Transportation Research Part B 76 (2015) 1–26

Contents lists available at ScienceDirect

Transportation Research Part B

journal homepage: www.elsevier.com/locate/trb

# Inference on mode preferences, vehicle purchases, and the energy paradox using a Bayesian structural choice model

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ARTICLE INFO

*Article history:*
Received 31 January 2014
Received in revised form 24 February 2015
Accepted 26 February 2015

*Keywords:*
Bayesian microeconometrics
Discrete choice models
Structural equation modeling
Energy paradox

ABSTRACT

Discrete choice modeling is experiencing a reemergence of research interest in the inclusion of latent variables as explanatory variables of consumer behavior. There are several reasons that motivate the integration of latent attributes, including better-informed modeling of random consumer heterogeneity and treatment of endogeneity. However, current work still is at an early stage and multiple simplifying assumptions are usually imposed. For instance, most previous applications assume all of the following: independence of taste shocks and of latent attributes, exclusion restrictions, linearity of the effect of the latent attributes on the utility function, continuous manifest variables, and an a priori bound for the number of latent constructs. We derive and apply a structural choice model with a multinomial probit kernel and discrete effect indicators to analyze continuous latent segments of travel behavior, including inference on the energy paradox. Our estimator allows for interaction and simultaneity among the latent attributes, residual correlation, nonlinear effects on the utility function, flexible substitution patterns, and temporal correlation within responses of the same individual. Statistical properties of the Bayes estimator that we propose are exact and are not affected by the number of latent attributes.


## 1. Introduction

Discrete choice models are a powerful tool for analyzing consumers' decisions among mutually exclusive alternatives. However, standard discrete choice models consider only observable hedonic attributes of the alternatives, failing to incorporate other relevant choice components. These additional components may be attitudinal constructs (such as pro-environmental preferences), as well as multi-dimensional attributes of quality (such as performance) that cannot be measured using a single item. Neglecting these components (omission of a relevant variable) or using proxy variables (measurement error) induce endogeneity. Hence, the incorporation of these underlying components is desirable to achieve consistent, efficient preference estimators. In addition, structural choice models that incorporate underlying attitudes through latent variables (see the seminal paper by Ben-Akiva et al. (2001)) offer an attractive improvement in modeling choice behavior, because the discrete choice model is only a part of the underlying behavioral process through which the modeler can better represent quality and attitudinal responses. In this paper we propose to use a multinomial probit kernel

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http://dx.doi.org/10.1016/j.trb.2015.02.012

with latent attributes and discrete (categorical ordered) effect indicators to enrich the representation of random consumer heterogeneity in transportation choices (cf. Burda and Harding, 2013).

Although the number of empirical applications of choice models with latent attributes is increasing at an exponential rate (Vij and Walker, 2014; Palma et al., 2013; Ben-Akiva et al., 2013; Fjendbo Jensen et al., 2013; Hess and Beharry-Borg, 2012; Hildebrandt et al., 2012; Rosenberger et al., 2012; Rungie et al., 2011, just to give a few recent examples, the standard frequentist estimator (a maximum simulated likelihood estimator, see Bolduc and Alvarez Daziano, 2010)) has several problems that have limited applied research. For instance, relatively flat areas of the simulated loglikelihood create problems of weak identification, local maxima may be multiple, and standard numerical approximations of both the gradient and the Hessian do not ensure convergence. In addition, computation cost of simulation-aided inference is high for medium-sized problems: finding the maximum simulated likelihood estimates can take days even when there are no convergence issues. In fact, maximizing the likelihood function exhibits the curse of dimensionality with respect to the number of latent variables.[1] In a very recently published article, Bhat and Dubey (2014) propose to use the maximum approximate composite marginal likelihood (Bhat, 2011) as an analytical approximation of the loglikelihood that is well behaved (even with numerical approximations of the Hessian), avoiding thus the non-convergence problems and dimensionality issues of the standard frequentist estimator. The method of Bhat and Dubey (2014) not only is able to handle a probit kernel and a combination of continuous and discrete indicators but also converges in minutes for problems with 500–2000 observations, whereas restricted specifications take 15 h or more with the standard frequentist estimator. The authors note, however, that larger sample sizes are required to best recover the effects of the latent variables on choice.

The purpose of this paper is to explore another estimator that avoids the curse of dimensionality, and addresses other issues such as having exact (small-sample) properties. The main contribution is thus the derivation of a general, simultaneous Bayes estimator for a multinomial probit model with a panel structure and latent attributes that are endogenous and manifested through effect indicators that are discrete, continuous, or both. Our estimator allows for interaction and simultaneity among the latent attributes, residual correlation, nonlinear effects on the utility function, flexible substitution patterns, and temporal correlation within responses of the same individual. We effectively propose to model choice as a covariance structure model with an augmented space of discrete and continuous dependent variables, and identification blocks that are exploited to derive the full conditional distributions for Gibbs sampling the posterior of interest.[2] There are several benefits in the estimator proposed. As discussed in the paper, estimation time is in the order of minutes (1–3 min for 500 observations and 10,000 repetitions of the sampler, 5–15 min for 2500 observations); the estimator is integral, gradient, and Hessian free; and inference on transformation of the parameters of interest is eased, through the possibility of post-processing Monte Carlo Markov chains to find posterior distributions and standard errors of welfare measures (willingness to pay, consumer surplus), underlying discount rates, and predicted probabilities and shares.

After analyzing the general behavior of the estimator using a Monte Carlo study, we give an empirical application with important insights that are relevant for better understanding travel behavior. By constructing a model of vehicle purchase and commuting behavior, we generalize previous findings (Bolduc et al., 2008; Bolduc and Alvarez Daziano, 2010; Daziano and Bolduc, 2013b) about urban transportation choices. In particular, we present the structural discrete choice model as an alternative approach for deriving a continuous, latent market segmentation of consumers. We also provide inference on the **energy paradox** or energy efficiency gap in vehicle fuel efficiency, which aims at explaining the observed slow consumer shift to energy efficient technologies with high-return rates (Jaffe and Stavins, 1994). In particular, we derive implicit discount rates (Hausman, 1979; Train, 1985) that allow for heterogeneity based on a latent variable that identifies cost-conscious consumers.

The rest of the paper is organized as follows. In Section 2 we specify both the structural and measurement equations of a generalized structural discrete choice model with a multinomial probit kernel and latent attributes that are manifested by effect indicators that can be either continuous or discrete. We also discuss identification of the parameters of the model, and we derive a Gibbs sampler based on reduced form of the model. In fact, we discuss that when introducing interactions, the Gibbs sampler is based on a pseudo-reduced form that requires special attention to take into account stochasticity in the parameters of the full conditional distributions. Section 2 ends with a Monte Carlo study that analyzes behavior of the estimator for a varying number of alternatives (5–10), alternative-specific latent variables, and sample sizes (500; 1500; 2500). In Section 3 we present the discrete-choice experiment about transportation choices – vehicle-purchase and commuting-mode choices – in Canadian urban centers. Even though we have used a subset of the same dataset in previous work, in this paper we overcome a series of simplifying assumptions that were originally used, and are actually still present in most current work on latent attributes in discrete choice. Furthermore, the commuting mode choice experiment is an addition, as our previous work has focused on specific models of vehicle choice. Section 4 summarizes posterior estimates of the joint model, including a forecasting exercise, and inference on implicit discount rates when comparing upfront costs versus future energy savings. Section 5 concludes by summarizing the main findings of this study.

[1] Each latent variable adds one dimension to the integral of the joint choice probability.

[2] Unlike the estimator analyzed in Daziano and Bolduc (2013b), no Metropolis–Hastings simulation is required for the estimator derived in this paper. Other extensions include simultaneity and interactions, which are both challenging in the Bayesian context.