Exploring the choice between in-store and online shopping

Author(s):
Schmid, Basil; Schmutz, Simon; Axhausen, Kay W.

Publication date:
2016-04

Permanent link:
https://doi.org/10.3929/ethz-b-000114973

Exploring the choice between in-store and online shopping

Basil Schmid

Simon Schmutz

Kay W. Axhausen

EIRASS Conference Paper **April 2016**

IVT Institut für Verkehrsplanung und Transportsysteme
Institute for Transport Planning and Systems

ETH
Eidgenössische Technische Hochschule Zürich
Swiss Federal Institute of Technology Zurich

EIRASS Conference Paper

Exploring the choice between in-store and online shopping

Basil Schmid
IVT
ETH Zürich
CH-8093 Zürich
phone: +41-44-633 30 89
fax: +41-44-633 10 57
basil.schmid@ivt.baug.ethz.ch

Simon Schmutz
IVT
ETH Zürich
CH-8093 Zürich
phone: +41-44-633 30 89
fax: +41-44-633 10 57
sschmutz@student.ch

Kay W. Axhausen
IVT
ETH Zürich
CH-8093 Zürich
phone: +41-44-633 39 43
fax: +41-44-633 10 57
axhausen@ivt.baug.ethz.ch

April 2016

Abstract

This paper aims at explaining the choice between online and in-store shopping for experience (groceries) and search (electronic appliances) goods in Zurich, Switzerland, applying an integrated choice and latent variable (ICLV) modeling approach: In a stated preference experiment 339 participants were requested to trade-off different attributes related to their choice between online and in-store shopping, with a separate questionnaire asking for their feelings and attitudes towards online shopping.
The first alternative-specific Hybrid Choice model in this research field is presented here, including one latent variable reflecting the acceptance level of online shopping which itself depends on basic socio-economic characteristics. An increased acceptance level implies a significantly higher shopping cost sensitivity, which can be explained by the expanded choice set when considering both alternatives as possible shopping channels. The relatively high value of travel time savings (VTTS) obtained of about 40 Swiss Francs per hour indicates a potential for new online shopping services when compared to the relatively low value of delivery time savings (VDTS) of less than 16 Swiss Francs per time unit, depending on shopping purpose and time interval.

Keywords

Online shopping, in-store shopping, attitudes towards online shopping, alternative-specific attributes, integrated choice and latent variable model (ICLV), value of time

1 Introduction

Identifying the driving forces that affect consumers' choices between in-store and online shopping is not only crucial for developing effective retailing strategies, but also for forecasting and exploring valuation indicators in the context of activity-based travel demand modeling. 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. This paper presents an innovative survey design and novel modeling approach by investigating the relative importance of attributes related to the choice between in-store and online shopping for two product categories: Search (electronic appliances) and experience (groceries) goods.

As part of a multi-stage survey on travel behavior in a *Post-Car World*, a choice experiment (Louviere et al., 2000) was conducted in Zurich, Switzerland, asking 339 participants to trade-off different alternative-specific attributes related to their choice between in-store and online shopping, with reference values depending on observed shopping behavior. For the in-store alternative, the absence of private cars is justified 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., 2016).

Using an innovative modeling framework, the integrated choice and latent variable (ICLV) approach (Ben-Akiva et al., 2002) incorporates participants' attitudes towards online shopping by simultaneously modeling one latent variable and the choice of the shopping channel. An interaction term of the latent variable with shopping costs is included to measure the heterogeneity in price sensitivity, one of the main driving forces when considering online shopping in Switzerland (Rudolph et al., 2015). The modeling framework used provides deeper behavioral insights and 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 latent variable.

The structure of the paper is organized as follows: Section 2 presents a literature review on the interdependencies and attributes 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 behavior and explains how the attitudes towards online shopping were assessed. Section 4 provides a overview on the modeling framework, including a short literature review and the mathematical formulation of the structural and measurement equations of the ICLV modeling approach. Section 5 presents the results of three models of increasing complexity and discusses the implications on choice behavior, valuation indicators and attribute elasticities. Section 6 provides a discussion of results, some concluding remarks and a short outlook.

2 Literature review

Information and communication technologies (ICT) have experienced a rapid increase in usage over the last 25 years, allowing a more flexible spatial and temporal fragmentation of activities and recombinations among them. Regarding shopping purposes, ICT enables a shift from traditional channels towards home-based online shopping, thus potentially substituting travel. In Switzerland, the online and mail order market share (of total retail business revenues) has reached the 7% mark in 2014, with growth rates in the double-digit range (Verband des Schweizerischen Versandhandels VSV und GfK, 2015), while total retail business revenues have experienced zero growth over the last five years. With online shopping market shares being highly product-dependent, it indicates a shift away from traditional shopping channels mainly for non-food products.

Mokhtarian (2004) mentions four main consequences of ICT on travel behavior. In the case of a *substitution* effect, Ferrell (2005) shows that for the San Francisco Bay Area, online shopping duration exhibits a negative effect on travel time and frequency of in-store shopping trips. However, ICT usage may also have a *complementary* effect, leading to more shopping (either in-store or online) or other activities mainly due to a resource reallocation. Farag et al. (2005) show that for the Netherlands, searching online for products increases the frequency of shopping trips, with the latter positively affecting the frequency of buying online (Farag et al., 2007). Moreover, a *modification* of shopping behavior might be present, affecting the shopping process, trip chaining and timing. Mokhtarian and Tang (2013) report a dependency between pre-purchase (product information/searching) and purchase channel (in-store or online) choices for clothing purchases in North Carolina, showing that ICT affects consumers' shopping processes in different ways. Finally, in the case of *neutrality*, online shopping is independent of in-store shopping. Regarding leisure activities including shopping, Mokhtarian et al. (2006) argue that apart from expanding individuals' choice sets, the potential effects of ICT on travel behavior are ambiguous and require further empirical investigations (see also 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?

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. Situation-specific attributes (service, delivery, travel, etc.) and personal characteristics (socio-economic background, etc.) 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. According to the authors, 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 volition for using a specific shopping channel. 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 pattern that has been revealed in many other related studies (Rudolph et al., 2004; Farag, 2006; Farag et al., 2007; Cao, 2009; Chocarro et al., 2013). In addition, several studies have shown a large product-specific heterogeneity in the factors affecting the choice between in-store and online shopping. Burke (2002) shows that for grocery shopping, convenience is very important, while for electronics and other appliances, service and product information are the key attributes. According to Chiang and Dholakia (2003), Rotem-Mindali and Salomon (2007) and Chocarro et al. (2013), apart from convenience, they find 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. These findings are confirmed when looking at stated online purchasing intentions for different product categories in Switzerland, with e.g. food accounting for 5-15% and electronics for 18-50% (Rudolph et al., 2015). Apart from product type and convenience, a main criteria to shop online often referred to is the (lower) price in combination with facilitated price comparisons (Chiang and Dholakia, 2003; Rotem-Mindali and Salomon, 2007; Farag, 2006; Rudolph et al., 2004). Bhatnagar et al. (2000) mention the general product risk which is higher for expensive and experience goods, leading to a decreasing propensity for online shopping. However, especially expensive electronics, soft- and hardware seem to partially compensate these risks by offering a high level of shopping convenience. Chocarro et al. (2013) argue that high involvement goods, i.e. 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. The approach used in this paper is comparable to Hsiao (2009): He conducted a stated preference experiment on book purchasing behavior in Taiwan by assessing channel-specific effects including the product price, travel time, travel cost and delivery time. The author argues 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 search goods.

3 Data and methods

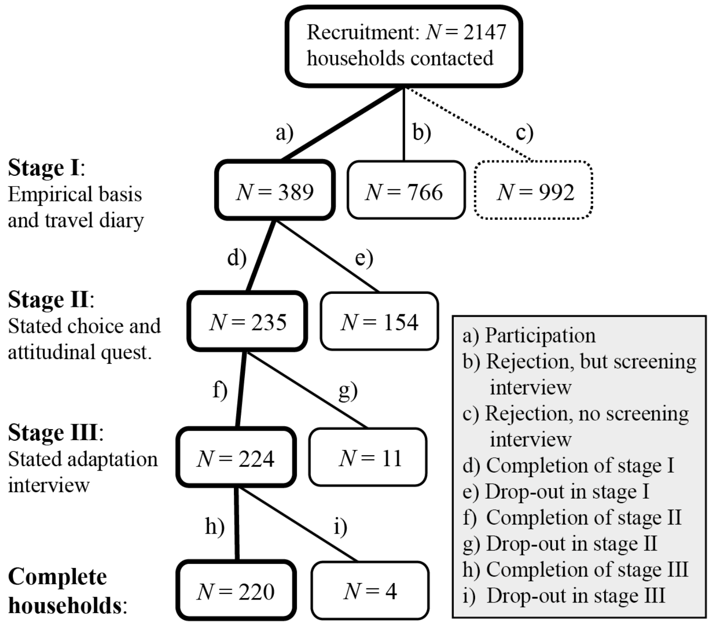
3.1 Overview and participation rates

The data used (*Post-Car World*, abbrev. PCW; see also http://postcarworld.epfl.ch/) is 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. The survey process is organized in three stages as shown in Fig. 1a. The sample was drawn from a commercially available address data base, covering the metropolitan area of Zurich, Switzerland. The questionnaires for stage I were sent to 389 households that agreed to participate during the telephonic recruitment interviews, of which 235 returned the complete questionnaires. The data analyzed for this paper was collected during stage II (stated choice and attitudinal questionnaires). 224 households (339 respondents) sent back these questionnaires and were willing to proceed with the stated adaptation interviews (stage III). Each full participant received an incentive of 50 CHF ≈ 50 US$ at the time of the interviews. Data has been collected since January 2015, and the fieldwork is still ongoing.

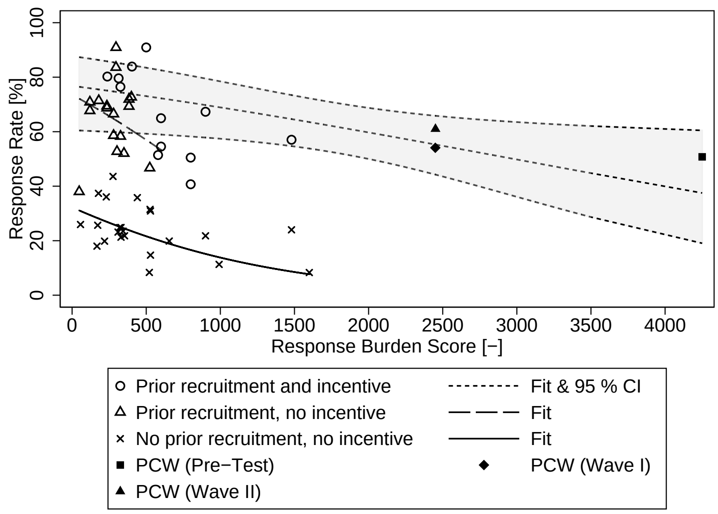
The empirical basis (stage I of the survey) is an enriched one-week travel diary that was required to explore the individual patterns in travel and shopping behavior and to obtain individual reference values for the stated choice task. The design of the diary is based on the *MOBIDrive* protocol (Axhausen et al., 2002): For each trip conducted, respondents were asked detailed information about time, space and movement. Data is organized in a longitudinal panel structure, where each new trip follows its predecessor. It implicitly reveals information about activity durations for nine different activity types: (1) Home activity, (2) accompanying trip, (3) work or education, (4) grocery and (5) durable good shopping, (6) service or attendance, (7) business trip, (8) leisure and (9) other activity.

Figure 1: Survey procedure and participation rates.

(a) PCW: Survey procedure and participation.



(b) Response burden and response rates @IVT referring to Axhausen et al. (2015).



To construct the stated choice questionnaires, great care was taken in the creation of the experimental designs (Louviere et al., 2000), selecting the attributes and the coding of the personalized choice sets based on revealed preference (RP) reference values from the first stage of the survey. Using a respondent's reported behavior on grocery or durable good shopping trips (activity types 4 and 5) to derive the attribute levels has been proven as a valid approach to enhance individual preference revelation (Rose et al., 2008).

A meta-analysis of response behavior, given the response burden of a study, has been conducted based on past studies of the Institute for Transport Planning and Systems (IVT). Its results are compared to the current study, as shown in Fig. 1b. The response burden was determined according to a predefined scheme presented in Axhausen et al. (2015), assigning weighted scores to different question types and aggregating them to calculate the total response burden score of a study. Exhibiting a high response burden, the response rates of the current study (PCW) of about 50 % in the pre-test and between 55 and 60 % in the two main waves - corresponding to the *COOP4* cooperation rate defined by the The American Association for Public Opinion Research (2015) - are above the predicted trend for studies with recruitment and incentives, hence speaks in favor of the large recruitment effort, the study design and the topic itself.

3.2 Online vs. in-store shopping choice experiment

A 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 or experience goods. 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 (Louviere, 2006). Reference values of shopping time, shopping cost, travel time and travel cost attributes are calculated based on reported shopping trips and average expenditures for groceries.[1]

The experiments were introduced (see below) 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 leisure activities (Hsiao, 2009), respondents were told that buying the specific goods is the one and only purpose of doing this shopping trip. To account for this issue, purchases have been explicitly defined as either daily or weekly grocery (i.e. food, drinks, cosmetics, etc.) or as durable

[1] Durable goods expenditures 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 survey period in stage I, a potential shopping location was chosen offering a high variety of goods and high level of accessibility, assigning this respondent to the durable goods experiment as 1) there were slightly more grocery than durable good shopping trips and 2) from a behavioral aspect it might be more problematic to postulate a travel distance to a grocery store. In such a case, reference travel time and travel cost to the store were randomly determined to be either for carsharing/carpooling or public transport. To avoid anchoring effects, a specific transport mode for the in-store alternative was not mentioned in the introductory text.

goods shopping (i.e. multimedia, HiFi or electronic household appliances), respectively. Depending on reported shopping trips, respondents were assigned to one of these two categories. 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 following attributes were hypothesized to affect the choice between online vs. in-store shopping (see also Table 1):

Online alternative:

- **Delivery cost** including duty: 0 CHF / 5 CHF / 10 CHF / 15 CHF
- **Delivery time** groceries: Within one day / 1-2 days / more than 2 days;
  durable (electronic) goods: 2-4 days / 4-7 days / more than 1 week

In-store alternative:

- **Travel cost**[2] 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: Average of carpooling and carsharing travel costs
  (2) public transport: Personalized PT travel costs
- **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

Both alternatives:

- **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; durable goods: 25 min, 40 min and 60 min).

[2]Travel costs are calculated based on current Swiss market prices for carsharing, carpooling or public transport. 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).

- **Size/weight of the good basket**: This environmental attribute (i.e. always the same value for both alternatives) is included in the choice experiments, indicating how convenient it is to do a specific shopping task.

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

Attributes	Online	In-store	Levels	μ	σ	ν
Shopping cost [CHF]	√	–	$-10\%, -5\%, 0\%$	235.2	190.4	0.8
Shopping cost [CHF]	–	√	$-5\%, 0\%, +5\%$	248.0	200.7	0.8
Time for shop. [min]	√	–	$-20\%, -10\%, +5\%$	38.1	16.2	1.3
Time for shop. [min]	–	√	$-10\%, 0\%, +10\%$	41.8	17.9	1.4
Delivery cost and duty	√	–	0, 5, 10, 15 CHF	7.6	5.6	0.0
Travel cost [CHF]	–	√	$-20\%, +10\%, +40\%$	5.2	3.5	3.1
Delivery time groceries	√	–	$<$ 1 day, 1-2 days, $>$ 2 days	–	–	–
Delivery time durables	√	–	2-3 days, 4-7 days, $>$ 1 week	–	–	–
Travel time [min]	–	√	$-30\%, 0\%, +30\%, \geq 3$ min	24.4	17.5	2.4
Size/weight of the good basket	√	√	Low, medium, high (same for both alternatives)	–	–	–

μ = mean, σ = standard deviation, ν = skewness; for attribute values in the choice experiment

Figure 2: Example choice situations.

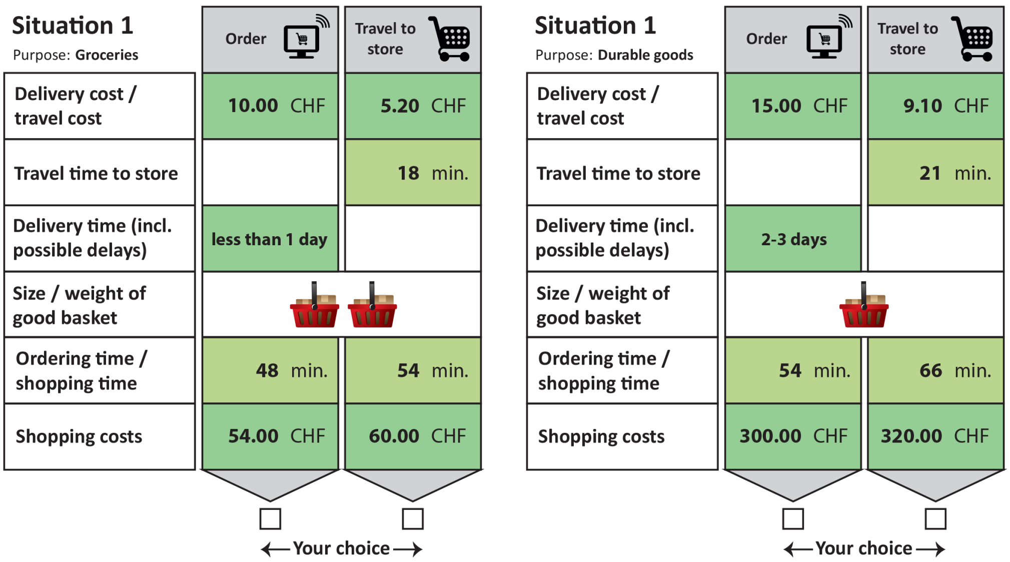


Table 1 highlights the pivot design approach to create the individual choice situations: Some attribute levels were varied relative to the reference values explained above. Note that the distributions of travel time and cost are highly right-skewed ($\nu > 0$) as most shopping trips were conducted for shorter distances. A *D*-efficient block design with 24 choice situations was calculated using *Ngene* (Rose and Bliemer, 2009), including weak parameter priors and assigning 8 choice situations to each participant.

3.3 Descriptive analysis of the sample

Descriptive figures of the recruited sample's behavior (PCW sample; 224 households, 339 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 too small to draw conclusions about representativeness, it highlights potential biases, which one should keep in mind when interpreting the results in Section 5. While the residential location area, gender, nationality 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 levels 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, which will be considered for a re-weighting of observations to correctly compute the population level valuation indicators.

3.4 Attitudes towards online shopping

A broad range of attitudinal traits were assessed together with the stated choice experiments in stage II of the survey that are hypothesized to affect mode, route and shopping preferences[3]. The implemented attitudinal questionnaires are based on the *MOBIDrive* protocol (Axhausen et al., 2002) and a survey by Rieser-Schüssler and Axhausen (2012). Specifically, different statements for 1) car ownership and environmental concerns, 2) public transport affinity, 3) risk and variety seeking, 4) hypothetical transport modes as well as 5) attitudes towards shopping in general, and online shopping specifically, were asked within 80 items using 4-point-Likert-scales. To focus on items reflecting the attitudes towards online shopping, 7 items were considered for the analyses presented here. An exploratory factor analysis was conducted to reduce the data to the most essential

[3]Apart from the experiment on the choice between in-store and online shopping discussed here, respondents were also asked to conduct mode and route choice experiments.

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

Variable	Value	MZ2010 (%)	PCW (%)
Household size	1	31.6	18.7
	2	37.4	31.3
	≥ 3	31.0	50.0
Household income	Not reported	24.1	5.7
	< 4'000 CHF	14.9	4.9
	4'000 - 6'000 CHF	17.5	3.3
	8'000 - 10'000 CHF	14.5	13.0
	10'000 - 12'000 CHF	10.6	11.4
	> 12'000 CHF	18.4	61.8
Household type	Single-person household	31.6	18.7
	Couple without kids	33.0	25.2
	Couple with kids	26.6	48.0
	Single-parent household	5.8	4.5
	Flat-sharing community	3.1	3.7
Residential location area	City centre	38.9	50.0
	Agglomeration	54.8	43.1
	Rural	6.3	6.9
Sex	Female	54.3	50.4
	Male	45.7	49.6
Age	18 - 35 years	20.7	10.5
	36 - 50 years	29.4	37.9
	51 - 65 years	27.4	46.8
	66 - 80 years	22.5	4.8
Nationality	Swiss	72.2	84.5
	Other	27.8	15.5
Education	Low	21.0	14.7
	Medium	54.9	22.3
	High	24.1	63.0
Car availability	Always	74.6	59.0
	Sometimes	18.0	26.3
	Never	7.3	14.7
Season tickets	None	37.3	11.0
	Half-fare card	51.8	72.9
	GA	10.9	16.1

elements, remove sources of covariance and measurement noise and use these findings to derive the hypotheses for the structural equation of the ICLV model in Section 4. Based on the factor-Eigenvalue plot, the results of a parallel analysis and considering the latent-root-criterion Hayton et al. (2004), one latent variable consisting of highly related items was retained, explaining the most important dimension of variability.

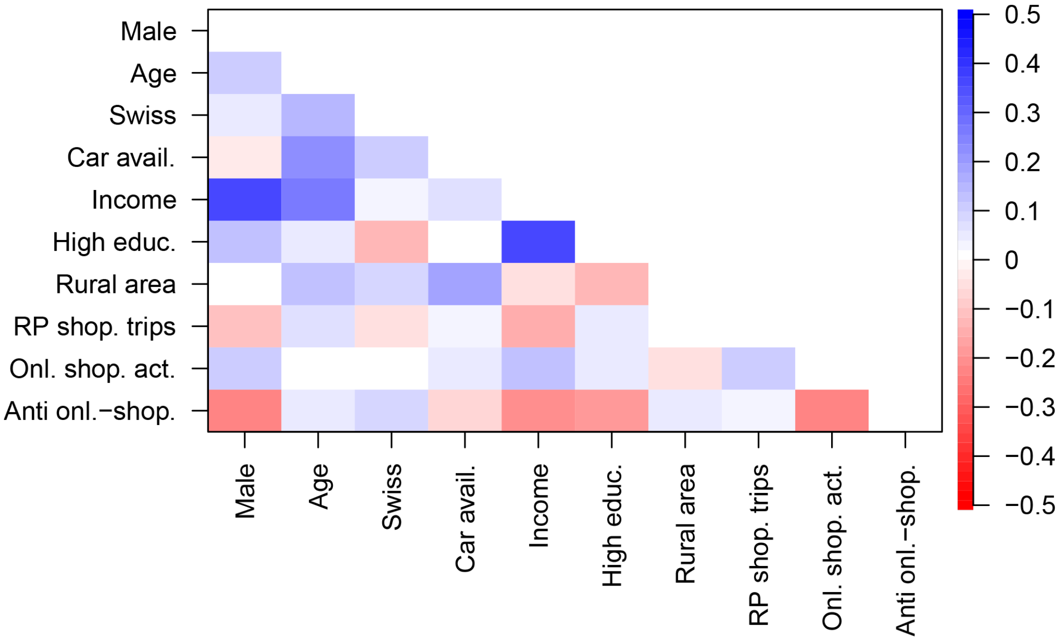
Factor loadings reported in Table 3 can be interpreted as correlations between the factor and corresponding items, with a higher loading (in absolute value) making the item more representative of the factor. Table 3 shows a sensible and statistically robust (high goodness-of-fit measures for factor reliability and correlation structure) factor structure suggesting the following description of the retained factor: The anti-online-shopping factor exhibits high positive loadings on items reflecting general risks and credit card fraud of online shopping. It shows a general reluctance towards internet usage, perceiving disadvantages regarding the physical trial of products as well as product delivery risks. Online price comparisons are not perceived as helpful, and products are only rarely purchased online.

Table 3: Factor loadings for 7 selected attitude items.

Questionnaire item	Factor loading
sh1: I often order products in the internet	–0.69
sh2: Online shopping is associated with risks	+0.48
sh3: Credit card fraud is one the reasons why I don't like online shopping	+0.69
sh4: The internet has more cons than pros	+0.54
sh5: A disadvantage of online shopping is that I cannot physically examine the products	+0.29
sh6: Online shopping facilitates the comparison of prices	–0.54
sh7: The risk of receiving a wrong product is one the main reasons why I don't like online shopping	+0.65

Estimation method: Maximum likelihood
Rotation method: Orthogonal varimax
Variance explained: 31.5 %. Cronbach's Alpha: 0.75
Kaiser-Meyer-Olkin measure of sampling adequacy: 0.80
Likelihood-ratio test: 1 factor vs. saturated: $p < 0.00$
Number of subjects: 339. Subject-to-Item ratio: 48.4

Figure 3: Correlation structure of socio-economic variables, shopping activities and anti-online-shopping attitudes.



As a basis to construct the attitudinal variable for subsequent analyses, individual factor scores are calculated based on Bartlett's method (Bartholomew et al., 2009), using normalized ($\widehat{\mu} \approx 0$; $\widehat{\sigma} \approx 1$) and unbiased maximum likelihood estimates of the "true" factor scores.

To derive the hypotheses for the structural model, i.e. which variables to include for explaining the distribution of attitudes towards online shopping in the sample based on socio-economic characteristics, Fig. 3 reveals the correlation structure between these variables and the "anti-online-shopping" factor scores (Anti onl.-shop.). Key variables are (see also Table 2 for some basic summary statistics):

- **Male** (dummy)
- **Age** (continuous)
- **Swiss** (dummy)
- **Car** always **available** (dummy)
- Personal **income** (continuous; transformed according to Mackie et al. (2003); see also Equations 1-4 in Section 4.1)
- High **education** (dummy for university degree)
- **Rural** residential location (dummy)

It shows that older female and Swiss non-car users without university degree and lower income living in rural residential locations tend to have the most negative attitudes towards online shopping. In addition, Fig. 3 shows that, as expected, participants with negative attitudes towards online shopping also engage in a lower number of online shopping activities (Onl. shop. act.) during the multi-day reporting period. What is interesting is that such people tend to have slightly more trips for grocery and durable goods shopping (RP shop. trips), which would favor the hypothesis that online and in-store shopping is to some extent compensatory.

4 Modeling framework

Substantial progress has been made in relaxing the assumption of basic multinomial Logit (MNL) models, which resulted in e.g. Mixed Logit or Generalized Logit model types. This development stayed on the random utility-maximization (RUM) path, i.e. it was still assumed that the modeled decisions are made following compensatory, utility-maximizing rules. The hybrid choice modeling (HCM) framework presented by Ben-Akiva et al. (2002) is an integration of RUM model functionalities such as error heterogeneity, random parameters and behavioral process enrichment such as latent variables (LVs).

The integration of LVs into RUM models (also referred to as ICLV: Integrated Choice and Latent Variable model) is an example of the general HCM framework which addresses the problem of attitudes and perceptions of persons, which are at the same time relevant to the choice process and hard to observe directly. The RUM model is therefore extended by latent variable(s) and the respective parameters as part of the utility formulation (Bolduc and Alvarez-Daziano, 2010). The LVs themselves are defined in the structural model with measurable socio-economic variables, and can therefore be seen as a generalized type of interaction between variables in the utility formulation, with a dedicated representation of disturbance. One example of LVs are attitudes, which might be used to express the individual valuation/importance of different attributes as a source of heterogeneity or taste variation in the choice process (Walker, 2002).

In order to estimate the coefficients in the structural model defining the LV, the model relations are completed by a measurement model, which links the LV with indicators assumed to be affected by the latent construct. The attitudinal part of the ICLV with the measured indicator variables - LV relationship is therefore often represented by a multiple-indicator multiple-cause (MIMIC) model (Jöreskog and Goldberger, 1975). Apart from better representing the decision process, this approach comes with an advantage for predictive purposes: Once the model coefficients are estimated, they can be applied to widely available socio-economic variables to predict the distribution of attitudes in the population.

The estimation of ICLV models is computationally demanding, and increases with the number of LVs, as simulation (maximum simulated likelihood) or Bayesian techniques are required to solve the multi-dimensional integrals of ICLV models with more than one LV (Bolduc and Alvarez-Daziano, 2010). Raveau et al. (2010) compare the sequential and simultaneous estimation of ICLV with real and synthetic data. Although the sequential estimation approach is consistent, they emphasize the advantages of the simultaneous method in terms of bias and efficiency, which in the first case can have implications on valuation indicators. Furthermore, it is the more flexible approach because of identification constraints in the sequential estimation.

Figure 4: Hybrid choice model.

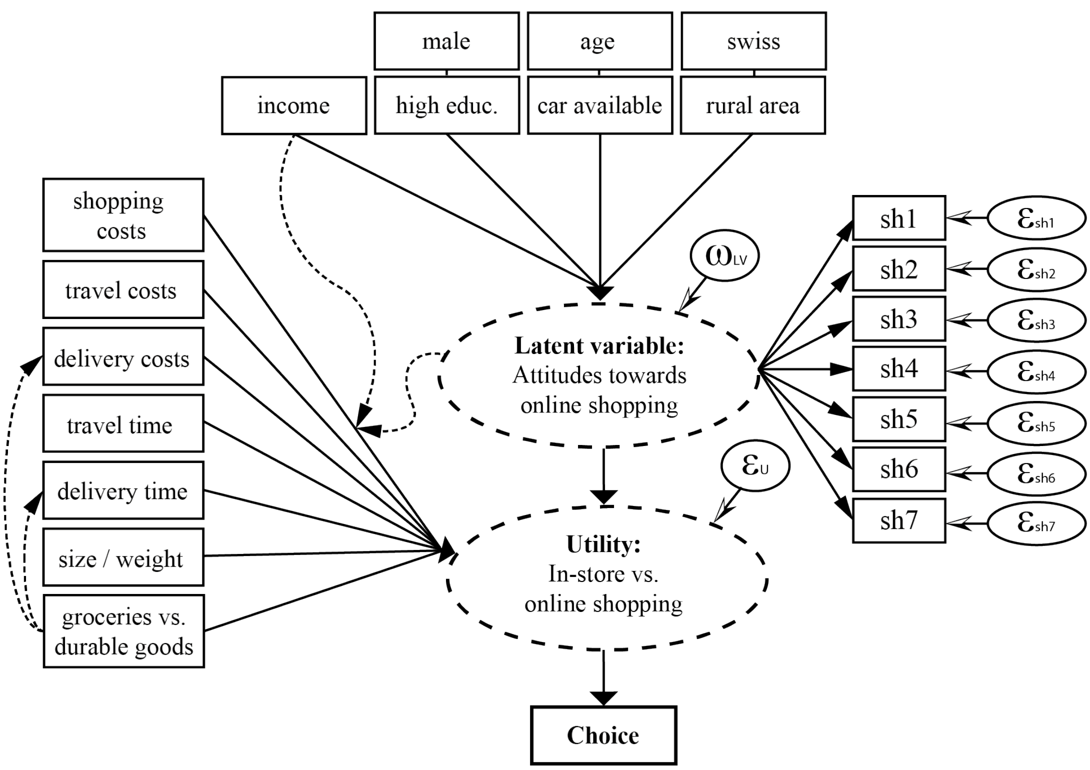


Fig. 4 gives an overview of the HCM approach to model the choice between online and in-store shopping, estimating one LV for the attitudes towards online shopping. The structural model therefore includes the specification of the alternative-specific utility equations and the relationship between attitudes and socio-economic variables, while the measurement model captures the relationship between the online shopping attitude indicators and the LV as well as the relationship between alternative-specific utilities and observed choices (see also Abou-Zeid et al. (2011), using a similar modeling approach). Each model component is described in the following subsections. While most socio-economic variables discussed in Section 3.4 are hypothesized to directly affect the LV only, personal income is, in addition, interacted with shopping costs via an income elasticity term. The LV itself is directly affecting the choice, as well as via the shopping costs to reveal potential heterogeneity in cost sensitivity. While different interactions with the shopping purpose have been tested, it was necessary to distinguish the effects of delivery time and cost for either groceries and durable goods.

4.1 Structural model

The utility equation of the choice model for shopping channel $i \in \{O, IS\}$ with attributes X_{i_n} and the latent online shopping variable LV_n is given by:

$$\begin{aligned} U_{O_n} = {} & X_{O_n}\beta_O + \beta_{sc} sc_{O_n} \left(\frac{inc_n}{\overline{inc}}\right)^{\lambda_{inc}} + \mu_{LV}(LV_n - \overline{LV_n}) + \\ & \mu_{sc,LV} sc_{O_n}(LV_n - \overline{LV_n}) + \epsilon_{O_n} \end{aligned} \tag{1}$$

$$\begin{aligned} U_{IS_n} = {} & X_{IS_n}\beta_{IS} + \beta_{sc} sc_{IS_n} \left(\frac{inc_n}{\overline{inc}}\right)^{\lambda_{inc}} + \\ & \mu_{sc,LV} sc_{IS_n}(LV_n - \overline{LV_n}) + \epsilon_{IS_n} \end{aligned} \tag{2}$$

where n is the total number of observed choices, X_{i_n} is a n x j matrix of choice attributes, β is a j x 1 coefficient vector, β_{sc} is the generic shopping cost coefficient for shopping costs sc_n, inc_n is the personal income with sample mean $\overline{inc}$ and income elasticity of shopping costs λ_{inc}, μ_{LV} is the coefficient for the latent variable LV_n with sample mean $\overline{LV_n}$, $\mu_{sc,LV}$ is the coefficient for the interaction between the latent variable and the shopping costs and ϵ_{i_n} is the alternative-specific n x 1 random disturbance vector.

The relative importance of choice attribute X_i compared to shopping costs is a function of income and the latent variable LV_n:

$$f(inc_n, LV_n) = \frac{\beta_{X_{i_n}}}{\beta_{sc}\left(\frac{inc_n}{\overline{inc_n}}\right)^{\lambda_{inc}} + \mu_{sc,LV}(LV_n - \overline{LV_n})} \tag{3}$$

In the case of $\lambda_{inc} < 0$ and $\mu_{cost,LV} > 0$, the shopping cost sensitivity increases with lower income and a higher LV-score, implying that all other choice attributes relative to shopping costs would be perceived as less important. For the "average" respondent, the equation simplifies to:

$$f(\overline{inc}, \overline{LV_n}) = \frac{\beta_{X_{in}}}{\beta_{sc}} \tag{4}$$

The latent variable equation is a function of observed socio-economic characteristics Z_n:

$$LV_n = \overline{LV_n} + Z_n\kappa + \omega_{LV_n}, \quad \omega_{LV} \sim N(0, \sigma_{\omega_{LV}}) \tag{5}$$

where Z_n is a n x q matrix of socio-economic characteristics, κ is a q x 1 coefficient vector and ω_{LV_n} is a n x 1 random disturbance vector.

4.2 Measurement model

The latent variable measurement equation with responses to the 7 online shopping questionnaire items I_{sh} discussed in Section 3.4 is given by:

$$I_{sh_n} = \overline{I_{sh}} + \tau_{I_{sh}} LV_n + \epsilon_{I_{sh_n}} \tag{6}$$

where $\overline{I_{sh}}$ are the mean ratings of the 4-point-Likert scales for each item I_{sh}, $\tau_{I_{sh}}$ are the coefficients for each item I_{sh}, LV_n is the latent variable and $\epsilon_{I_{sh_n}}$ is a n x 1 random disturbance vector for each item I_{sh}.

The choice for shopping channel $i \in \{O, IS\}$ is modeled by maximizing the alternative-specific utility U_i:

$$if \quad U_{O,n} > U_{IS,n} : choice_{i,n} = \begin{cases} \text{Online shopping} \\ else \text{ In-store shopping} \end{cases} \tag{7}$$

4.3 Estimation

β, μ, λ_{inc}, $\overline{LV_n}$, κ, $\sigma_{\omega_{LV}}$, $\overline{I_{sh}}$, $\tau_{I_{sh}}$ and $\sigma_{I_{sh}}$ are the parameters to be estimated (45 in total), using maximum likelihood estimation in PythonBiogeme version 2.4 (Bierlaire and Fetiarison, 2009). Conditional on the latent variable, and thus on ω_{LV_n}, the choice probaility and the item density functions are independent. Therefore, the likelihood of individual n choosing alternative $i \in \{O, IS\}$ is the joint probability of observing the choice and the 7 online shopping items I_{sh_n}, given choice attributes and socio-economic characteristics $X_{i,n}$ and Z_n, respectively. The likelihood is calculated by integrating the product of conditional probabilities over the distribution of ω_{LV_n} (Abou-Zeid et al., 2011):

$$Likelihood = \int_{\omega_{LV_n}} P(choice_{i,n}|X_{i,n}, \omega_{LV_n}) \prod_{sh=1}^{7} f_{sh_n}(I_{sh_n}, \omega_{LV_n})\phi(\omega_{LV})d\omega_{LV_n} \tag{8}$$

where

$$P(choice_{i,n}|X_{i,n}, \omega_{LV_n}) = \frac{exp(U_i(X_{i,n}, Z_n, LV_n))}{\sum_j^2 exp(U_j(X_{j,n}, Z_n, LV_n))} \tag{9}$$

and

$$f_{sh_n}(I_{sh_n}, \omega_{LV_n}) = \frac{1}{\sigma_{I_{sh}}}\phi\left(\frac{I_{sh_n} - \overline{I_{sh}} - \tau_{I_{sh}} LV_n}{\sigma_{I_{sh}}}\right) \tag{10}$$

and ϕ is the standard normal density function.

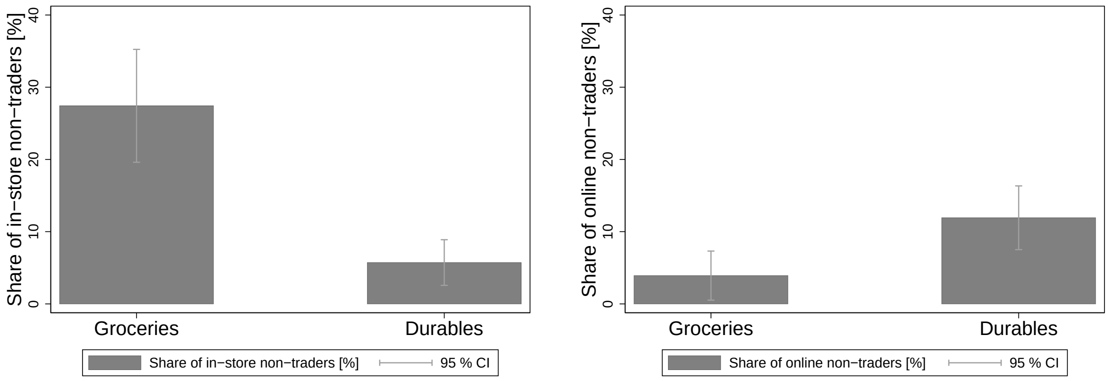
5 Results

5.1 Descriptive analysis of choice behavior

The analyzed sample comprises 2698 choice observations for 339 participants: 38% were assigned to the groceries and 62% to the durable goods experiment. The market shares of online and in-store shopping choices depend on the shopping purpose: In the groceries experiment, 65% chose the in-store and 35% the online alternative, while in the durable goods experiment, 39% chose the in-store and 61% ordering the online alternative. Although the total market share of online shopping is remarkably high for both purposes possibly resulting from the omission of any private vehicles for the in-store alternative, it clearly shows the tendency that for groceries, people prefer going to a store. This is also reflected by the share of participants always choosing the same alternative within all 8 choice situations, also referred to as "non-traders": While the overall share of non-traders is about 20 %, the share of non-traders in the durable goods experiment is almost half compared to the groceries experiment (17% and 32%, respectively; $p_\Delta < 0.01$). Almost 30% of participants that were assigned to the groceries experiment always chose the in-store alternative, whereas 12% that were assigned to the durable goods experiment always chose the online alternative ($p_\Delta < 0.01$). Although providing limited trade-off

Figure 5: Non-trading behavior by shopping purpose.

(a) Share of in-store non-traders (b) Share of online non-traders



information, non-trading behavior is still consistent with random utility theory. In a "labeled" choice experiment, this can be due to the experiment itself by offering too small trade-off variations with respect to these participants' underlying preferences.

5.2 Estimation results

Three different models were estimated which were found to represent best the different aspects of shopping channel choice behavior.[4] As explaining taste heterogeneity is a main goal of this paper, a multinomial Logit (MNL) approach without random effects was applied, in order to provide explicit behavioral insights regarding the influences of measured characteristics, attitudes and income elasticity as shown in past Swiss studies on mode or shopping destination choice (Axhausen et al., 2007; Erath et al., 2007; Rieser-Schüssler and Axhausen, 2012; Weis et al., 2012). The base model in Table 4 explains choices with attributes specific to each shopping channel, including a non-linear interaction parameter for the income elasticity of shopping cost. The factor model adds the anti-online shopping attitude based on the factor scores derived in Section 3.4, while the hybrid model simultaneously estimates the choice, measurement[5] and latent variable equations as explained in Section 4. Regarding AICc, for finite sample size corrected Akaike Information Criterion for assessing the goodness of fit of a model (Wagenmakers and Farrell, 2004), the improvement from the base to the factor model is highly significant, with an increase in

[4] Note that several model specifications (e.g. interaction terms with shopping purpose or attitudes) have been tested, but have been rejected due to insignificance of parameters and interpretation issues.

[5] The results of the measurement model in Table 9 (Appendix A1) confirm the results of the factor analysis in Table 3, again leading to an interpretation of the LV as negative attitudes towards online shopping, i.e. the "anti-online-shopping" LV.

log-likelihood by 92 points. This suggests that a substantial part of otherwise unobserved heterogeneity is captured by the attitudes towards online shopping.

In terms of goodness of fit, the hybrid model is not directly comparable to the first two models, as the likelihood is jointly determined over the whole set of parameters. Compared to the null log-likelihood, this leads to large efficiency gain, as generally discussed in the work of Raveau et al. (2010), and improvement in overall model fit, leading to a final ρ^2 of 65%. Regarding the robustness of the estimated parameters, the results show that most coefficients and standard errors only change marginally from the base or factor to the hybrid model.

Estimated coefficients of the choice models (Equations 1 and 2) presented in Table 4 show the expected signs on utility: Shopping cost, travel time, travel cost, delivery time and delivery cost all exhibit a negative effect (note that time spent for online/in-store shopping was excluded in the models as it did not show any significant and substantial effect). Due to unequal time spacing, the effect of delivery time was specified as a dummy variable relative to the base category, described as either "less than 1 day" for groceries or "2-3 days" for durable goods. It is interesting to see that for groceries, the effect of medium delivery time (i.e. "1-2 days") is not significantly different relative to the base category, as it is the case for durable goods (i.e. "4-7 days"; $p < 0.05$). A possible explanation is that as shown in Section 5.1, online shopping for groceries is rather unusual anyway, making no large difference in utility if the delivery time is "less than 1 day" or "1-2 days". However, while a long delivery time for groceries (i.e. "more than 2 days") exhibits a very strong and negative effect on utility, the effect for durable goods is, although still negative ($p < 0.01$), less strong than for groceries, as shown by the positive coefficient of the interaction term. This makes sense as the planning horizon for durable goods purchases is generally longer, with a long delivery time not affecting the choice as strong as for groceries. A similar finding occurred for delivery cost, with an effect that is almost twice as large for groceries than for durable goods. Possible explanations are that 1) delivery costs are at fixed levels, and their share of total shopping costs is larger for groceries than for durable goods, thus are perceived as more negative and 2) people could better avoid delivery costs for groceries by just visiting a nearby store.

Focusing on the factor and hybrid model, the shopping purpose dummy for durable goods shows a weak positive effect on ordering online, reflecting the purpose-specific market shares in Section 5.1. Increasing size/weight of the goods baskets has a strong and positive impact on ordering online, being over twice as large for high than for medium attribute levels. The "anti-online-shopping" factor/LV shows, not surprisingly, a strong and negative effect on online shopping. More interesting is the significant interaction term of shopping

Table 4: Estimation results: Choice models.

Base category: In-store (IS) shopping	Base model Coef./(SE)	Factor model Coef./(SE)	Hybrid model Coef./(SE)
Shopping cost	-0.021^{***}	-0.024^{***}	-0.025^{***}
	(0.003)	(0.003)	(0.004)
Income elasticity of shopping cost	0.041	-0.034	-0.054
	(0.070)	(0.054)	(0.052)
"Anti-onl.-shop." factor/LV x shop. cost	–	0.007^{***}	0.019^{***}
		(0.002)	(0.006)
Travel time (IS)	-0.022^{***}	-0.024^{***}	-0.025^{***}
	(0.003)	(0.003)	(0.003)
Travel cost (IS)	-0.036^{**}	-0.035^{**}	-0.037^{**}
	(0.014)	(0.015)	(0.015)
Medium delivery time (ONL)	-0.110	-0.142	-0.152
	(0.180)	(0.185)	(0.189)
Med. delivery time x durables (ONL)	-0.182	-0.172	-0.172
	(0.228)	(0.235)	(0.240)
High delivery time (ONL)	-0.813^{***}	-0.873^{***}	-0.894^{***}
	(0.198)	(0.204)	(0.208)
High delivery time x durables (ONL)	0.256	0.243	0.243
	(0.247)	(0.256)	(0.262)
Delivery cost (ONL)	-0.093^{***}	-0.099^{***}	-0.101^{***}
	(0.015)	(0.015)	(0.015)
Delivery cost x durables (ONL)	0.057^{***}	0.055^{***}	0.055^{***}
	(0.018)	(0.019)	(0.019)
ASC (ONL)	-1.550^{***}	-1.540^{***}	-1.570^{***}
	(0.215)	(0.222)	(0.273)
Purpose durables (ONL)	0.529^{**}	0.425^{*}	0.448^{*}
	(0.231)	(0.239)	(0.243)
Medium size (ONL)	1.050^{***}	1.100^{***}	1.130^{***}
	(0.105)	(0.110)	(0.113)
Large size (ONL)	2.250^{***}	2.410^{***}	2.460^{***}
	(0.126)	(0.132)	(0.136)
"Anti-online-shopping" factor/LV (ONL)	–	-0.466^{***}	-1.210^{***}
		(0.049)	(0.137)
# estimated parameters	14	16	45
Choice observations (participants)		2698 (339)	
Log-likelihood null	-1870.1	-1870.1	-66075.5
Log-likelihood model	-1485.5	-1393.5	-23098.9
McFadden ρ^2	0.21	0.26	0.65
Iterations	16	29	139

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

cost and the "anti-online-shopping" factor/LV, meaning that participants with a lower acceptance level of online shopping exhibit a substantially lower shopping cost sensitivity. This can be explained by the shrunken alternative set when considering in-store shopping as the dominant purchase channel. In such a case, ceteris paribus, the choice between the two channels is less price-driven compared to "pro-online-shoppers". Given the choice attributes and even after including the attitudes towards online shopping, the alternative-specific constant (ASC) of online shopping is substantial and negative, indicating that there are still unexplained reasons for not choosing this shopping channel.

While shopping cost shows the expected significant and negative effect on utility, in the base model income elasticity of shopping cost exhibits a positive sign (a negative sign of $\widehat{\lambda_{inc}}$ would indicate a decreasing price sensitivity for higher income, with a value of 0 indicating a lack of interaction). Without including attitudes in the model, there is an omitted variable bias: As it is shown in Fig. 3 and confirmed in Table 5, higher income is associated with a more negative "anti-online-shopping" factor/LV (i.e. a more positive "pro-online-shopping" attitude). When omitting attitudes in the model, it looks like more income leads to a higher cost sensitivity, but this effect comes from the fact that high income participants have a more positive attitude towards online shopping, leading to a higher shopping cost sensitivity as shown by the significant interaction effect. When including attitudes, $\widehat{\lambda_{inc}}$ is estimated consistently, with a t-value greater than one in the hybrid model revealing the expected negative effect.

Table 5 shows the results of the latent variable equation (Equation 5) of the hybrid model, confirming the findings in Section 5.1 of the influence of socio-economic characteristics on the attitudes towards online shopping: Female and Swiss non-car users without university degree and lower income living in rural residential locations exhibit the most negative attitudes towards online shopping. In addition, a quadratic age function has been applied. The derivative with respect to age reveals a minimum "anti-online-shopping" attitude with the age of 32 years, as illustrated in Fig. 6b. It is interesting to note that in Switzerland, people at this age essentially grew up with ICT: In the beginning of the 90ties, there was an exorbitant growth rate of households acquiring PCs with internet access. Fig. 6a shows the distribution of the predicted "anti-online-shopping" LV, i.e. $\widehat{LV_n} = LV_n - \overline{LV_n}$, which, as a direct implication of the model specification, is approximately normally distributed with mean zero. The range of the predicted LV, $\widehat{LV_n} \in \{-0.71, \ldots, 0.56\}$, also defines of the thresholds of the shopping cost sensitivity via the interaction term.

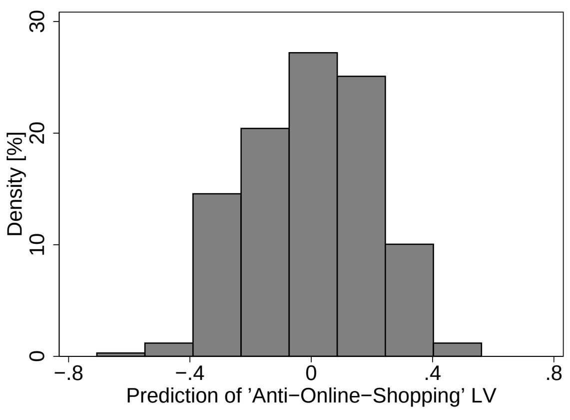
Table 5: Estimation results: Latent variable ("anti-online-shopping") model.

	Anti-onl.-shop. LV_n Coef./(SE)
$\overline{LV_n}$	2.160***
	(0.118)
Age	−0.012**
	(0.005)
$Age^2/100$	0.019***
	(0.006)
Car availability	−0.125***
	(0.022)
High education	−0.111***
	(0.024)
Income	−0.084***
	(0.015)
Rural	0.119***
	(0.041)
Male	−0.247***
	(0.024)
Swiss	0.106***
	(0.030)
$\sigma_{\omega_{LV}}$	0.469***
	(0.016)

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Figure 6: Revealing the unobserved: Distribution of the latent variable.

(a) Sample distribution of the "anti-online-shopping" latent variable.



(b) Contribution of the quadratic age function to the latent variable.

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). In the case of a linear additive utility function, valuation indicators are calculated as a ratio between two coefficient estimates as shown in Equations 3 and 4. The direct and cross point elasticities presented in Table 6 show the responsiveness of market shares to changes in 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 6: Direct-(cross)-elasticities of the hybrid model.

Total market shares	Online 51%	In-store 49%
Shopping cost	−2.83 (2.96)	−3.12 (2.98)
Shopping cost (max. $\widehat{LV_n}$)	−1.61 (1.69)	−1.78 (1.70)
Shopping cost (min. $\widehat{LV_n}$)	−4.37 (4.57)	−4.82 (4.61)
Travel time	–	−0.31 (0.29)
Travel cost	–	−0.10 (0.09)
Delivery cost groceries	−0.37 (0.39)	–
Delivery cost durables	−0.17 (0.18)	–

*: Not significant at the 5% level.

Focusing on shopping costs, the relatively high direct and cross elasticities shown in Table 6 are independent of the shopping purpose (no significant interaction of shopping cost and purpose was found): Ceteris paribus, on average, a 1% increase in in-store shopping cost decreases the predicted market share of in-store shopping by 3.12% and increases the predicted market share of online shopping by 2.98%. These elasticities differ substantially over the whole range of the LV, e.g. for the direct elasticity ranging from a decrease in the in-store market share of 1.78% for extreme "anti-online-shoppers" to a decrease of 4.82% for extreme "pro-online-shoppers". Thus, by knowing some basic socio-economic characteristics of a target consumer segment, one could predict the responsiveness to shopping costs and based on that, develop an effective pricing strategy for store and/or online retailers.

Table 6 shows the key valuation indicators and compares them to related studies, focusing on the value of travel time (VTTS) and delivery time (VDTS) savings. The current study reveals relatively high VTTS of about 40 CHF/hour when including attitudes in the model and considering the travel cost coefficient as a reference, with VTTS increasing by about 50% when considering the generic shopping cost coefficient instead, which was also used in Erath et al. (2007), leading there to very high VTTS of up to 160 CHF/hour. Findings indicate that shopping costs are perceived as less negative than travel costs, possibly because travel as "derived demand" is only indirectly associated with the satisfaction of needs. Online retailers should take note of the even larger differences for the relative valuation of delivery costs: From a behavioral perspective, incorporating delivery costs in shopping costs would substantially 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.

Table 7: Valuation indicators.

Coefficient ratios	Base model	Factor model	Hybrid model
VTTS shopping trips (travel cost) [CHF/h]	36.46	41.02	39.89
VTTS shopping trips (shop. cost) [CHF/h]	62.86	61.01	60.00
VDTS medium delivery time groceries* [CHF/t.u.]	1.19	1.43	1.50
VDTS high delivery time groceries [CHF/t.u.]	8.76	8.80	8.85
VDTS medium delivery time durables [CHF/t.u.]	8.09	7.12	7.01
VDTS high delivery time durables [CHF/t.u.]	15.43	14.29	14.12
Travel cost / shopping cost [-]	1.72	1.49	1.50
Delivery cost groceries / shopping cost [-]	4.42	4.17	4.11
Delivery cost durables / shopping cost [-]	1.72	1.85	1.87

*: Not significant at the 5% level. t.u.: Time unit as defined in Table 1, relative to the base categories.

Given the relatively high VTTS, findings indicate a potential for online retailers, also when comparing to the relatively low VDTS (with delivery cost coefficient as a reference): VDTS for medium delivery time ("1-2 days"; relative to "less than 1 day") of groceries is about 1.50 CHF/time unit and not even significant, for long delivery time ("more than 2 days"; relative to "less than 1 day") it is about 9 CHF/time unit as it is for medium delivery time ("4-7 days"; relative to "2-3 days") of durable goods (about 7 CHF/time unit). The highest value occurs for long delivery time ("more than 1 week"; relative to "2-3 days") of durable goods, with about 14 CHF/time unit however still low compared to the average VTTS. Note that average total travel time savings of 49 minutes for a home-based round trip correspond to a monetary value of about 33 CHF. For delivery time, providing exact monetary values is difficult due to the dummy specification. Applying a linear interpolation to delivery time and re-estimating the model, VDTS is about 2.50 CHF/day for durables and 6.50 CHF/day for groceries: In terms of delivery cost, delivery time savings of 5 days are valued less than the average travel time savings of one shopping round trip.

Hsiao (2009) conducted a similar choice experiment in Taiwan on 300 participants' preferences between in-store and online shopping of books, revealing an average VDTS of 0.53 US$/day and arguing that in terms of monetary values, avoiding a shopping trip with an average VTTS of about 5.30 US$/hour produces more benefits than waiting for the delivery of an ordered book, observing a comparable relative magnitude between VTTS and VDTS 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.

5.4 Validation with revealed preference (RP) data

Additional analyses were conducted to see how RP data from the online and travel diaries - i.e. the number of online shopping activities and shopping trips per day - coincide with the predictions of the latent variable based on the coefficient estimates in Table 5. Fig. 7 shows the average number of online activities and shopping trips (incl. 95% confidence bands) per day for the 339 participants (2709 person-days) who also conducted the choice experiment. In-store shopping trips for either grocery or durable good purchases are mostly conducted on Saturdays, while online shopping activities - including ticket ordering, flight and hotel bookings, clothes, electronic appliances, furniture, books/magazines and food - show a decreasing pattern from Monday to Sunday. Two random-effects Poisson regressions (Cameron and Trivedi, 2013) were estimated, accounting for the discrete nature of the trip and activity counts per person-day and the within-subject error term correlation, as reported in Table 8. The predicted "anti-online-shopping" LV, $\widehat{LV_n}$, exhibits a strong and negative effect on the number of online shopping activities, confirming the expectations that people with negative attitudes towards online shopping conduct less related activities. Of greater interest is that $\widehat{LV_n}$ shows a positive effect ($p = 0.20$) on the number of trips, indicating a potential substitution effect mediated via the attitudes. To be validated and extended when more data is available are (1) if this effect is becoming statistically significant and (2) if more online shopping activities (frequency, duration, etc.) lead to a negative or positive net-effect in out-of-home shopping activities and related characteristics (travel time, in-store shopping duration, etc.).

Figure 7: Online shopping activities and shopping trips.

(a) # daily online shopping activities. (b) # daily shopping trips.

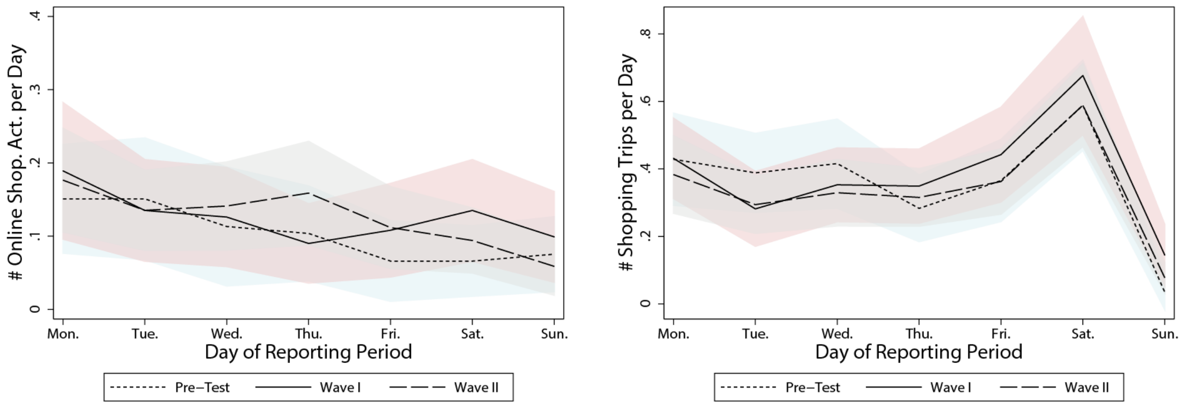


Table 8: Estimation results: Random-effects Poisson regressions.

Variable	# shop. trips per day Coef./(SE)	# onl. shop. act. Coef./(SE)
Const.	−1.200 ***	−2.115 ***
	(0.15)	(0.26)
Weekday	0.000	−0.124 ***
	(0.01)	(0.04)
Saturday	0.532 ***	0.129
	(0.09)	(0.22)
Sunday	−1.469 ***	−0.112
	(0.21)	(0.28)
$\widehat{LV_n}$	0.321	−1.221 ***
	(0.25)	(0.45)
σ_ϵ	0.625 ***	1.050 ***
	(0.05)	(0.10)
# estimated parameters	8	8
Observations (participants)	2709 (339)	
$Prob. > \chi^2$	0.00	0.00

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Survey wave dummies not reported in the table

6 Conclusions

Data on 339 participants was collected during the pre-test and the two main waves of a multi-stage travel survey on mobility and shopping behavior in a *Post-Car World*: The absence of private cars in the choice set is justified by car-reducing policy developments. As part of this project, a choice experiment was conducted based on revealed shopping activities, asking participants to trade-off different attributes related to their choice between in-store vs. online shopping. In addition, a broad range of attitudinal traits were assessed, including attitudes towards online shopping, which were integrated in a simultaneous estimation framework.

To the authors knowledge, this paper presents the first alternative-specific integrated choice and latent variable (ICLV) model in field of shopping behavior, which is distinguished from other modeling approaches by enhanced behavioral richness, estimation efficiency and consistency, leading to a more realistic representation of individual decision making. By including one latent variable (LV) reflecting the attitudes towards online shopping, i.e. the "anti-online-shopping" LV, the structural model reveals a sample distribution of this LV conditional on fundamental socio-economic characteristics. Given a specific target consumer segment, one can predict the channel-specific market shares and based on that, develop an effective operating strategy for store and/or online retailers. The prediction of the LV is validated by exhibiting a strong effect on the number of online shopping activities during the multi-day reporting period.

Two shopping purposes are distinguished - experience (groceries) and search (electronic appliances) goods - and participants were assigned to either one of these two categories. Results show a clear pattern for purpose-specific shopping channel preferences, with grocery shopping mainly being conducted in stores. Apart from delivery time and cost showing a clear purpose-specific effect on utility, other attributes such as shopping cost were found to be purpose-independent. While income elasticity of shopping cost is negative but not significant at common levels, the interaction with the LV is highly significant ($p < 0.01$), indicating that people with more negative attitudes towards online shopping exhibit a lower cost sensitivity. This can be explained by the shrunken alternative set when mainly considering in-store shopping as the dominant purchase channel. In such a case, ceteris paribus, the choices are less price-driven. In addition, shopping costs are perceived as less unpleasant relative to travel and 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 substantially increase customers' utilities and therefore the market shares of online shopping.

Results reveal a potential for online shopping services, given the relatively high value of travel time savings (VTTS) of about 40 CHF/h for shopping trips compared to the purpose-specific value of delivery time savings (VDTS) ranging between 1.50 and 14.10 CHF/time unit (applying a linear interpolation to delivery time and re-estimating the model, delivery time savings for durable goods are about 2.50 CHF/day and for groceries 6.50 CHF/day). For longer distances, avoiding a shopping trip produces more benefits than waiting for the delivery of ordered products, especially for durable goods. 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).

Other limitations of this study mainly result from the general nature of stated preference experiments. First, the reader has to be aware that results are not easily generalizable for other product categories. Especially in terms of 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 requires further investigations. 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 - 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 participants 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 latent variable and its interaction with shopping cost should be interpreted with caution (Chorus and Kroesen, 2014). Apart from the cross-sectional nature (and thus limitations) of the model to derive direct policy implications for *changes* in the attitudes, it is not clear if 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.

The *Post-Car World* project is still ongoing, and data from another 150 respondents are expected. The modeling framework will be extended regarding the (1) panel structure of the choice data, accounting for unobserved heterogeneity, (2) inclusion of latent constructs for risk aversion, variety seeking, technological affinity and shopping enjoyment that are hypothesized to affect the choices and attribute sensitivities and (3) extension of the utility function with additional socio-economic, shopper-type (planning horizon, mode choice, etc.) and latent variable interactions to get deeper behavioral insights.

7 References

Abou-Zeid, M., M. Ben-Akiva, M. Bierlaire, C. Choudhury and S. Hess (2011) Attitudes and value of time heterogeneity, paper presented at the *90st Annual Meeting of the Transportation Research Board*, Washington, D.C., January 2011.

Adler, T. and M. Ben-Akiva (1979) A theoretical and empirical model of trip chaining behavior, *Transportation Research Part B: Methodological*, **13** (3) 243–257.

Axhausen, K. W., S. Hess, A. König, J. J. Bates and M. Bierlaire (2007) State-of-the-art estimates of Swiss value of travel time savings, paper presented at the *86th Annual Meeting of the Transportation Research Board*, Washington, D.C., January 2007.

Axhausen, K. W., B. Schmid and C. Weis (2015) Predicting response rates updated: A natural experiment, *Working Paper*, **1063**, Institute for Transport Planning and Systems, Zurich.

Axhausen, K. W., A. Zimmermann, S. Schönfelder, G. Rindsfüser and T. Haupt (2002) Observing the rhythms of daily life: A six-week travel diary, *Transportation*, **29** (2) 95–124.

Bartholomew, D. J., I. J. Deary and M. Lawn (2009) The origin of factor scores: Spearman, Thomson and Bartlett, *British Journal of Mathematical and Statistical Psychology*, **62** (3) 569–582.

Ben-Akiva, M., D. McFadden, K. Train, J. Walker, C. Bhat, M. Bierlaire, D. Bolduc, A. Börsch-Supan, D. Brownstone, D. S. Bunch et al. (2002) Hybrid choice models: Progress and challenges, *Marketing Letters*, **13** (3) 163–175.

Bhatnagar, A., S. Misra and H. R. Rao (2000) On risk, convenience, and Internet shopping behavior, *Communications of the ACM*, **43** (11) 98–105.

Bierlaire, M. and M. Fetiarison (2009) Estimation of discrete choice models: Extending BIOGEME, paper presented at the *9th Swiss Transport Research Conference (STRC)*, Ascona.

Bolduc, D. and R. Alvarez-Daziano (2010) On estimation of hybrid choice models, *Choice Modelling: The State-of-the-Art and the State-of-Practice: Proceedings from the Inaugural International Choice Modelling Conference*, 259–287.

Burke, R. R. (2002) Technology and the customer interface: What consumers want in the physical and virtual store, *Journal of the Academy of Marketing Science*, **30** (4) 411–432.

Cameron, A. C. and P. K. Trivedi (2013) *Regression Analysis of Count Data*, Cambridge University Press.

Cao, X. (2009) E-shopping, spatial attributes, and personal travel: a review of empirical studies, *Transportation Research Record*, **2135**, 160–169.

Chiang, K.-P. and R. R. Dholakia (2003) Factors driving consumer intention to shop online: An empirical investigation, *Journal of Consumer Psychology*, **13** (1) 177–183.

Chocarro, R., M. Cortiñas and M.-L. Villanueva (2013) Situational variables in online versus offline channel choice, *Electronic Commerce Research and Applications*, **12** (5) 347–361.

Chorus, C. G. and M. Kroesen (2014) On the (im-)possibility of deriving transport policy implications from hybrid choice models, *Transport Policy*, **36**, 217–222.

Dijst, M., S. Farag and T. Schwanen (2008) A comparative study of attitude theory and other theoretical models for understanding travel behaviour, *Environment and Planning A*, **40** (4) 831–847.

Erath, A., N. Frank, R. Lademann and K. Axhausen (2007) The impact of travel time savings on shopping location choice or how far do people go to shop cheaply?, paper presented at the *14th EIRASS Conference in Advances in Activity Based Approaches*, San Francisco.

Farag, S. (2006) *E-Shopping and its Interactions with In-Store Shopping*, Utrecht University.

Farag, S., T. Schwanen and M. Dijst (2005) Empirical investigation of online searching and buying and their relationship to shopping trips, *Transportation Research Record*, **1926**, 242–251.

Farag, S., T. Schwanen, M. Dijst and J. Faber (2007) Shopping online and/or in-store? A structural equation model of the relationships between e-shopping and in-store shopping, *Transportation Research Part A: Policy and Practice*, **41** (2) 125–141.

Ferrell, C. (2005) Home-based teleshopping and shopping travel: Where do people find the time?, *Transportation Research Record*, **1926**, 212–223.

Hayton, J. C., D. G. Allen and V. Scarpello (2004) Factor retention decisions in exploratory factor analysis: A tutorial on parallel analysis, *Organizational Research Methods*, **7** (2) 191–205.

Hsiao, M.-H. (2009) Shopping mode choice: Physical store shopping versus e-shopping, *Transportation Research Part E*, **45** (1) 86–95.

Jöreskog, K. G. and A. S. Goldberger (1975) Estimation of a model with multiple indicators and multiple causes of a single latent variable, *Journal of the American Statistical Association*, **70** (351a) 631–639.

Louviere, J. J. (2006) What you don't know might hurt you: Some unresolved issues in the design and analysis of discrete choice experiments, *Environmental and Resource Economics*, **34** (1) 173–188.

Louviere, J. J., D. A. Hensher and J. D. Swait (2000) *Stated Choice Methods - Analysis and Application*, Cambridge University Press, Cambridge.

Mackie, P. J., M. Wardman, A. S. Fowkes, G. Whelan, J. Nellthorp and J. J. Bates (2003) Values of travel time savings in the UK, *Research Report*, Department for Transport, Institute for Transport Studies, University of Leeds and John Bates Services, Leeds and Abingdon.

Mokhtarian, P. L. (2004) A conceptual analysis of the transportation impacts of B2C e-commerce, *Transportation*, **31** (3) 257–284.

Mokhtarian, P. L., I. Salomon and S. L. Handy (2006) The impacts of ict on leisure activities and travel: A conceptual exploration, *Transportation*, **33** (3) 263–289.

Mokhtarian, P. L. and W. L. Tang (2013) Trivariate probit models of pre-purchase/purchase shopping channel choice: Clothing purchases in northern California, *Choice Modelling: The State of the Art and the State of Practice - Selected Papers from the Second International Choice Modelling Conference*, 243–273.

Raveau, S., R. Álvarez-Daziano, M. Yáñez, D. Bolduc and J. de Dios Ortúzar (2010) Sequential and simultaneous estimation of hybrid discrete choice models: Some new findings, *Transportation Research Record*, **2156**, 131–139.

Rieser-Schüssler, N. and K. W. Axhausen (2012) Investigating the influence of environmentalism and variety-seeking on mode choice, *Transportation Research Record*, **2322**, 31–41.

Rose, J. M., M. C. Bliemer, D. A. Hensher and A. T. Collins (2008) Designing efficient stated choice experiments in the presence of reference alternatives, *Transportation Research Part B: Methodological*, **42** (4) 395–406.

Rose, J. M. and M. C. J. Bliemer (2009) Constructing efficient stated choice experimental designs, *Transport Reviews*, **29** (5) 587–617.

Rotem-Mindali, O. and I. Salomon (2007) The impacts of E-retail on the choice of shopping trips and delivery: Some preliminary findings, *Transportation Research Part A: Policy and Practice*, **41** (2) 176–189.

Rudolph, T., O. Emrich, T. Böttger, K. Kleinlercher and T. Pfrang (2015) Der Schweizer Online-Handel: Internetnutzung Schweiz 2015, Universität St. Gallen, Forschungszentrum für Handelsmanagement.

Rudolph, T., B. Rosenbloom and T. Wagner (2004) Barriers to online shopping in Switzerland, *Journal of International Consumer Marketing*, **16** (3) 55–74.

Salomon, I. and F. Koppelman (1988) A framework for studying teleshopping versus store shopping, *Transportation Research Part A: General*, **22** (4) 247–255.

Schmid, B. and K. W. Axhausen (2015) Post-Car World: Survey methods and response behavior in the pre-test, paper presented at the *14th International Conference on Travel Behavior Research (IATBR)*, Windsor.

Schmid, B., S. Schmutz and K. W. Axhausen (2016) Explaining mode choice, taste heterogeneity and cost sensitivity in a Post-Car World, paper presented at the *95th Annual Meeting of the Transportation Research Board*, Washington, D.C.

The American Association for Public Opinion Research (2015) *Standard Definitions: Final Dispositions of Case Codes and Outcome Rates for Surveys*, AAPOR, `http://www.aapor.org`.

Verband des Schweizerischen Versandhandels VSV und GfK (2015) Online- und Versandhandel Schweiz 2014, presentation, Hergiswil, Switzerland, March 2015.

VSS norm (2009) SN 641 822a: Kosten-Nutzen-Analysen im Strassenverkehr: Zeikosten im Personenverkehr, VSS, Zürich.

Wagenmakers, E.-J. and S. Farrell (2004) AIC model selection using Akaike weights, *Psychonomic Bulletin and Review*, **11** (1) 192–196.

Walker, J. L. (2002) The mixed logit (or logit kernel) model: Dispelling misconceptions of identification, *Transportation Research Record*, **1805**, 86–98.

Weis, C., P. Fröhlich, M. Vrtic and P. Widmer (2014) Einfluss der Verlässlichkeit der Verkehrssysteme auf das Verkehrsverhalten, *Working Paper*, Forschungsauftrag für das Bundesamt für Strassen und SVI, Bern.

Weis, C., M. Vrtic, P. Widmer and K. W. Axhausen (2012) Influence of parking on location and mode choice: A stated choice survey, paper presented at the *91st Annual Meeting of the Transportation Research Board*, Washington, D.C.

A Appendix

Table 9: Estimation results: Measurement model.

	Dep. variable: I_{sh_n} Coef./(SE)		Dep. variable: I_{sh_n} Coef./(SE)		Dep. variable: I_{sh_n} Coef./(SE)
$\overline{I_{sh_1}}$	4.590^{***}	LV_{sh_1}	-1.240^{***}	σ_{sh1}	-0.454^{***}
	(0.094)		(0.051)		(0.019)
$\overline{I_{sh_2}}$	1.330^{***}	LV_{sh_2}	0.640^{***}	σ_{sh2}	-0.483^{***}
	(0.062)		(0.033)		(0.015)
$\overline{I_{sh_3}}$	-0.313^{***}	LV_{sh_3}	1.330^{***}	σ_{sh3}	-0.335^{***}
	(0.098)		(0.053)		(0.018)
$\overline{I_{sh_4}}$	0.246^{***}	LV_{sh_4}	0.773^{***}	σ_{sh4}	-0.484^{***}
	(0.067)		(0.036)		(0.015)
$\overline{I_{sh_5}}$	2.350^{***}	LV_{sh_5}	0.473^{***}	σ_{sh5}	-0.225^{***}
	(0.068)		(0.036)		(0.014)
$\overline{I_{sh_6}}$	4.710^{***}	LV_{sh_6}	-0.988^{***}	σ_{sh6}	-0.280^{***}
	(0.088)		(0.048)		(0.016)
$\overline{I_{sh_7}}$	0	LV_{sh_7}	1	σ_{sh7}	-0.325^{***}
	–		–		(0.016)

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$