping cost		4.89***		4.19***
		(0.79)		(0.70)

(*continued on next page*)

Table 2 (*continued*)

Base category: In-store (S) shopping	REDMNL	REDMIX	HCMNL	HCMIX
	Coef./(SE)	Coef./(SE)	Coef./(SE)	Coef./(SE)
Pro-online-shopping LV (O)			3.12***	2.51***
			(0.61)	(0.49)
Pro-online LV × electronics (O)			−0.91	−1.15**
			(0.59)	(0.57)
Pro-online LV × shopping cost			−3.71***	−3.84***
			(1.25)	(1.12)
Pro-online shopping LV1: Age			−1.11***	−1.02***
			(0.29)	(0.30)
Male			0.32***	0.31***
			(0.07)	(0.07)
Income			0.14***	0.12***
			(0.04)	(0.04)
High education			0.33***	0.31***
			(0.09)	(0.09)
Store accessibility			−0.19*	−0.18
			(0.10)	(0.12)
Married			0.20***	0.20***
			(0.07)	(0.07)
SD of pro-online shopping LV			0.52***	0.60***
			(0.04)	(0.03)
Pro-online shopping LV: onl1			1	1
onl2			−0.54***	−0.56***
			(0.06)	(0.06)
onl3			−0.99***	−1.05***
			(0.08)	(0.08)
onl4			−0.58***	−0.59***
			(0.06)	(0.06)
onl5			−0.39***	−0.38***
			(0.06)	(0.06)
onl6			0.81***	0.77***
			(0.07)	(0.06)
onl7			−0.68***	−0.74***
			(0.07)	(0.07)
onl8			0.75***	0.75***
			(0.08)	(0.07)
onl9			−0.70***	−0.71***
			(0.05)	(0.05)
onl10			0.67***	0.69***
			(0.07)	(0.08)
SD onl1			0.64***	0.59***
			(0.03)	(0.02)
SD onl2			0.67***	0.65***
			(0.02)	(0.02)
SD onl3			0.81***	0.74***
			(0.03)	(0.03)
SD onl4			0.63***	0.60***
			(0.02)	(0.02)
SD onl5			0.76***	0.75***
			(0.03)	(0.03)
SD onl6			0.75***	0.75***
			(0.03)	(0.02)
SD onl7			0.76***	0.72***
			(0.03)	(0.03)
SD onl8			0.85***	0.83***
			(0.03)	(0.03)
SD onl9			0.60***	0.56***
			(0.02)	(0.02)
SD onl10			0.85***	0.83***
			(0.03)	(0.03)
# estimated parameters	30	32	59	61
# respondents/choices	466/3722			
# draws	1000			
LL_{null}	−2579.9		*NA*	
LL_{final}	−2021.9	−1651.7	−7078.9	−6905.8
$LL_{choicemodel}$	−2021.9	−1651.7	−1690.0	−1651.9
AICc	4108.1	3372.2	14293.2	13952.4

Note: Shopping cost, shopping time and travel time are scaled down by factor 100.
Robust standard errors: ***: $p < 0.01$, **: $p < 0.05$, **: $p < 0.1$.

travel time, delivery time and delivery cost show much less strong negative effects on utility for E than for G (but are still significantly different from zero; $p < 0.05$).[13] 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 about three times larger for G than for E (which, for the latter, implies the same average marginal disutility as for shopping cost). Possible explanations are that 1) delivery costs are at fixed levels, and their share of total shopping cost is substantially larger for G than for E (see also Table 1), thus are perceived more negative and 2) people could more easily avoid delivery costs for G by just visiting a nearby grocery store, perceiving them as an actual loss (also referred to as ”money illusion”; see e.g. Tversky and Kahneman (1986)). Online retailers should take note of that when designing effective pricing strategies: From a behavioral perspective, incorporating delivery in shopping costs would increase consumers' utilities and therefore the market shares, as e.g. Amazon has been doing for years.

The pro-online shopping LV shows, not surprisingly, a strong and positive effect on the choice of online shopping, which is lower for E than for G (HCMIX: $p < 0.05$; note that in both hybrid models, the net effect is still positive and significant; $p < 0.01$). This confirms the hypothesis that it takes less overcoming to purchase typical search goods such as E online, whereas for G, only respondents with positive attitudes towards online shopping consider online shopping as an alternative. Also, there is a strong interaction effect of shopping cost and the pro-online shopping LV, indicating 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.

The LV structural model describes attitudes in terms of observable socio-economic characteristics, exhibiting interesting relationships between respondent profiles: Younger and male respondents with high income and education exhibit a significantly ($p < 0.01$) higher pro-online shopping attitude, characterizing a technology-oriented generation of younger and well-educated men. While obtaining very similar user profiles as e.g. in Farag et al. (2005), the positive effect of being married is interesting, which, one may argue, is associated with a lower time budget, whereby online shopping can be seen as a good alternative (Bellman et al., 1999). Also, while Farag et al. (2005) finds a positive effect of urbanity, which is, in our data, is positively correlated with store accessibility (see also Fig. 1), we find a negative (though not significant) effect of store accessibility on pro-online shopping attitudes, indicating some sort of habitual self-selection.

Finally, the coefficients of the measurement model are all highly significant and show the expected signs, confirming the results of the factor analysis regarding the interpretation of the LV.

5.3. *Parameter decomposition*

There are some notable differences between the direct effects of socio-economic characteristics when comparing the reduced form

Table 3
Direct, indirect and total effects in the HCMIX model.

Attribute (HCMIX)	Outcome	Direct effect	Indirect effect	Total effect
Male	Utility of online shopping (G)	−0.88	**0.78**	−0.09
Male	Utility of online shopping (E)	0.34	0.42	0.77
Male	Shopping cost sensitivity	−0.07	**−1.19**	−1.27
Age	Utility of online shopping (G)	−0.47	**−2.56**	−3.04
Age	Utility of online shopping (E)	−1.36	−1.39	−2.75
Age	Shopping cost sensitivity	5.72	**3.92**	**9.65**
Income	Utility of online shopping (G)	**0.56**	**0.30**	**0.87**
Income	Utility of online shopping (E)	0.20	0.16	0.36
Income	Shopping cost sensitivity	0.92	**−0.46**	0.46
High education	Utility of online shopping (G)	−0.43	**0.79**	0.36
High education	Utility of online shopping (E)	−0.46	0.43	−0.03
High education	Shopping cost sensitivity	0.20	**−1.20**	−1.00
Store accessibility	Utility of online shopping (G)	0.37	−0.44	−0.07
Store accessibility	Utility of online shopping (E)	−0.64	−0.24	−0.88
Store accessibility	Shopping cost sensitivity	−0.55	0.68	0.13
Married	Utility of online shopping (G)	−0.14	**0.50**	0.36
Married	Utility of online shopping (E)	0.55	0.27	0.82
Married	Shopping cost sensitivity	−0.39	**−0.77**	−1.16

Note: Effects reported for the utility of online shopping measure deviations from the alt.-spec. constant.
Effects reported for shopping cost sensitivity measure deviations from the mean effect β_{cost}.
Bold: Effect significant at p < 0.05.

[13] Standard errors were calculated using the delta method (Daly et al., 2012a).

with the hybrid models: While in the reduced form model, we directly measure the total effects of socio-economic characteristics on utility, in the hybrid models we allow for a mediation via the LV (see also Fig. 2), which are the indirect effects. The sum of direct and indirect effect is the total effect (see also e.g. Vij and Walker, 2016). This decomposition, as shown in Table 3, leads to interesting behavioral insights:

All effects of respondent characteristics on the LV are statistically significant (except store accessibility with $p = 0.12$ in the HCMIX model; see also Table 2), whereas all direct effects are not (except for income on the probability of online shopping when purchasing G, as respondents with higher income may face more stringent time constraints; in this case, the share of total effect mediated via the pro-online shopping LV is 35%). It can be argued that the ICLV approach helps to structure the underlying sources of heterogeneity in a more efficient way, which can be seen as a dedicated type of interaction between socio-economic variables and attitudes affecting utility mainly via the LV.[14]

Without the inclusion of attitudes, the significant and positive interaction effect between age and shopping cost in the reduced form models has a peculiar interpretation: Arguing that, ceteris paribus, older respondents are less cost sensitive is, from a behavioral perspective, questionable. However, given the increased cost sensitivity of respondents with pro-online shopping attitudes, and that age exhibits a significant and negative effect (which can be explained by a general reluctance towards new technologies of older respondents; see also e.g. Lian and Yen (2014)), the total effect of age on cost sensitivity is mainly mediated via respondents' attitudes, whereby the direct effect is not significantly different from zero.

While in the reduced form models, gender shows no significant effects, conditional on attitudes, men exhibit a significantly stronger preference for online shopping when purchasing E compared to G ($p < 0.05$; the direct net effect for E is not significantly different from zero). Given that E are typical search goods, it can be seen as more efficient to buy them online, which men stronger consider in their decision process. However, the total effect of male is not significant, as men also have higher pro-online shopping attitudes: In fact, for E, all indirect (and total) effects are not significantly different from zero, reflecting the smaller effect of pro-online shopping attitudes when purchasing E as discussed in Section 5.2.

The total effect of income on shopping cost sensitivity is not significantly different from zero and half of size in the reduced form compared to the hybrid models, which stands in contrast to a typically observed decreasing marginal utility of income. The main explanation can be found in the LV structural model: People with high income have more positive attitudes towards online shopping (which can be explained by the increased accessibility to technological devices), which implies a higher cost sensitivity through the LV interaction, thus diluting the direct interaction effect between income and shopping cost. Including the pro-online shopping LV helps to more accurately identify the direct (positive) interaction effect of income with shopping cost (which even becomes significant in the HCMNL model; $p < 0.05$).

To summarize, including attitudes towards online shopping not only leads to more behaviorally sound interpretations, but also to a moderate increase in estimation efficiency for parameters jointly estimated on both the choice and attitudinal data. The ICLV approach helps to structure respondent heterogeneity via the LV efficiently and more intuitively, and excluding all direct effects would not lead to a significant decrease in choice model fit.

5.4. Marginal probability effects

The marginal probability effects (MPE) presented in Table 4 show the average responsiveness of choice probabilities (i.e. %-point changes) to a change in attribute k while keeping all other attributes fixed (see e.g. Winkelmann and Boes, 2006). Given our complex model structure, we approximate the derivative of the choice probability with respect to a marginal change in a continuous attribute (e.g. shopping cost) by taking the difference between the initial and predicted (simulated) probability after a 1% increase in that attribute, denoted by k^*[15]:

$$MPE^k = \sum_{n=1}^{N} \sum_{t=1}^{T_n} \sum_{r=1}^{R} \frac{1}{NT_nR} \left(P\left(choice_{i,n,t} \middle| X_{i,n,t}^{k^*}, Z_n, \widehat{\Omega}, \Psi^r \right) - P\left(choice_{i,n,t} \middle| X_{i,n,t}^{k}, Z_n, \widehat{\Omega}, \Psi^r \right) \right) \tag{17}$$

Although predicted changes in real-world market shares are not reliable when using SP data (e.g. Glerum et al., 2013), results give insights in how people trade-off shopping cost, travel and delivery time when directly facing the attributes of these two alternative shopping channels under well-defined experimental conditions. Again, the reader has to be alerted that presented results only hold under the current hypothetical situation, and cannot be generalized to real world applications.

Ceteris paribus, for G, a 1% increase in shopping cost decreases the predicted choice probabilities of either in-store or online shopping by about 0.4%-points, while for E, the effects are substantially larger given the higher average costs for E, exhibiting MPEs of about 1.7%-points. Clearly, compared to other choice attributes, shopping costs can be seen as the strongest predictor of shopping channel choice relevant for policy making.

Most socio-demographic effects are substantially larger when purchasing G, which, as discussed above, can be attributed to the more unusual setting for online shopping, also reflected by the significantly larger effect of the LV in the case of G. However, being married

[14] Of note, a LR test between the HCMIX and the HCM LV1 model (which excludes all direct effects; see also Appendix, Table A.3), indicates an insignificant increase in choice model fit (increase in LL by 6.2 units with 18 additional degrees of freedom in the HCMIX model; $p = 0.83$). This is not the case when comparing the REDMIX with a simple MIXL model without any direct (= total) effects: The increase in LL by 23.6 units with 18 additional degrees of freedom is highly significant ($p < 0.01$).

[15] The same concept applies for changes in dummy variables of socio-demographic characteristics, investigating a discrete change from Z_n^k to $Z_n^{k^*}$ while keeping $X_{i,n,t}$ fixed. Note that Ψ^r in Equation (17) corresponds to $LV_{online,n}^r$ and ψ_n^r.

Table 4
Average marginal probability effects (MPE) in the REDMIX, HCMIX and HCM LV1 models.

Attribute (HCMIX)	G: Online [%]	G: In-store [%]	E: Online [%]	E: In-store [%]
Shopping cost (+1%)	−0.36	−0.38	−1.68	−1.65
Travel time (+1%)		−0.12		−0.08
Delivery time (+1%)	−0.15		−0.08	
Delivery cost (+1%)	−0.12		−0.04	
Male (dummy)	−7.38		3.27	
Age (+10 years)	−5.08		−0.91	
Income (+25%)	3.81		1.41	
High education (dummy)	3.81		1.15	
Store accessibility (dummy)	−0.72		−9.10	
Married (dummy)	3.99		10.34	
Attribute (REDMIX)	**G: Online [%]**	**G: In-store [%]**	**E: Online [%]**	**E: In-store [%]**
Shopping cost (+1%)	−0.37	−0.39	−1.73	−1.71
Travel time (+1%)		−0.11		−0.08
Delivery time (+1%)	−0.16		−0.07	
Delivery cost (+1%)	−0.12		−0.04	
Male (dummy)	−4.44		3.47	
Age (+10 years)	−3.99		−0.82	
Income (+25%)	3.67		1.56	
High education (dummy)	3.37		2.00	
Store accessibility (dummy)	−0.21		−8.36	
Married (dummy)	4.31		8.92	
Attribute (HCM LV1)	**G: Online [%]**	**G: In-store [%]**	**E: Online [%]**	**E: In-store [%]**
Shopping cost (+1%)	−0.39	−0.41	−1.95	−1.94
Travel time (+1%)		−0.12		−0.08
Delivery time (+1%)	−0.16		−0.07	
Delivery cost (+1%)	−0.12		−0.04	
Male (dummy)	0.14		0.53	
Age (+10 years)	−0.66		−0.58	
Income (+25%)	1.45		1.37	
High education (dummy)	7.03		7.11	
Store accessibility (dummy)	−4.25		−3.92	
Married (dummy)	4.65		4.49	

and store accessibility become larger for E (and the effect of male even changes signs) compared to G: In-store shopping could more easily be avoided for E, for which these characteristics show a substantial discriminatory power.[16]

When comparing the above models in terms of choice attribute MPEs, there are no substantial differences, which is not the case for socio-demographic characteristics: Although results are qualitatively comparable, MPEs are slightly different in the HCMIX and REDMIX model, which can be attributed to the additional information entering via the LV structural model. This is also reflected by the superior out-of-sample forecasting performance, using a random training subsample with 70% of observations: While the in-sample hitrate in both models is 88.3%, the out-of-sample hitrate is 71.8% in the HCMIX and 71.6% in the REDMIX model, with the former exhibiting an out-of-sample choice model LL of 6.2 units larger (LR test: $p < 0.01$; note that the measurement model is not considered for forecasting; Yáñez et al. (2010); Daziano and Bolduc (2013b)), speaking in favor of the hybrid model.

5.5. *Valuation indicators*

Our results are inconsistent with the traditional microeconomic framework of consumer behavior (see e.g. Jara-Diaz, 2007) in the sense that coefficients for travel, delivery and shopping cost significantly differ, raising the question of how the marginal utility of income (= minus the marginal dis-utility of cost) - typically resulting from a single cost coefficient in mode choice models - should be treated to calculate the valuation indicators in the current application. However, similar results have been found in marketing (e.g. Erdem et al., 2002) or other transportation studies (e.g. toll road or parking studies; see e.g. Hensher and Rose, 2009; Hess and Rose, 2009; Weis et al., 2012), for which Hensher (2011) suggests using a weighted average of the different cost coefficients by the

[16] Results should be interpreted more from a qualitative viewpoint, as the total effects of socio-economic characteristics are in most cases not significant. For the sake of completeness, Table 3 also includes the MPEs derived for the HCM LV1 model. While the effects of choice attributes are again almost identical, now the effects of socio-economic characteristics are solely mediated via the LV, with *all* indirect (= total) effects now being significant (also for E; $p < 0.05$; except for store accessibility), leading to more confident statements. The strongest effect now occurs for high education, showing an average increase in the probability of online shopping by more than 7%-points.

Table 5
Weighted average cost coefficients and median valuation indicators.

	MIXL	HCM LV1	REDMIX	HCMIX
	Value	Value	Value	Value
Mean of C_n	−6.26	−6.16	−6.04	−5.53
Median of C_n	−6.71	−6.63	−6.37	−6.22
SD of C_n	2.71	2.82	2.77	2.86
VTT shopping trips groceries (G) [CHF/h]	41.90	48.19	42.99	54.38
VTT shopping trips electronics (E) [CHF/h]	27.97	26.31	30.52	29.25
VDT delivery time groceries (G) [CHF/day]	9.28	9.28	9.40	9.83
VDT delivery time electronics (E) [CHF/day]	1.10	1.14	1.19	1.16

corresponding attribute levels.

Given that the utility contribution of shopping cost follows a distribution dictated by the random coefficient, the LV and/or the socio-demographic interaction terms (Equation (18)), we first simulated the conditional distribution of the shopping cost coefficient $\widetilde{\lambda_{cost,n}}$ (Equation (19)), which we then inserted in Equation (20) to calculate the weighted average marginal dis-utility of cost C_n at the individual level:

$$\lambda^r_{cost,n} = \widehat{\beta}_{cost} + Z_{online,n}\widehat{\Delta}_{online,cost} + \psi^r_{cost,n} + \widehat{\varphi}_{LV_{online},cost} \cdot LV^r_{online,n} \tag{18}$$

$$\widetilde{\lambda_{cost,n}} = \frac{\sum_{r=1}^{R} \widetilde{L}_n\left(choice_{i,n,t}, I_{w,n} \middle| X_{i,n,t}, Z_{z,n}, \widehat{\Omega}, \lambda^r_{cost,n}\right)\lambda^r_{cost,n}}{\sum_{r=1}^{R} \widetilde{L}_n\left(choice_{i,n,t}, I_{w,n} \middle| X_{i,n,t}, Z_{z,n}, \widehat{\Omega}, \lambda^r_{cost,n}\right)} \tag{19}$$

$$C_n = \sum_{t=1}^{T_n} \frac{1}{T_n} \frac{\widetilde{\lambda_{cost,n}} \sum_i cost_{i,n,t} + \widehat{\beta}^{G,E}_{delivery\ cost} delivery\ cost^{G,E}_{n,t}}{\sum_i cost_{i,n,t} + delivery\ cost^{G,E}_{n,t}} \tag{20}$$

Table 5 presents the key valuation indicators (WTP), focusing on the value of travel time (VTT) and delivery time (VDT) with C_n in the denominator. As suggested by Bliemer and Rose (2013), we present WTP values for a median respondent given their robustness to extreme outliers (see e.g. Hess, 2007), also resulting from our WTP distributions being theoretically unidentified (Daly et al., 2012c), wherefore we do not report the WTP standard deviations (for further discussion, see also e.g. Hensher and Greene, 2003; Sillano and Ortúzar, 2005; Hess, 2007). Of note, the standard deviation of C_n slightly increases when including the LV, accounting for an additional amount of cost heterogeneity that is not captured by the random coefficient.

The current study reveals relatively high median VTT of about 50 CHF/hour for G and 30 CHF/hours for E. With VTT for shopping trips in Switzerland being highly transportation mode, shopper-type and study dependent (see e.g. Erath et al., 2007; VSS Norm, 2009; Weis et al., 2017), ranging between 6 CHF/hour for public transportation 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, especially in the case of E (i.e. a typical search good; see also Hsiao (2009)): With VDT for G of about 9 CHF/day and for E of 1.20 CHF/day, even for G, delivery time of four days is still valued less than the average travel time of one grocery shopping round trip.[17] Again, the reader has to be alerted that presented results only hold under the current hypothetical situation, and cannot be generalized to real world applications.

Results indicate 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 including attitudes (MIXL[18] and REDMIX) may lead to less appropriate results than the corresponding hybrid models (HCM LV1 and HCMIX). For example, VTT for G increases by roughly 25% when comparing the HCMIX with the REDMIX model. Interestingly, this difference mainly results from a more negative utility of travel time when purchasing G in the HCMIX specification, while other coefficients mainly remain unchanged.[19] Findings also imply that respondents with pro-online shopping attitudes exhibit lower WTPs, as their cost sensitivity is higher while sharing identical (non-distributed) time coefficients[20], a result that - given the current experimental assumptions - has to be challenged.

[17] Note that average total travel time of 47 min for a home-based shopping trip corresponds to a monetary value of about 40 CHF for groceries and 25 CHF for electronic appliances.

[18] Note that the MIXL is a Mixed Logit model without including socio-demographic characteristics, serving as a benchmark to compare with the hybrid model without any direct effects of socio-demographic characteristics (HCM LV1).

[19] Similar findings are obtained when comparing the MIXL with the HCM LV1 model.

[20] Interactions of pro-online shopping attitudes and travel/delivery time were tested, but were found to be insignificant and small.

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: Groceries (G), a typical experience good, and standard electronic appliances (E), a typical search good.

The integrated choice and latent variable (ICLV) approach comes along with an enhanced estimation efficiency and helps to structure respondent heterogeneity via the latent variable efficiently and more intuitively. As we can show for the current application, this leads to a more behaviorally sound representation of individual decision making when comparing to the reduced form Mixed Logit model.

By including two latent variables (LVs) reflecting the attitudes towards online shopping and the pleasure of shopping, the LV structural model reveals information of individual attitudes conditional on observable socio-economic characteristics, which in turn affect the choice of the shopping channel: Given a specific target consumer segment, one can predict alternative-specific market shares and/or heterogeneity in attribute sensitivities such as shopping costs, and based on that, develop an effective retailing strategy.

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 expanded choice set when effectively considering both purchasing channels. Interestingly, the interaction of income and 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 an increased price-driven trade-off behavior and diluting the interaction effect. Furthermore, results from the LV structural model indicate that the strongest socio-economic factor explaining attitudes is education: Well-educated respondents 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.

Results show a clear pattern of purpose-specific shopping channel preferences, supporting the hypothesis for experience goods that grocery shopping (G) is mainly conducted in stores, and that respondents with positive attitudes towards online shopping choose the online alternative more often. This effect is dampened in the case when purchasing standard electronic appliances (E), given the more common situation to purchase E online. To summarize, while all these findings confirm the hypotheses in Section 4, we find no evidence that the pleasure of shopping adds substantial behavioral insights in explaining the choice between in-store and online shopping.

From a travel behavior perspective, results reveal a further potential for online shopping services, given the relatively high value of travel time (VTT) of about 50 CHF/h for G and 30 CHF/h for E compared to the value of delivery time (VDT) ranging between 9 CHF/day for G and 1.20 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, VTT 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). Also, in the case of grocery shopping, 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 SP experiments and the limited, contrived and constrained experimental setting. 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 G and E. 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 1) home-based and single purpose shopping trips, 2) ignoring multi-channel shopping, 3) ignoring store attributes, price, brand and quality perceptions, 4) abstracting from social motives and 5) excluding private cars for the in-store alternative - although important for the coherence of choice situations and the overall project guidelines - might have affected choice behavior in an unpredictable way.

Third, a general limitation of SP surveys one should always be aware of is the difficulty of respondents to decide exclusively based on the presented attributes and to abstract from any hidden factors in their decision making process.

Finally, the causality of the reported effects regarding the LVs 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.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.jocm.2018.03.001.

Glossary

AICc	For finite sample size corrected Akaike Information Criterion
CHF	Swiss Francs (1 CHF ≈1 US$)
E	Standard electronic appliances
G	Groceries
HCM	Hybrid choice model
HCMIX	Hybrid choice model with direct effects and random parameters
HCMNL	Hybrid choice model with direct effects
ICLV	Integrated choice and latent variable
ICT	Information and communication technology
IID	Independent and identically distributed
LV	Latent variable
MIMIC	Multiple indicators multiple causes
MIXL	Mixed Logit
MLHS	Modified Latin hypercube sampling
MNL	Multinomial Logit
MPE	Marginal probability effect
OL	Ordered Logit
PCW	Post-Car Word (project name)
REDMIX	Reduced form Mixed Logit
REDMNL	Reduced form Multinomial Logit
RP	Revealed preference
SD	Standard deviation
SM LV1	Sequential model (using first-stage LV predictions to include in choice model)
SP	Stated preference
VDT	Value of delivery time
VTT	Value of travel time
WTP	Willingness to pay

Appendix

Institut für Verkehrsplanung und Transportsysteme
Institute for Transport Planning and Systems

ETH
Eidgenössische Technische Hochschule Zürich
Swiss Federal Institute of Technology Zurich

2 In-store or online shopping

This questionnaire addresses the following persons in your household. We ask this person to fill out the survey forms on the following pages.

Prename: **Jonathan**	Year of birth: **1960**

Imagine you live in the near future and decide about doing your purchases by either **ordering online** or **travelling to a nearby store** that you can only access by means of public transportation, carsharing or carpooling. Hence, you experience either delivery cost or travel cost.

Please note that you do not have a private car available and that your purchases are for one single purpose: Buying **standard electronic devices for entertainment** or **electronic household appliances.**

Assume that the products are identical, regardless of whether you order or travel to the store (same brand, quality, etc.). On the following two pages you find 8 single choice situations. In each situation, the available alternatives are described with the following attributes:

- **Delivery cost** (incl. possible custom fees) or **travel cost** for the trip to the store
- **Travel time** to the store
- **Delivery time** (incl. possble delays)
- Approximate **Size / Weight** of the purchases
  - : Easy to carry (e.g. water kettle, smartphone, hairdryer, etc.)
  - : Heavy / inconvenient to carry (e.g. Computer, TV set, coffee machine, etc.)
  - : Very heavy or inconvenient to transport (e.g. large Hifi set, lawn mower, fridge, etc.)
- **Time** for **ordering** or for **purchase** in the shop (incl. waiting time at the cashier)
- **Cost** of purchase

Please consider that the attribute values shown in the choice situations only party relate to the information you declared in the first part of the study and can therefore be different to situations of your personal experience. Please attempt to **base your choices solely on the shown values and characteristics**. Carefully trade off the attributes against each other and choose the one alternative you consider best in your personal opinion, i.e. ordering online or travel to the store.

Fig. A.1. Introduction text and framing of the shopping SP experiment (included in the survey as a follow-up SP to mode and route choice).

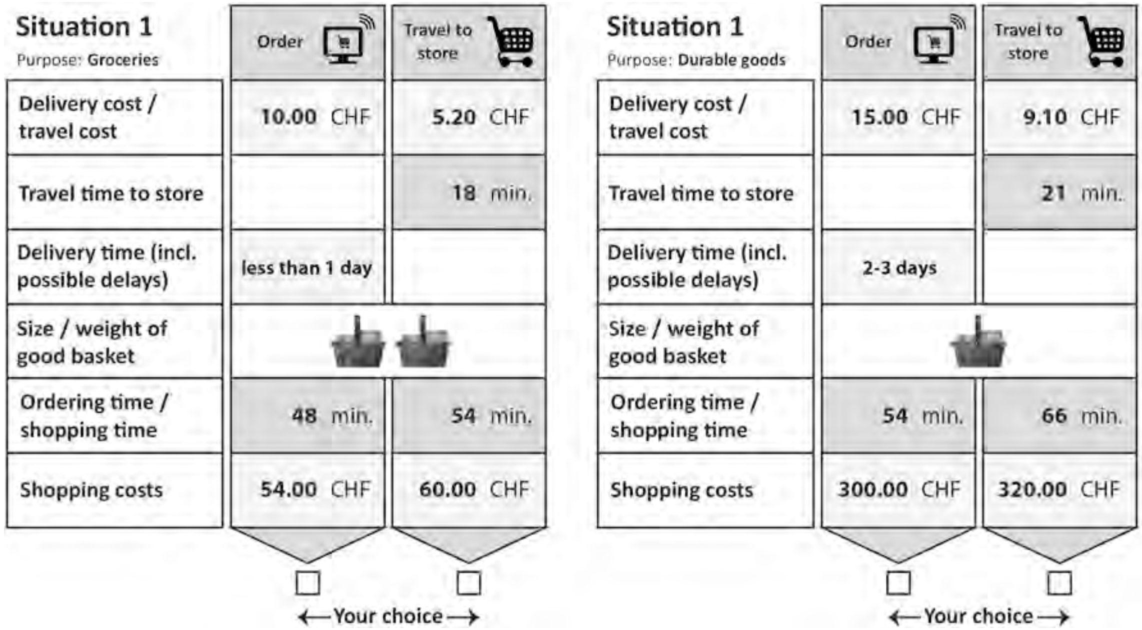


Fig. A.2. Example choice situations.

Table A.1
Descriptive statistics: Swiss census data (2010) versus PCW sample.

Variable	Value	MZMV 2010 (%)	PCW (%)
Household members	1	31.6	18.4
	2	37.4	29.1
	≥3	30.0	52.4
Household income	Not reported	24.1	4.9
	≤12′000 CHF	57.5	34.7
	>12′000 CHF	18.4	60.4
Personal income	≤6′000 CHF	–	49.4
	>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
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 ≤10 min. of walk	–	90.1
	Next shop >10 min. of walk	–	9.9

(continued on next page)

Table A.1 (*continued*)

Variable	Value	MZMV 2010 (%)	PCW (%)
Working hours	Weekly working hours ≤5 h	–	10.7
	Weekly working hours >5 h	–	89.3

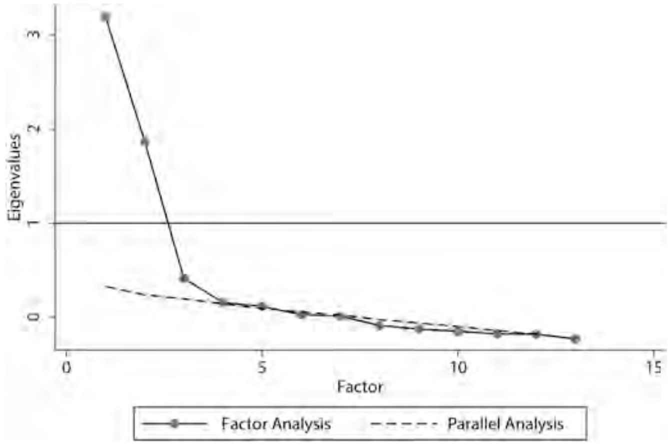
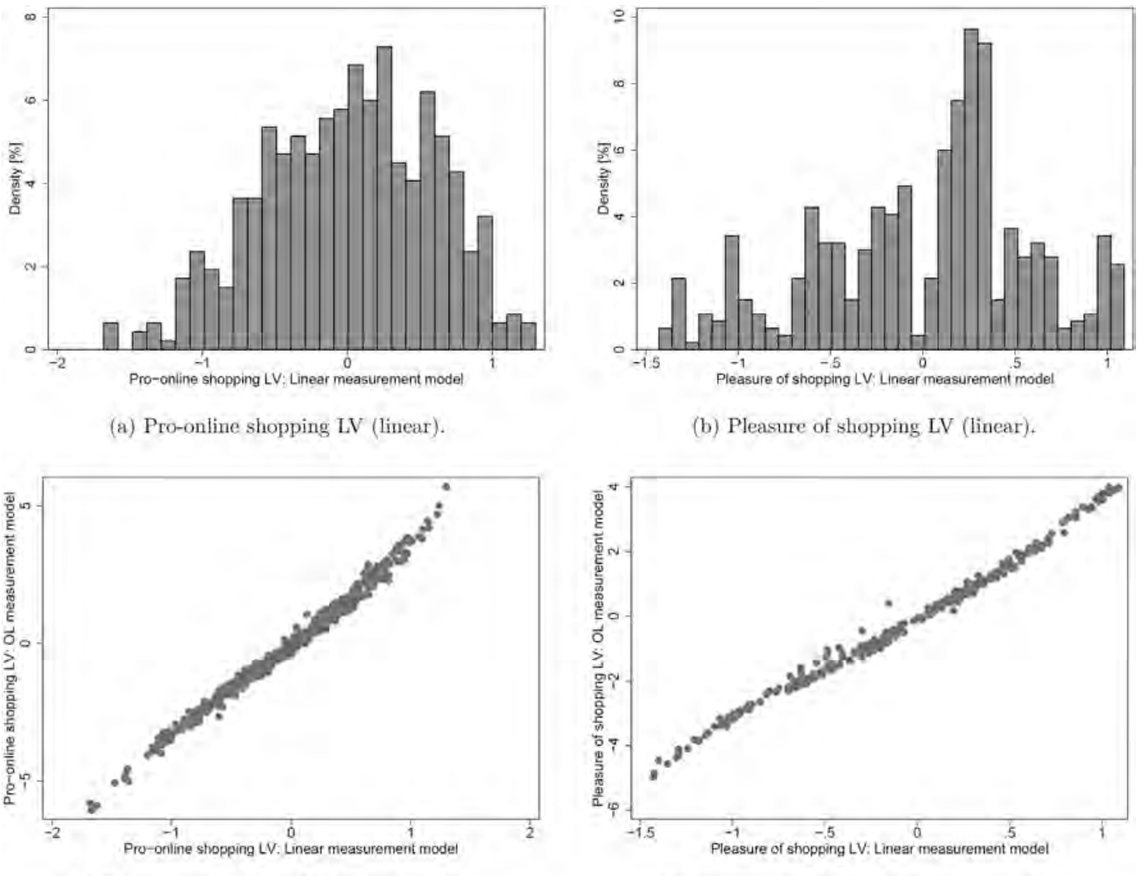


Fig. A.3. Scree-plot for exploratory factor analysis, suggesting a two-factor-solution (factor 1: Pro-online shopping; factor 2: Pleasure of shopping.).



(a) Pro-online shopping LV (linear).

(b) Pleasure of shopping LV (linear).

(c) Pro-online shopping LV (linear vs. Ordered Logit measurement model).

(d) Pleasure of shopping LV (linear vs. Ordered Logit measurement model).

Fig. A.4. Posterior distributions of latent variables.

Table A.2
Estimation results: MIMIC model for the two latent variables.

Variable	Pro-online shopping	Pleasure of shopping
	Coef./(SE)	Coef./(SE)
Male	0.31***	−0.28***
	(0.07)	(0.05)
Age	−1.05***	
	(0.28)	
High education	0.33***	0.19***
	(0.08)	(0.07)
Income	0.19***	
	(0.06)	
Store accessibility	−0.17*	0.24***
	(0.10)	(0.09)
Married	0.18***	−0.11**
	(0.06)	(0.05)
Non-working		0.19**
		(0.08)
Car available		0.05*
		(0.03)
SD	0.57***	0.50***
	(0.04)	(0.04)
onl1	1	
onl2	−0.59***	
	(0.06)	
onl3	−1.10***	
	(0.08)	
onl4	−0.62**	
	(0.06)	
onl5	−0.39***	
	(0.06)	
onl6	0.77***	
	(0.07)	
onl7	−0.77***	
	(0.07)	
onl8	0.77***	
	(0.08)	
onl9	−0.73***	
	(0.06)	
onl10	0.72***	
	(0.08)	
ple1		1
ple2		−1.34***
		(0.10)
ple3		−1.37***
		(0.10)
# parameters	38	
# respondents	466	
# draws	1000	
LL_{model}	−6698.7	

Robust SE's: ***: p < 0.01, **: p < 0.05, *: p < 0.1.
Note: Item SD's not reported in the table.

Table A.3
Estimation results: Sequential (SM LV) and hybrid choice (HCM LV) models without direct effects of socio-economic variables.

Base category: In-store (S) shopping	SM LV1	SM LV2	HCM LV1	HCM LV2
	Coef./(SE)	Coef./(SE)	Coef./(SE)	Coef./(SE)
Alternative-specific constant (O)	−1.47***	−2.10***	−1.47***	−1.58***
	(0.29)	(0.42)	(0.29)	(0.30)
SD of random intercept (O)	2.08***	2.06***	1.99***	1.86***
	(0.15)	(0.15)	(0.16)	(0.17)
Shopping cost	−5.94***	−6.02***	−5.85**	−6.10***
	(0.62)	(0.65)	(0.61)	(0.74)
SD of shopping cost	4.87***	4.90***	4.55***	4.36***
	(0.74)	(0.79)	(0.75)	(0.87)

(*continued on next page*)

Table A.3 (*continued*)

Base category: In-store (S) shopping	SM LV1	SM LV2	HCM LV1	HCM LV2
	Coef./(SE)	Coef./(SE)	Coef./(SE)	Coef./(SE)
In-store shopping time (S)		−2.47**		−2.35**
		(1.18)		(1.15)
SD of in-store shopping time (S)		0.34		1.70**
		(0.42)		(0.70)
Delivery cost (O)	−0.18***	−0.18***	−0.18***	−0.18***
	(0.02)	(0.02)	(0.02)	(0.02)
Delivery cost × electronics (O)	0.13***	0.13***	0.13***	0.13***
	(0.02)	(0.02)	(0.02)	(0.02)
Delivery time (O)	−1.03***	−0.99***	−1.03***	−1.01***
	(0.14)	(0.14)	(0.14)	(0.14)
Delivery time × electronics (O)	0.90***	0.86***	0.90***	0.88***
	(0.14)	(0.14)	(0.14)	(0.14)
Travel time (S)	−5.28***	−5.46***	−5.34***	−5.21***
	(1.27)	(1.28)	(1.26)	(1.29)
Travel time × electronics (S)	2.15	2.45*	2.31*	2.42*
	(1.34)	(1.35)	(1.34)	(1.39)
Size/weight small (O)	–	–	–	–
Size/weight medium (O)	1.30**	1.38**	1.99***	2.01***
	(0.55)	(0.55)	(0.18)	(0.18)
Size/weight large (O)	3.30***	3.36***	3.98***	3.97***
	(0.60)	(0.60)	(0.26)	(0.27)
Size/weight × age (O)	2.43**	2.35**	2.46**	2.17*
	(1.15)	(1.15)	(1.16)	(1.14)
Size/weight × male (O)	−0.93***	−0.98***	−0.94***	−1.04***
	(0.27)	(0.27)	(0.27)	(0.27)
Pro-online-shopping LV (O)	2.31***	2.23***	2.21***	1.88***
	(0.36)	(0.36)	(0.36)	(0.38)
Pro-online LV × electronics (O)	−0.63	−0.55	−0.57	−0.16
	(0.44)	(0.44)	(0.44)	(0.47)
Pro-online LV × shopping cost	−3.26***	−3.31***	−3.49***	−3.33***
	(0.82)	(0.85)	(1.25)	(1.17)
Pleasure of shopping LV (O)		1.15		1.82**
		(1.11)		(0.91)
Pleasure LV × electronics (O)		−1.15		−1.68
		(1.46)		(1.10)
Pleasure LV × in-store shop. time (S)		4.50		6.04***
		(2.99)		(2.34)
Pleasure LV × in-store shop. time × electronics (S)		−3.89		−5.52**
		(3.54)		(2.68)
Pro-online shopping LV1: Age			−1.13***	−0.98***
			(0.30)	(0.31)
Male			0.31***	0.26***
			(0.07)	(0.07)
Income			0.14***	0.15***
			(0.04)	(0.04)
High education			0.31***	0.29***
			(0.08)	(0.09)
Store accessibility			−0.18*	−0.23**
			(0.11)	(0.12)
Married			0.20***	0.07
			(0.07)	(0.05)
SD of pro-online shopping LV			0.59***	0.59***
			(0.03)	(0.04)
Pro-online shopping LV: onl1			1	1
onl2			−0.56***	−0.54***
			(0.06)	(0.07)
onl3			−1.04***	−1.02***
			(0.08)	(0.08)
onl4			−0.59***	−0.58***
			(0.06)	(0.06)
onl5			−0.38***	0.08
			(0.06)	(0.07)
onl6			0.77***	0.78***
			(0.06)	(0.06)
onl7			−0.74***	−0.72***
			(0.07)	(0.07)

(*continued on next page*)

Table A.3 (*continued*)

Base category: In-store (S) shopping	SM LV1	SM LV2	HCM LV1	HCM LV2
	Coef./(SE)	Coef./(SE)	Coef./(SE)	Coef./(SE)
onl8			0.75***	0.74***
			(0.07)	(0.08)
onl9			−0.71***	−0.71***
			(0.05)	(0.05)
onl10			0.69***	0.69***
			(0.07)	(0.07)
SD onl1			0.59***	0.59***
			(0.02)	(0.03)
SD onl2			0.65***	0.66***
			(0.02)	(0.02)
SD onl3			0.74***	0.75***
			(0.03)	(0.03)
SD onl4			0.60***	0.61***
			(0.02)	(0.02)
SD onl5			0.75***	0.79***
			(0.03)	(0.03)
SD onl6			0.74***	0.74***
			(0.02)	(0.02)
SD onl7			0.71***	0.72***
			(0.03)	(0.03)
SD onl8			0.83***	0.83***
			(0.03)	(0.03)
SD onl9			0.56***	0.56***
			(0.02)	(0.02)
SD onl10			0.83***	0.83***
			(0.03)	(0.03)
Pleasure of shopping LV: Sex				−0.31***
				(0.07)
High education				0.23***
				(0.08)
Store accessibility				0.23
				(0.15)
Non-working				0.17**
				(0.08)
Married				−0.11**
				(0.05)
Car available				0.05*
				(0.03)
SD of pleasure of shopping LV				0.51***
				(0.04)
Pleasure of shopping LV: ple1				1
ple2				−1.38***
				(0.11)
ple3				−1.31***
				(0.10)
SD ple1				0.74***
				(0.03)
SD ple2				0.33***
				(0.04)
SD ple3				0.37***
				(0.03)
# estimated parameters	17	23	43	61
# respondents/choices	466/3722			
# draws	1000			
LL_{null}	−2579.9		*NA*	
LL_{final}	−1614.7	−1610.1	−6913.3	−8318.2
$LL_{choicemodel}$	−1614.7	−1610.1	−1658.1	−1659.1
AICc	3264.8	3268.8	13921.5	16777.2

Note: SM LV models include LV first-stage predictions based on MIMIC model in Table A.2.
Note: Shopping cost, shopping time and travel time are scaled down by factor 100.
Robust standard errors: ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

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