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A new estimation approach to integrate latent psychological constructs in choice modeling

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ABSTRACT

In the current paper, we propose a new multinomial probit-based model formulation for integrated choice and latent variable (ICLV) models, which, as we show in the paper, has several important advantages relative to the traditional logit kernel-based ICLV formulation. Combining this MNP-based ICLV model formulation with Bhat's maximum approximate composite marginal likelihood (MACML) inference approach resolves the specification and estimation challenges that are typically encountered with the traditional ICLV formulation estimated using simulation approaches. Our proposed approach can provide very substantial computational time advantages, because the dimensionality of integration in the log-likelihood function is independent of the number of latent variables. Further, our proposed approach easily accommodates ordinal indicators for the latent variables, as well as combinations of ordinal and continuous response indicators. The approach can be extended in a relatively straightforward fashion to also include nominal indicator variables. A simulation exercise in the virtual context of travel mode choice shows that the MACML inference approach is very effective at recovering parameters. The time for convergence is of the order of 30–80 min for sample sizes ranging from 500 observations to 2000 observations, in contrast to much longer times for convergence experienced in typical ICLV model estimations.

1. Introduction

Economic choice modeling has been the mainstay of human behavioral modeling in many fields, including geography, urban planning, marketing, sociology, and transportation. The typical paradigm is based on a latent construct representing the value or utility that an individual decision-maker assigns to each of many available and mutually exclusive alternatives. The choice of an alternative is assumed to be the result of that alternative's utility being higher than its competitors in the perception space of the decision-maker. This utility itself is typically mapped to observed characteristics of the decision-maker (such as the socio-demographics of an individual in work mode choice modeling) and observed characteristics of the alternatives (such as travel time and travel costs by alternative modes in work mode choice modeling). To acknowledge that there may be unobserved characteristics of decision-makers (such as attitudes and lifestyle preferences) that are likely to impact choice, one of three approaches has been used in the literature. The *first approach* allows the intrinsic preference

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for alternatives as well as the sensitivities to alternative attributes to vary across decision-makers, using discrete (non-parametric) or continuous (parametric) random distributions to capture sensitivity variations (or taste heterogeneity). Early examples include the studies by Revelt and Train (1996) and Bhat (1997, 1998), and there have now been many applications of this approach, using latent multinomial logit and mixed logit formulations. A problem with this approach, though, is that some of the attitudes may be correlated with explanatory variables. Thus, an individual who is environmentally-conscious (say an unobserved variable) may locate herself or himself near transit stations, generating a correlation between the unobserved variable and a transit travel time variable used as an explanatory variable. Such correlations lead to inconsistent estimation. Besides, this method treats unobserved psychological preliminaries of choice (*i.e.*, attitudes and preferences) as being contained in a "black box" to be integrated out. The *second approach* uses indicators of attitudes directly as explanatory variables in choice models. Such a technique has been used by Koppelman and Hauser (1978), Bhat et al. (1993), and many other subsequent studies. But this approach assumes that the indicators of attitudes directly represent the underlying attitudes that actually impact choice, which may not be the case. Rather, the indicators may be proxies of attitudes that are captured with some measurement error. Ignoring measurement error will, in general, lead to inconsistent estimation (see Ashok et al., 2002). Further, the attitude indicators may be correlated with other unobserved individual-specific factors that influence choice, rendering the estimation potentially inconsistent. In addition, the lack of a structural model to relate the attitudes to observed explanatory variables implies that the estimated model cannot be used in forecasting mode. The *third approach* is to undertake a factor analysis of the indicators to develop latent variables, typically using a multiple indicator multiple cause (MIMIC) model in which the latent variables are explained by a combination of observable indicators and observed (individual and alternative-specific) covariates. Essentially, factor analysis has the purpose of reducing the high number of correlated attitudinal indicators to a more manageable and relatively orthogonal set of latent variables, which are subsequently used as "error-free" explanatory variables (along with other covariates) in the choice model of interest. But such an approach, like the second approach discussed earlier, is, in general, econometrically inconsistent. This is because latent variables specific to individual alternatives (such as comfort level of traveling on a bus in a mode choice model), or latent variables interacted with variables that vary across alternatives (such as perceptions of security that may interact with the travel time on the mode), lead to heteroscedasticity across the errors of the alternatives in the choice model, and latent variables applicable to a subset of alternatives (such as the sociable nature of the individual that may affect the utility ascribed to all transit modes) generate correlation patterns across the errors of the alternatives. Further, if the latent variables are interacted with individual-specific observed variables (such as the comfort level of traveling on the bus affecting bus utility through its interaction with the travel time on the bus), the result is also heterogeneity across individuals in the entire covariance matrix of alternatives (this is an issue that does not seem to have been acknowledged in the previous literature). Such a complex covariance matrix structure across alternatives and across individuals necessitates the explicit consideration of stochasticity in the latent variables.

A rapidly growing field of study that integrates latent psychological constructs such as attitudes and preferences within traditional choice models takes the form of a hybrid model that is commonly referred to as the Integrated choice and latent variable (ICLV) model (see Ben-Akiva et al., 2002; Bolduc et al., 2005). In this approach, the objective is to gain a deeper understanding into the decision process of individuals by combining traditionally used "hard" covariates with "soft" psychometric measures associated with individual attitudes and perceptions. In this way, there is recognition that latent individual-specific variables (attitudes and perceptions) may be just as important as observed covariates in shaping choice and that their inclusion is likely not only to shed more light on the actual decision process but also potentially enhance the predictive ability of the model (Temme et al., 2008; Bolduc and Alvarez-Daziano, 2010). A typical ICLV model includes a latent variable structural equation model that relates latent constructs of attitudes and perceptions to observed covariates. Further, the latent constructs (or variables) themselves are viewed as being manifested through the attitudinal and perception indicator variables in a latent measurement equation model, which recognizes the presence of measurement error in capturing the intrinsic latent constructs. In the event that one of more of the indicators are not observed on a continuous scale, but observed on an ordinal or nominal scale, the measurement equation also serves the role of mapping the continuous latent constructs to the ordinal or nominal scale of the observed attitudinal indicator variables. Finally, the "soft" latent variables and the "hard" observed variables are used together to explain choice in a random utility maximizing choice model set-up.

While the number of applications of ICLV models has been on the rise in recent years (see, for example, Johansson et al., 2006; Bolduc et al., 2005; Temme et al., 2008; Daly et al., 2012; Alvarez-Daziano and Bolduc, 2013), the use of such models is severely hampered by (1) the restrictive specifications used in application, (2) the difficulties encountered in estimation, and (3) the amount of time it takes to estimate these models (typically of the order of a day for one specification run). Thus, earlier applications of the ICLV model typically use an independent and identically distributed Gumbel error term for the stochastic component of the utility of alternatives, imposing *a priori* the notion that, net of the latent attitudinal factors and observed covariates, there is no remaining correlation across the utilities of alternatives.[2] Similarly, the error correlations in the latent variables are almost always ignored within the latent variable structural equation model, as has also been pointed out by Vij and Walker (2014). Such correlations in the latent variables may arise because of common underlying unobserved individual *values* that are precursors to attitude formation and that may impact multiple attitude variables at once (see

[2] While a more general covariance structure can be incorporated through the use of normally-mixed error-components or random coefficients (or a combination), this adds more to the integration dimension and makes an already very difficult MSL estimation problem more difficult, which is certainly one important reason why earlier applications of the logit-kernel ICLV have not introduced such general covariance structures.