Integrating psychometric indicators in latent class choice models

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Abstract

Latent class models are a convenient and intuitive way to introduce taste heterogeneity in discrete choice models by relating attributes of the decision makers with unobserved behavioral classes, hence allowing for a more accurate market segmentation. Estimation and specification of latent class models can be improved with the use of psychometric indicators that measure the effect of unobserved attributes in the individual preferences. This paper proposes a method to introduce these additional indicators in the specification of integrated latent class and discrete choice models, through the definition of measurement equations that relate the indicators to attributes of the decision maker. The method is implemented for two mode-choice case studies and compared with alternative methods to introduce indicators. Results show that the proposed method generates significantly different estimates for the class and choice models and provide additional insight into the behavior of each class.

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1 Introduction

Traditionally, travel demand models have considered quantitative variables, like travel time, cost and decision maker socioeconomics, as the principal variables that explain mode choice (Ben-Akiva and Lerman, 1985). However, there are more complex, unobserved factors that may have a relevant effect in the way choices in general are made. Some of these latent factors are the decision maker's lifestyle, personal attitudes or perceptions (McFadden, 1986). Though these soft features have an obvious effect on choice, it is not straightforward to characterize and integrate them into choice models. We address that aspect in the present research.

The introduction of latent factors into discrete choice models has been treated under two main approaches: latent variable models (LVM) and latent class models (LCM). The latent variable approach deals with the explicit modeling of unobserved psychological characteristics of the decision maker, such as attitudes and perceptions. The latent class approach assumes that the population can be segmented into discrete groups that have different preferences or perceptions and, therefore, have different choice behaviors.

Psychometric indicators are additional information that can be used to specify and estimate latent constructs. They usually reflect the preferences of decision makers on topics that are (closely or not so) related to the choice that is being analyzed/modeled. Examples of psychometric indicators range from the answers to questions about the level of agreement with a statement or the "grade" that is given to the quality of a service or object (Likert, 1932), to the set of adjectives that individuals use to characterize the topic in question (Glerum and Bierlaire, 2012).

Although the use of indicators should clearly help to estimate better latent class models, its use has been mostly developed and applied in the latent variable approach (Hess et al., 2011). However, the LCM approach has characteristics that make it, in some cases, preferable over other methods to capture heterogeneity (Greene and Hensher, 2003; Shen, 2009) and, if possible, should be improved with the intregration of psychometric data. The use of latent classes in discrete choice models also allows for the identification of market segments that can be used to design more effective (segment-specific) policies or marketing strategies.

This paper proposes a method to introduce psychometric indicators in the specification of discrete choice models with latent classes. The method uses ordinal logit models as measurement relationships between the observed answers and the "utility" a respondent of a particular class will perceive for providing each of these answers. The novel feature of this method consists of specifying the measurement relationships as class-specific structural relations between the aforementioned utility and the attributes of the decision maker/respondent. The structure of the proposed model is inspired by the Generalized Random Utility Model (Walker and Ben-Akiva, 2002). The method is applied on two datasets for transport mode choice but should be easily implemented in other choice contexts.

The paper is organized as follows. Section 2 reviews the use of latent class models in discrete choice models and the importance of psychometric indicators to characterize the classes. Section 3 presents the modeling approach adopted in this research and designed to provide a better specification of such models. Section 4 presents a first application of the methodology on a transportation mode choice case study conducted in the Nice area (France). Section 5 provides a second application of the methodology on a mode choice case study in the low-density areas of Switzerland. Section 6 concludes on the advantages of the proposed modeling approach.

2 Latent class models in discrete choice analysis

Widely used in social sciences for quantitative analysis (Lazarsfeld and Henry, 1968), latent class models were not proposed in the form of choice models with class-membership probabilities until the work of Kamakura and Russell (1989). Class-membership models explain the probability of an individual belonging to a consumer segment as a function of the consumer's characteristics; they are a powerful instrument because they allow to relate attributes of the decision maker with unobserved behavioral classes and, therefore, simplify the market segmentation process.

There is evidence in the literature suggesting that latent class models are a very convenient, flexible and intuitive way to introduce taste heterogeneity in discrete choice models. For example, Bhat (1997) applied the latent class approach to the transport mode choice problem finding that the endogenous segmentation into classes allows for better data fit and more intuitive results compared to other approaches used to capture heterogeneity. Greene and Hensher (2003), Shen (2009) and Hess et al. (2011) analyzed the LCM approach, comparing it with alternative methodologies like the Mixed Logit Model (McFadden and Train, 2000) concluding that, while both offer a good way to capture unobserved heterogeneity, experimental results suggest that the latent class approach allows for a better behavioral interpretation of the results. Keane and Wasi (2012) compared the latent class approach with several other models that account for taste heterogeneity. Although not being the best in terms of model fit, the LCM approach was identified as the one allowing the most intuitive understanding of the patterns of heterogeneity.

Several application of integrated choice and latent class models can be found in the transport and land use-related literature. For example, the aforementioned works by Bhat (1997) and Shen

(2009), applied the LCM approach to the choice of transport mode while Greene and Hensher (2003) did it for route choice. In the area of land use, Walker and Li (2007) identified different lifestyle classes among the population of a city, showing that the segments are key determinants in the choice of residential location. Zhang et al. (2009) used a latent class structure to model different intra-household choice mechanisms regarding car ownership, finding different behaviors between classes of households that would have not been identified without the segmentation. Wen and Lai (2010) used the latent class approach in the airline choice problem, identifying significantly different willingness to pay across consumer segments. Similar result were obtained by Wen et al. (2012) but in the context of the choice of mode to access stations of a high-speed train. Koutsopoulos and Farah (2012) used latent classes to identify and model different patterns (or regimes) of driving behavior for a microscopic traffic simulator.

2.1 Psychometric indicators

Psychometric indicators can be used improve the specification and estimation process of latent constructs (like classes) because they are a measurable manifestation of the effect of unobserved attributes in the preferences of individuals (Walker and Ben-Akiva, 2002). Moreover, the use of indicators in discrete choice models may help to identify latent classes that are not captured or described by the choice data alone (Ben-Akiva, McFadden, Train, Walker, Bhat, Bierlaire, Bolduc, Börsch-Supan, Brownstone, Bunch et al., 2002). Despite this, most methodological developments are focused on the use of indicators to estimate choice models using a LVM approach (Ben-Akiva, Walker, Bernardino, Gopinath, Morikawa and Polydoropoulou, 2002), with few examples applied under the LCM approach.

Ben-Akiva and Boccara (1995) introduced the use of indicators to the estimation of models with a latent choice set by measuring the user's perceived availability of an alternative and modeling a linear relationship between this indicator, the modeled availability and the "desirability" (a proxy of the utility) of each alternative. They find that using this approach generates better predictive results than a standard logit model and that the use of indicators allows for more robust estimates.

Gopinath (1995) postulated the existence of two classes of shippers in the maritime freight choice context and used indicators to measure the latent attitude of the shippers towards different freight services attribute. The latent attitudinal variables was then used as an explanatory variable of the class-membership model. Similarly, Hosoda (1999) estimated mode choice models for shopping trips with latent classes that are functions of continuous latent variables like the "level of consciousness" of the traveler. In these last two cases, indicators are indirectly related to the class-membership model because they are first used to measure attitudinal latent variables which are then used as explanatory variables in class-membership models.

In the context of tourism destination choice, Boxall and Adamowicz (2002) modeled natural park choice in Central Canada and used psychometric indicators related to motivations for taking a trip, identifying four groups of travelers. The likelihood of membership in these classes was influenced by socioeconomic characteristics but also latent motivations which were related to the indicators. Thus, the group membership is a direct function of how the decision-makers respond to the questions and the model could not be used for predicting demand.

In a similar context, Morey et al. (2006) developed a fishing-location choice model based on three classes of fishermen that were identified using attitudinal data about the characteristics of a particular fishing location. However, the response probabilities to the psychometric indicators are estimated as single, class-specific parameters and are not structurally related to attributes of the decision makers. A similar approach is proposed by Collins and Lanza (2010) in the context of social and health sciences and by Atasoy et al. (forthcoming) in the context of transport mode choice.

In the surveyed literature, the class-membership probabilities are not directly related to indicators through measurement relationships that take into account the attributes of the decision makers. This paper proposes a method to do so, through the use of ordinal models. The specification of the class-specific measurement relationships leads to a better characterization of the classes since it integrate psychometric information. Moreover it allows to interpret the responses to psychometric indicators behaviorally.

3 Methodology

In this section we first present the general framework of latent class models. In a second stage, we introduce the use of psychometric indicators to help identify the classes.

3.1 Latent class model

Latent class models assume that discrete segments of the population have different choice behaviors, explained by different perceptions of the attributes of the alternatives, different taste parameters or different decision protocols. These differences can often be linked to the lifestyle, attitudes and even political or ideological views of the decision maker. In the context of discrete choice analysis, this translates into a class-specific utility function of choosing alternative i by decision maker n:

$$U_{in}^{s} = V(X_{in}, X_n, \beta^s) + \varepsilon_{in}^{s} \tag{1}$$

where $V(X_{in}, X_n, \beta^s)$ is the deterministic part of the utility function, X_{in} is a vector of attributes of the alternative i for decision maker n, X_n is a vector of characteristics of n and β^s is a vector of parameters (to be estimated) that is specific to class s. The term ε_{in}^{s} is a random component accounting for unobserved attributes and characteristics that can also be class-specific. Assuming an i.i.d. Extreme Value distribution for the random component, we can write the probability of an individual n choosing alternative i, conditional on the class s to which he belongs, as a logit:

$$P_n(i|s) = \frac{e^{V(X_{in}, X_n, \beta^s)}}{\sum_{j \in C_s} e^{V(X_{jn}, X_n, \beta^s)}} \tag{2}$$

where C_s is the set of alternatives considered by individuals belonging to class s.

Since classes are latent or unobserved, it is not possible to deterministically relate an individual to a class. It is possible however to assume that the membership to a class depends on the characteristics of the decision maker and that this relation is described by a *class-membership function* f, such that

$$F_{ns} = f(X_n, \gamma^s) + \xi_{ns}, \tag{3}$$

where F_{ns} is a latent continuous variable that is related to the probability of belonging to class s and can be perceived as the "utility" to belong to one class, and γ^s is a vector of parameters to be estimated. Assuming that ξ_{ns} are i.i.d. $EV(0,1)$, the probability for an individual n to belong to a particular class s is given by:

$$P_n(s) = \frac{e^{f(X_n, \gamma^s)}}{\sum_{r \in S} e^{f(X_n, \gamma^r)}} \tag{4}$$

where S is the set of classes.

Using (2) and (4) we can write the complete probability of individual n choosing an alternative i as the following expression:

$$P_n(i) = \sum_{s \in S} P_n(i|s) P_n(s). \tag{5}$$

The vector of parameters β^s and γ^s of the utility functions in equations (2) and (4), with $s \in S$, can be estimated by maximum likelihood.

3.2 Latent class model with psychometric indicators

Psychometric indicators can be introduced by assuming that the probability of giving a agreement level I_k to the kth question/indicator, with $k = 1, \dots, K$ will depend on the class of the respondent. This allows to write the joint probability of choosing i and answering I_k for individual n as:

$$P_n(i, I_k) = \sum_{s \in S} P_n(i|s) P_n(s) \prod_{k=1}^{K} P_n(I_k|s) \tag{6}$$

where $P_n(I_k|s)$ is the probability of answering I_k to the kth indicator if the respondent n belongs to class s. As mentioned in Section 2.1, this probability is usually estimated directly as a single parameter or a constant (Morey et al., 2006; Collins and Lanza, 2010; Atasoy et al., forthcoming).

We propose to model the response probability $P_n(I_k|s)$ as a function of the attributes of the respondent (or decision maker), conditional on the class. For this we consider a continuous latent construct that varies with both the characteristics and the class of the respondent, and we derive an ordered logit model from it. Our hypothesis is that, by doing so, we enhance the characterization of the class-membership model.

We focus on the case where indicators take the form of questions where an ordered response is provided. A typical example of this is when the respondent is asked about his level of agreement to a certain statement, where such level of agreement is classified in a Likert scale (Likert, 1932). The response probability must be modeled as a function of the characteristics of the decision maker only. It is convenient to do so using an ordinal logit approach, since the responses to the indicators consist of a few integer values. We define the *item response function* g relative to the answer of individual n to indicator I_k as:

$$G^s_{I_k,n} = g(X_{kn}; \alpha^s_k) + \nu^s_{kn} \tag{7}$$

where α^s_k is a indicator- and class-specific vector of parameters to be estimated, $\nu^s_{kn} \sim \text{Logistic}(0,1)$ is a disturbance term and $G^s_{I_k,n}$ is a latent continuous variable that can be seen as the "utility" of giving a particular level of agreement to indicator I_k. We assume that the value of the unobservable variable $G^s_{I_k,n}$ increases with the level of agreement ℓ to indicator k and that the probability of answering ℓ comes defined by:

$$P_n(I_k = \ell|s) = P(\tau^s_{\ell-1} < G^s_{I_k=\ell,n} \leq \tau^s_\ell) \tag{8}$$

where $\ell = 1,\ldots,L$ is the level of agreement to indicator I_k and τ^s_ℓ are strictly increasing class-specific thresholds defining an ordinal relation between the utility $G^s_{I_k,n}$ and the answers to I_k. The probability of an individual n providing an answer ℓ to indicator I_k is:

$$P_n(I_k = \ell|s) = \frac{1}{1+\exp(-(\tau^s_\ell - g(X_{kn};\alpha^s_k)))} - \frac{1}{1+\exp(-(\tau^s_{\ell-1} - g(X_{kn};\alpha^s_k)))} \tag{9}$$

Because a complete set of thresholds τ_ℓ, for $\ell = 1,\ldots,L-1$, cannot be fully identified, it is necessary to manually fix one of them (Greene and Hensher, 2009). For example, if the first threshold is fixed to zero ($\tau^s_1 = 0$), then only the difference between thresholds (δ_ℓ) has to be estimated if the following definitions are considered:

$$\begin{aligned} \tau^s_2 &= 0 + \delta^s_1 \\ \tau^s_3 &= \tau^s_2 + \delta^s_2 \\ &\ldots \\ \tau^s_{L-1} &= \tau^s_{L-2} + \delta^s_{L-2} \end{aligned} \tag{10}$$

The parameters of the joint model of choice, class-membership and response to psychometric indicators can be simultaneously estimated by maximizing the following likelihood function:

$$\mathscr{L} = \prod_n \left\{ \sum_s \left\{ P_n(i|s) \prod_k P_n(I_k|s) \right\} P_n(s) \right\}, \tag{11}$$

where we adopt the following simplified notations:

$$P_n(i|s) := \prod_i P_n(i|s)^{y_{in}} \tag{12}$$

$$P_n(I_k|s) := \prod_\ell P_n(I_k = \ell|s)^{y_{k\ell n}} \tag{13}$$

where y_{in} is a variable that assumes the value of 1 if individual n chose alternative i and 0 otherwise, and $y_{k\ell n}$ assumes the value of 1 if individual n chose answer ℓ to the indicator (or question) I_k. The proposed approach is applied in two case studies of mode choice, presented next.

4 Nice case study

We consider first a data set from a travel survey performed in 2008 for a region around the city of Nice, France (CERTU, 2008). The survey reports performed trips by purpose and mode (origin, destination and travel time) for a given day and socioeconomics of the travelers. Additionally, the survey requested respondents to provide their opinion on different statements related to their living environment and to different transport modes. The responses were rated on a three-point Likert scale, ranging to 1 for a disagreement response to 3 for an agreement. Information for the non-chosen transport modes of each trip was collected using a script for automatic web-parsing that collected information from the official website of the public transport system and from GIS data of the road network. More details on the survey and data processing can be found in Nguyen (2012). Only morning trips to work including the additional opinions-questionnaire were considered for estimation, adding up to a total of 1687 trips.

4.1 Model specification

We follow the same exploratory approach described in Walker and Li (2007) for the definition of the class-specific choice model and the class-membership model specifications. This means that we define a generic specification for the utility of each transport mode alternative that does not vary across classes, except for the values of the class-specific parameters (β^s). For the class-membership model we do not explore the optimal number of classes to consider, first because it is out of the scope of this paper and second because the relatively small amount of observations in the data does not allow for segmentation in more than two classes.

From the exploratory approach, we identified two classes, namely *well-off suburban families* (class 1) and *eco-friendly city dwellers* (class 2).

The class-membership functions depend on socioeconomic characteristics of the decision maker and its household. They are defined as follows:

$$\begin{aligned} f(X_n, \gamma^1) &= \mathrm{ASC}^1 + \gamma^1_{SPC}\mathrm{SPC}_n + \gamma^1_{size}\mathrm{size\_hh}_n + \gamma^1_{cars}\mathrm{cars}_n \qquad (14) \\ f(X_n, \gamma^2) &= 0 \end{aligned}$$

where ASC^1 is the class-specific constant for latent class 1. We consider three main explanatory variables (x_n): the size of the household ($\mathrm{size\_hh}_n$), the number of cars in the household (cars_n)

and a dummy if the socio-professional category[1] of the traveler (SPC_n) is high[2], as a proxy of a high income level .

For the class-specific mode choice model we consider only two alternatives: Car (including both as driver and as passenger) and Public Transport (PT). Cost (C) and travel time (TT) are the main attributes of each alternative but additional information regarding the availability of car for each households and spatial attributes of the origin and destination zones of the trip is also available. The class-specific utility functions for each alternative are the following:

$$\begin{aligned} V(X_{CAR}, X_n, \beta^s) &= \beta^s_{cost}\text{C}_{CAR} + \beta^s_{TT}\text{TT}_{CAR} + \beta^s_{car\_av}\text{cars}_n + \beta^s_{c\_OD}\text{c\_OD}_n + \beta^s_{park}\text{park}_n \\ V(X_{PT}, X_n, \beta^s) &= \text{ASC}^s_{PT} + \beta^s_{cost}\text{C}_{PT} + \beta^s_{TT}\text{TT}_{PT} + \beta^s_{PT\_av}\text{PT\_O}_n + \beta^s_{c\_D}\text{c\_D}_n \end{aligned} \tag{15}$$

where c_OD_n is a dummy variable indicating that the trip performed by individual n has both its origin and destination in the central zones of the area of study (urban center of Nice) while c_D_n is a similar indicator but considering only a central destination of the trip. PT_O_n is a measure of the density of public transport stops by square kilometer at the origin of the trip and park_n is a dummy variable indicating that individual n has available parking at her destination.

Of all the opinions and statements included in the survey we consider the following two to be used as indicators:

- I1: *We need to build more parking lots downtown.*
- I2: *The future of urban transportation for the central city is the bicycle.*

We select these two indicators because they measure attitudes towards specific transport modes that are in the extremes of the transport mode spectrum (motorization and environmental-wise). While a positive answer to statement I1 indicates a desire for a more car-based city, agreement with statement I2 indicates a desire for a "greener" city. While the relation of statement I1 with a preference for one of the alternatives (the car) is clear, statement I2 is about a mode that is not considered among the alternatives of the mode choice problem. However, our hypothesis is that a positive perception of biking as an urban transport mode indicates a more human-centered vision of the city and this should have an influence in mode choice between car and public transport. It is important to notice that both statements are about the central urban area; this means that agreement with both or any of them indicates concern for the city center, while indifference or

[1]The socio-professional categories are a classification of job types according to required education level and expected income. They are defined, computed and provided by the French Statistical Office.

[2]intellectual and managerial professions

disagreement probably indicates that the respondent is indifferent with what happens to the city center and probably develops her activities outside of it. Because the data contains very few neutral responses (less than 5% for both indicators), we aggregate the responses in two levels: agreement and disagreement. We include the neutral responses in the disagreement level, since both are associated with a certain lack of interest.

We define the item response functions of each indicator as follows:

$$g(X_{1n};\alpha_1^s) = \text{ASC}_{I1}^s + \alpha_{cars}^s \text{cars}_n \tag{16}$$

$$g(X_{2n};\alpha_2^s) = \text{ASC}_{I2}^s + \alpha_{c\_O}^s \text{c\_O}_n \tag{17}$$

We assume that the item response function of indicator I1 depends on the number of cars in the household of the respondent and, therefore, we expect a positive parameter for α_{cars} since a higher utility relative to the choice of the level of I1 will be associated to an agreement with the statement. Indicator I2 depends on the location of the origin of the trip being inside of central Nice. Besides the obvious fact that the statement refers to the city center, the hypothesis is that central residents (all trips considered in estimation start from the residential location) are more likely to be bike users (or have a positive perception of these mode) because the city center concentrates more biking infrastructure than the surrounding suburbs and most bike trips are performed in the central region, where activity opportunities are located at reasonable distances for bicycle trips.

4.2 Estimation results

Three models are estimated for the Nice case study. First, we consider a standard latent class model (LCM1) that does not include indicators and therefore uses the probability expression given by equation (5) with the utility specifications defined by (14) and (15). Its parameters are obtained by maximizing the following likelihood function.

$$\mathscr{L}_{\text{LCM1}} = \prod_n \{P_n(i|\text{class }1)\cdot P_n(\text{class }1) + P_n(i|\text{class }2)\cdot P_n(\text{class }2)\} \tag{18}$$

The second model (LCM2) is an extension of the first one but considers indicators, therefore using the probability expression given by equation (6). For this model the response probabilities $P_n(I_k|s) := \pi_{ks}$ are estimated directly as parameters for each class and possible answer to the indicator. The likelihood function is given by:

$$
\begin{aligned}
\mathscr{L}_{\text{LCM2}} = \prod_n \{ & P_n(i|\text{class } 1) \cdot \pi_{11} \cdot \pi_{21} \cdot P_n(\text{class } 1) \\
& + P_n(i|\text{class } 2) \cdot \pi_{12} \cdot \pi_{22} \cdot P_n(\text{class } 2) \}
\end{aligned} \tag{19}
$$

Finally, the third model (LCM3) is also an extension of the first one but uses the method proposed in this paper to measure indicators and, therefore, the response probabilities are estimated using equation (9) with the utility specifications given by (16). The following likelihood function is maximized:

$$
\begin{aligned}
\mathscr{L}_{\text{LCM3}} = \prod_n \{ & P_n(i|\text{class } 1) \cdot P_n(I1|\text{class } 1) \cdot P_n(I2|\text{class } 1) \cdot P_n(\text{class } 1) \\
& + P_n(i|\text{class } 2) \cdot P_n(I1|\text{class } 2) \cdot P_n(I2|\text{class } 2) \cdot P_n(\text{class } 2) \}
\end{aligned} \tag{20}
$$

We remark that all three models have the same specification for the utility function relative to the choice model and for the class-membership function. Estimation results for all three models are shown in Table 1.

For all three models, the parameters for the mode choice model have the expected sign and no change of sign is observed across models. It was noticed that the difference between classes was not significant for some parameters and they were merged in a single parameter. This is the case for all parameters in the choice model, with the exception of the constants, the cost and travel time parameters . Class 1 is more sensitive to travel time than class 2 while class 2 perceives a higher dis-utility for the cost than class 1. Both classes have a higher probability of choosing car if it is available and the probability of choosing public transport increases with the presence of stops near of the residential location. If the trips starts or ends in the central city, the probability of choosing car diminishes while the opposite happens for public transport. Availability of parking space at the destination makes the car more attractive for both classes.

The sign and magnitude of parameters of the class-membership model help to characterize the classes. In all three models, the probability of belonging to class 1 increases with the socio-professional category, the number of cars and the size of the household. This means that class 1 probably corresponds to members of high income, large families that have a tendency to use the car. This is also consistent with the observed higher sensitive to time and lower sensitive to cost observed for class 1.

In terms of indicator measurement, the estimated probabilities of model LCM2 are consistent with the shares by type of answer observed in the data. It is possible to see that class 1 tends to give

Table 1: Estimation results - Nice case study

		LCM1		LCM2		LCM3	
	parameter	estimate	t-test	estimate	t-test	estimate	t-test
Mode choice	ASC_{PT}^{1}	2.09	0.75*	2.01	0.55*	0.080	0.03*
	ASC_{PT}^{2}	-1.21	-1.42*	-1.30	-1.59*	-1.14	-2.08
	β_{cost}^{1}	-0.499	-1.41*	-0.413	-0.81*	-0.458	-1.80*
	β_{cost}^{2}	-1.81	-3.14	-1.60	-3.26	-1.42	-4.61
	β_{TT}^{1}	-0.346	-2.03	-0.324	-1.59*	-0.213	-1.07*
	β_{TT}^{2}	-0.125	-2.98	-0.115	-3.23	-0.113	-4.24
	β_{car_av}	1.59	1.50*	1.59	1.27*	1.09	1.08*
	β_{c_OD}	-1.22	-2.74	-1.23	-2.81	-1.17	-3.01
	β_{PT_av}	0.0115	1.76*	0.0113	1.84*	0.0108	1.95*
	$\beta_{c\_D}^{s}$	1.35	2.43	1.24	2.25	1.11	2.26
	β_{park}	2.82	5.26	2.77	5.31	2.64	5.52
Class	ASC^{1}	-1.64	-1.03*	-2.05	-1.30*	-3.90	-1.48*
	γ_{SPC}^{1}	1.00	1.45*	1.39	1.97	1.80	1.97
	γ_{cars}^{1}	1.46	0.58*	1.96	0.80*	2.61	0.96*
	γ_{size}^{1}	2.55	1.28*	2.17	0.98*	5.26	1.36*
Indicator measurement	$P(I1_{agree}\|1)$	-	-	0.80**	2.82	-	-
	$P(I1_{agree}\|2)$	-	-	0.71**	7.11	-	-
	$P(I2_{agree}\|1)$	-	-	0.55**	6.98	-	-
	$P(I2_{agree}\|2)$	-	-	0.68**	6.30	-	-
	ASC_{I1}^{1}	-	-	-	-	1.44	2.27
	α_{cars}^{1}	-	-	-	-	-0.0844	-0.29*
	ASC_{I1}^{2}	-	-	-	-	0.550	1.90*
	α_{cars}^{2}	-	-	-	-	0.314	1.46*
	ASC_{I2}^{1}	-	-	-	-	0.894	2.04
	$\alpha_{c\_O}^{1}$	-	-	-	-	-1.11	1.80*
	ASC_{I2}^{2}	-	-	-	-	0.565	2.44
	$\alpha_{c\_O}^{2}$	-	-	-	-	0.189	0.61*
Log-like for choices		-144.10		-144.41		-145.31	
Log-likelihood for I1		-		-371.20		-370.01	
Log-likelihood for I2		-		-429.52		-426.31	

*Parameter not significant at the 95% confidence level

** only the probabilities for agreement answers are provided, the probabilities for disagreement answers can be computed as $1-P(I_k|s)$

more agreement answers to the parking-related question (I1) while, at the same time, tends to give less agreement answers to the bicycle-related question (I2). This reinforces the idea that class 1 corresponds to car-using families of high income.

For model LCM3, since the indicators have only two possible levels of agreement, there is only one threshold, which is arbitrarily set to zero without loss of generality (Greene and Hensher, 2009). This means that, for both indicators, a positive utility triggers an agreement response while a negative utility triggers a disagreement response. Results for this model indicate that class 1 will almost systematically provide an agreement answer to indicator I1, regardless of the number of cars (because α^1_{cars} is of low magnitude and extremely not significant) while class 2 also tends to give agreement answers but increasing with the number of cars. Answers to question I2 also tend to be of agreement for class 1, except for when they are dwellers of the central city. Class 2 individuals tend to increase their level of agreement to I2 if they are located in central Nice. This result provides some behavioral insight on the perceptions and attitudes of each class, indicating that class 1 is more irrestrictively biased towards the car and likes the idea of more bicycles as long as they are not disturbed by them. Class 2 seems to be more consistent, providing more importance to parking if they are car users and having a positive bias towards the bicycle, especially if they are potential users. It is important to notice that, when computing the shares by answer for each indicator of LCM3 using equation (9), they have very similar values to those observed in LCM2 and the data.

The main differences between LCM2 and LCM3, besides the additional behavioral interpretations allowed by the last one, are the differences in relative importance of the characteristics that affect the class-membership functions. For example, LCM2 tends to give smaller relative importance to the size of the household (γ^1_{size}) than LCM1, while LCM3 does the opposite. In addition to this, the class-membership parameters of LCM3 have a higher significance level, which allows to consider that the size of the households actually does have a more relevant role in the market segmentation.

In terms of predicting capabilities, all models perform similarly, as it can be seen in Table 2, where estimated market shares of car and PT by class and overall classes are shown. However, in terms of estimation of value of time (VOT), LCM1 and LCM2 lead to a rather high VOT for class 1 while LCM3 provides a value of 27 Euros/hour, which is closer to the reference value of 10 Euros/hour for the year 2001[3] (CGP, 2001).

The application of the present methodology on the data set from the Nice case study showed

[3]Using the official annual interest rates for France this value is 13,3 Euros/hour in 2008. Source: http://epp.eurostat.ec.europa.eu/portal/page/portal/interest_rates/data/main_tables

Table 2: Market shares and value of time - Nice case study

		Car share [%]	PT share [%]	VOT [Euro/hour]
LCM1	Class 1	87.09	12.91	41.60
	Class 2	73.96	26.04	4.14
	Overall	80.60	19.40	21.89
LCM2	Class 1	87.11	12.89	47.07
	Class 2	75.20	24.80	4.31
	Overall	80.49	19.51	21.53
LCM3	Class 1	88.25	11.75	27.90
	Class 2	75.95	24.05	4.77
	Overall	80.57	19.43	12.43

promising results. Though the results are meaningful and hint the benefits of the proposed specification, many parameters do not show a high level of significance. This is despite the fact that extensive specification testing was performed on the Nice data set. This motivated the application of the methodology on a more reliable data set coming from a different case study. This application is presented in the next section.

5 Switzerland case study

Data from a revealed preferences travel survey conducted in 2009 in rural areas of Switzerland was collected (EPFL, 2011). The travel survey describes socioeconomics and the complete tour of trips of the respondent for a given weekday including mode, purpose, departure and arrival times. Additionally, as psychometric indicators, the survey collected responses in terms of level of agreement to a series of statements about the environment, the transport system, lifestyle preferences and mobility habits (for more details see Hurtubia et al., 2010). The answers were collected using a five point Likert scale ranging from strong disagreement (level 1) to a strong agreement (level 5). After data cleaning and processing, the observations of trips and set of answers to the psychometric indicators of 1763 respondents were considered for estimation. In total, 2265 trips with an associated choice of transport mode were recorded, given that a respondent could report several trips per day.

5.1 Specification

This case study is an extension of the model and results presented by Atasoy et al. (forthcoming). For comparison purposes, the specification of utility functions, definition of latent classes and selection of psychometric indicators are the same as those proposed in the aforementioned article.

Atasoy et al. (forthcoming) identified class 1 as individuals living with their families who have high income while class 2 corresponds to single individuals who live alone or with their parents.

The class-membership functions are the following

$$
\begin{aligned}
f(X_n,\gamma^1) &= \mathrm{ASC}^1 + \gamma^1_{child} child_n + \gamma^1_{inc} high\_inc_n \qquad (21)\\
f(X_n,\gamma^2) &= \gamma^2_{single} single_n
\end{aligned}
$$

The class-membership model depends on three main socioeconomic attributes of the decision maker: a dummy variable indicating if the traveler n belongs to a household with children ($child_n$), a dummy indicating if the income in the household is above CHF 8000 per month ($high\_inc_n$) and a dummy indicating if individual n lives alone or with his parents ($single_n$).

The mode choice model considers three alternatives: Private Motorized Modes (PMM), including car as driver, car as passenger, motorcycle and taxi, Public Transport (PT), including bus, metro and train, and Soft Modes (SM) including bicycle and walking. The class-specific utilities for mode choice are described in each column of Table 3. Because there was no observations of soft modes chosen by individuals falling in the "single" category, this alternative was made unavailable for class 2.

In Table 3, TT_{PMM} and TT_{PT} are the travel times for private modes and public transport respectively, *cars* is the number of cars in the household, *children* is the number of children under age 15 in the household and *bikes* is the number of bicycles available to the members of the household. *French* is a dummy variable indicating if the respondent lives in the French part of Switzerland, *WorkTrip* is a dummy indicating that the purpose of the trip was work, *Urban* is a dummy indicating the origin or destination of the trips is in an urban area and *Student* is a dummy indicating if the respondent is a student (up to the university or trainee level).

After a factor analysis process, Atasoy et al. (forthcoming) selected the following statement of the survey to be used as indicators:

- I1 (PT and children): *It is hard to take public transport when I travel with my children.*
- I2 (Flexibility of car): *With my car, I can go where I want whenever I want.*
- I3 (Family oriented): *I would like to spend more time with my family and friends.*

Table 3: Mode choice model specification - Swiss case study

	Variable (Class 1)			Variable (Class 2)	
Parameter	V_{PMM}	V_{PT}	V_{SM}	V_{PMM}	V_{PT}
ASC^1_{PMM}	1	-	-	-	-
ASC^2_{PMM}	-	-	-	1	-
ASC^1_{SM}	-	-	1	-	-
β^1_{cost}	$Cost_{PMM}$	$Cost_{PT}$	-	-	-
β^2_{cost}	-	-	-	$Cost_{PMM}$	$Cost_{PT}$
$\beta^1_{TT,PMM}$	TT_{PMM}	-	-	-	-
$\beta^2_{TT,PMM}$	-	-	-	TT_{PMM}	-
$\beta^1_{TT,PT}$	-	TT_{PT}	-	-	-
$\beta^2_{TT,PT}$	-	-	-	-	TT_{PT}
$\beta^1_{distance}$	-	-	$Dist_{SM}$	-	-
β_{cars}	$cars$	-	-	$cars$	-
$\beta^1_{children}$	$children$	-	-	-	-
$\beta^2_{children}$	-	-	-	$children$	-
$\beta_{language}$	$French$	-	-	$French$	-
β^1_{work}	$WorkTrip$	-	-	-	-
β^2_{work}	-	-	-	$WorkTrip$	-
β_{urban}	-	$Urban$	-	-	$Urban$
$\beta_{student}$	-	$Student$	-	-	$Student$
β^1_{bikes}	-	-	$bikes$	-	-

The item response functions of each indicator are the following.

$$g(X_{1n};\alpha^s_1) = ASC^s_{I1} + \alpha^s_{Children} HasChildren_n \tag{22}$$

$$g(X_{2n};\alpha^s_2) = ASC^s_{I2} + \alpha^s_{cars} cars_n \tag{23}$$

$$g(X_{3n};\alpha^s_3) = ASC^s_{I3} + \alpha^s_{family} HasChildren_n working_n \tag{24}$$

The answer to indicator I1 will be affected by a dummy indicating the presence of children in the household; the number of cars in the household affects the answer to question I2 and the answer to indicator I3 depends on the interaction of two dummy variables indicating that the person has children and a full time job.

5.2 Estimation results

As in the case study of Section 4, three models were estimated for the Swiss case. The first one is simply an integrated choice and latent class model without indicators (LCM1), with likelihood

$$\mathscr{L}_{\text{LCM1}} = \prod_n \{P_n(i|\text{class } 1) \cdot P_n(\text{class } 1) + P_n(i|\text{class } 2) \cdot P_n(\text{class } 2)\} \tag{25}$$

The second one incorporates indicators and estimates the item response probabilities directly as parameters (LCM2). It has the following likelihood:

$$\begin{aligned} \mathscr{L}_{\text{LCM2}} = \prod_n \{ & P_n(i|\text{class } 1) \cdot \pi_{11} \cdot \pi_{21} \cdot \pi_{31} \cdot P_n(\text{class } 1) \\ & + P_n(i|\text{class } 2) \cdot \pi_{12} \cdot \pi_{22} \cdot \pi_{32} \cdot P_n(\text{class } 2)\}, \end{aligned} \tag{26}$$

where $P_n(I_k|s) := \pi_{ks}$. The third one uses the methodology proposed in this paper (LCM3) and has likelihood

$$\begin{aligned} \mathscr{L}_{\text{LCM3}} = \prod_n \{ & P_n(i|\text{class } 1) \cdot P_n(I1|\text{class } 1) \cdot P_n(I2|\text{class } 1) \cdot P_n(I3|\text{class } 1) \cdot P_n(\text{class } 1) \\ & + P_n(i|\text{class } 2) \cdot P_n(I1|\text{class } 2) \cdot P_n(I2|\text{class } 2) \cdot P_n(I3|\text{class } 2) \cdot P_n(\text{class } 2)\} \end{aligned} \tag{27}$$

As for the Nice case study, all models have the same specification for the utility functions relative to the choice model and the class-membership function. Results for the choice model and the class-membership model are shown in Table 4. The estimated item response probabilities for LCM2 and the parameters for the indicator measurements of LCM3 are shown in Tables 6 and 7 of the Appendix respectively.

The choice model parameters for cost time and show the expected sign for all classes in the three models, with a significant variation in magnitude between models. Class 2 shows a systematic higher sensitivity to cost and travel time for all modes in the three models. Most of the remaining parameters show intuitive values and no change of sign across models, with some exceptions. For example $\beta^2_{children}$ is negative and significant for LCM1 and it becomes positive and not significant for LCM3. However, the result for LCM3 seems to be more intuitive given the fact that individuals in class 2 are likely to be single and without children. Another case of change of sign is that of β^2_{work} which is positive and not significant for LCM1 and becomes negative with a higher significance in LCM3.

The estimates for the class-membership model confirm that class 1 corresponds to high income individuals living with their family while class 2 corresponds to single individuals with lower income. An important difference in magnitude is observed in these parameters among the three modeling approaches. LCM2 assigns a higher relative weight to the presence of children in the household as an explanatory variable while LCM3 assigns a relatively higher weight to the income

Table 4: Estimation results - Swiss case study

	Parameters	LCM1 estimate	LCM1 t-test	LCM2 estimate	LCM2 t-test	LCM3 estimate	LCM3 t-test
Mode choice	ASC^1_{PMM}	-0.417	-0.417*	-0.945	-3.83	-1.25	-4.30
	ASC^2_{PMM}	-0.571	-1.49*	-0.936	-3.37	-0.731	-2.54
	ASC^1_{SM}	0.587	1.67*	0.512	1.70*	0.642	2.07
	β^1_{cost}	-4.15	-2.12	-2.70	-3.14	-1.23	-1.53*
	β^2_{cost}	-30.5	-4.83	-30.2	2.82	-39.1	-6.98
	$\beta^1_{TT,PMM}$	-0.211	-0.42*	-1.61	-4.77	-1.30	-3.80
	$\beta^2_{TT,PMM}$	-26.8	-4.96	-11.1	-6.83	-10.6	-6.46
	$\beta^1_{TT,PT}$	-0.257	-0.98*	-0.692	-3.62	-0.701	-3.55
	$\beta^2_{TT,PT}$	-8.91	-4.85	-4.45	-5.90	-3.91	-5.35
	$\beta^1_{distance}$	-18.4	-8.42	-19.9	-9.54	-19.8	-9.10
	β_{cars}	1.24	10.18	1.23	11.34	1.29	11.18
	$\beta^1_{children}$	0.403	2.76	0.404	4.83	0.346	3.47
	$\beta^2_{children}$	-0.434	-1.89	-1.03	-1.72*	0.211	0.97*
	$\beta_{language}$	1.20	0 5.71	1.20	6.79	1.20	6.22
	β^1_{work}	-0.990	-3.98	-0.785	-4.85	-0.623	-3.37
	β^2_{work}	0.0881	0.22*	-0.130	-0.43*	-0.396	-1.34*
	β_{urban}	0.528	3.20	0.390	2.82	0.459	3.23
	$\beta_{student}$	3.73	8.37	3.70	8.45	3.95	8.86
	β^1_{bikes}	0.400	4.96	0.205	3.21	0.214	3.26
Class	ASC_{class}	-0.215	-0.86*	-0.629	-3.25	-0.589	-3.39
	γ^1_{child}	0.136	0.51*	3.92	4.84	0.967	5.41
	γ^1_{inc}	0.693	2.76	0.460	2.22	0.684	4.50
	γ^2_{single}	0.408	1.34*	0.704	3.57	0.743	3.33
Log-like for choices		-994.7		-1032.5		-1006.7	
Log-likelihood for I1		-		-2068.4		-2033.1	
Log-likelihood for I2		-		-2202.6		-2151.5	
Log-likelihood for I3		-		-2160.6		-2153.5	

*Parameter not significant at the 95% confidence level

Table 5: Market shares and value of time - Swiss case study

Models		PMM [%]	PT [%]	SM [%]	VOT PMM [CHF/h]	VOT PT [CHF/h]
LCM1	Class 1	60.97	28.73	10.30	3.06	3.72
	Class 2	60.41	39.59	-	52.63	17.53
	Overall	61.23	33.81	4.96	28.97	10.94
LCM2	Class 1	54.91	36.13	8.96	35.78	15.38
	Class 2	65.73	34.27	-	22.05	8.84
	Overall	62.7	32.35	4.94	29.53	12.40
LCM3	Class 1	51.79	38.01	10.2	63.27	16.21
	Class 2	70.98	29.02	-	34.16	5.99
	Overall	61.74	33.69	4.57	36.94	18.40

level. In general the inclusion of indicators (in both LCM2 and LCM3) allows for the estimation of more significant parameters in the class-membership model.

Regarding the measurement of indicators, both LCM2 and LCM3 generate response probabilities (see Table 6) that are consistent with observed response rates. Some additional behavioral interpretation is possible when looking at the indicator measurement parameters of LCM3 (see Table 7 in the appendix). For example, for indicator I1 (difficulty of using public transport with children), it is possible to see that class 2 has a strong inertial tendency to be indifferent, confirming that individuals in class 2 are likely to have no children. On the other hand, individuals in class 1 show a more heterogeneous behavior in their responses, which tends to be of disagreement when the household has children.

The models forecast market shares with some differences. In terms of value of time LCM1 predicts a counter-intuitive higher value of time for class 2. The models including indicators (LCM2 and LCM3) produce a more intuitive VOT for each class, although LCM3 predicts a much higher VOT for private motorized modes (PMM) in class 1. The reference VOT for Switzerland is 27.66 CHF/hour for business travels by car (Axhausen et al., 2008). However, estimation data was obtained from a survey that was conducted in rural areas of Switzerland, where income tends to be higher, while the reference VOT considers both rural and urban areas. This, besides the fact that many individuals in class 1 have at least a wage of 50 CHF/hour[4], justifies considering the results provided by LCM3 as reasonable since, under some circumstances, the value of travel time savings should be close to the wage level (Jara-Diaz, 2007). This, however, requires further research to reach a conclusion.

[4]computed as CHF 8000 divided by 160 hours of work per month

6 Conclusions

We propose a new type of model specification that incorporates psychometric indicators into integrated choice and latent class models through an ordinal logit model. Moreover the ordinal logit model relates the answers to the indicators with socioeconomic characteristics of the respondents, hence allowing for a better characterization of the latent classes.

The method is tested in two mode choice case studies for the region of Nice, France and rural areas of Switzerland. Results show that the inclusion of the ordinal measurement of psychometric indicators generates significantly different estimates for the class-membership model. The additional behavioral insights provided by the parameters of the indicator-measurement equations allows for a richer analysis of the latent classes, giving the analyst more tools to identify different market segments.

The proposed method forecasts values of time of different magnitude when compared with latent class models that estimate the item response probabilities of the indicators as single parameters. In the Nice case study, the method proposed in this paper produced values that were clearly closer to the reference ones. In the Swiss case study our method predict much higher values of time for the high income class.

One of the advantages of the proposed methodology is the closed form of the ordinal logit used for measurement of the indicators. This allows for a simpler estimation procedure, without the need of integration techniques as it is in most cases when latent variables are included in choice models.

Some of the estimates in the models presented here have a low significance level and some of the utility functions for classes and indicators have considerably simple specifications. This is due to the complexity of the models and the relatively scarce number of observations available for each case study. We believe that using a larger set of observations should allow to incorporate more explanatory variables in the class-membership and indicator measurement utilities, therefore expanding the possibilities of behavioral analysis and market segmentation.

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Appendix

Table 6: Item response probabilities for LCM2 - Swiss case study

	$s=1$		$s=2$	
Probability	estimate	t-test	estimate	t-test
$P(I1=1\|s)$	0.166	13.00	0.002	0.78*
$P(I1=2\|s)$	0.246	16.14	0.008	0.67*
$P(I1=3\|s)$	0.306	14.11	0.958	34.60
$P(I1=4\|s)$	0.176	13.45	0.029	2.36
$P(I1=5\|s)$	0.106	**	0.003	**
$P(I2=1\|s)$	0.031	5.60	0.020	3.31
$P(I2=2\|s)$	0.033	5.73	0.027	3.94
$P(I2=3\|s)$	0.121	11.10	0.169	10.80
$P(I2=4\|s)$	0.371	23.87	0.364	18.03
$P(I2=5\|s)$	0.444	**	0.420	**
$P(I3=1\|s)$	0.013	3.63	0.004	1.35*
$P(I3=2\|s)$	0.047	6.84	0.040	4.80
$P(I3=3\|s)$	0.254	17.08	0.414	19.78
$P(I3=4\|s)$	0.491	29.91	0.430	20.46
$P(I3=5\|s)$	0.195	**	0.112	**

*Parameter not significant at the 95% confidence level

** The probability for $I=5$ is computed directly as $1-\sum_{k=1}^{4} P(I=k|s)$, $\forall s$ and, therefore, does not have an associated t-test

Table 7: Indicator measurement parameters for LCM3 - Swiss case study

	$s=1$		$s=2$	
parameter	estimate	t-test	estimate	t-test
ASC^s_{I1}	2.04	12.97	5.18	3.13
$\alpha^s_{Children}$	-1.28	-6.85	3.87	10.50
$\delta^s_{1,I1}$	1.57	15.02	0.461	0.35*
$\delta^s_{2,I1}$	1.96	10.77	7.40	4.08
$\delta^s_{3,I1}$	1.18	6.66	1.94	9.12
ASC^s_{I2}	2.26	8.60	3.31	9.81
α^s_{cars}	5.11	7.03	2.84	4.29
$\delta^s_{1,I2}$	0.845	5.15	0.781	3.51
$\delta^s_{2,I2}$	1.32	9.82	1.32	9.82
$\delta^s_{3,I2}$	1.79	17.44	1.74	17.06
ASC^s_{I3}	3.86	12.88	6.26	3.20
α^s_{family}	0.309	2.05	0.987	5.76
$\delta^s_{1,I3}$	1.31	5.26	3.33	1.76*
$\delta^s_{2,I3}$	2.07	13.51	2.69	13.96
$\delta^s_{3,I3}$	2.39	19.99	2.08	18.84

*Parameter not significant at the 95% confidence level