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Preference heterogeneity in energy discrete choice experiments: A review on methods for model selection

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ABSTRACT

Discrete choice experiments are increasingly utilized to inform policy makers in various fields in energy on consumer preferences and willingness to pay values. When translating the results into policy recommendations, it is often difficult for non-experts to understand the underlying implications of different models and associated behavioral assumptions. In this paper, I review proposed methods to compare the two most frequently applied models, the random parameters logit model and the latent class logit model and investigate the challenges in and implications of model choice for policy makers and practitioners. As an example application, I use data from a discrete choice experiment on private households' preferences for electricity supply quality in Hyderabad, India. The procedures used in the comparative analysis – measures of fit, tests for non-nested models, kernel density estimates of conditional willingness to pay values and choice probabilities – emphasize the difficulties in finding the 'correct' model. The methods presented here can be readily used by other researchers to better understand model performance which ultimately contributes to improving model choice in applied energy research.

1. Introduction

Discrete choice experiments (DCE) have become an integral tool for researchers and policy makers to investigate consumer preferences and demand for non-marketed goods in energy. Several DCEs have informed policy makers for example on the acceptance of renewable energies [1–6], supplier choice [7–10], and the costs of power supply interruptions [11–14]. In parallel to the rise in DCE studies, methodical advances changed the practice in discrete choice modeling. In particular, the consensus to incorporate unobserved preference heterogeneity into random utility functions has guided model choice for the last years. Its current practice suggests to use the random parameters logit model (RPL) and the latent class logit model (LCL) or extensions of these two models.[2] The RPL is characterized by accommodating unobserved preference heterogeneity as a continuous function of the utility parameters. In contrast, the LCL derives preference heterogeneity from different classes, each characterized by its own parameters. The implied behavioral assumptions are meaningful to describe human behavior but mostly, as Hensher and Greene [18] point out, there is no theoretical foundation for choosing any of the available distributions or number of classes. For applied researchers and practitioners, it is often difficult to decide for a model and there exist no clearly defined rules to decide for a specific model.

This paper reviews and exemplifies procedures for model choice for DCEs which can guide researchers to derive policy implications in the energy sector. The procedures help to better understand the interpretation of different models. Unlike existing papers comparing RPL and LCL, this paper provides an overview of frequenly applied methods to compare DCE models and exemplifies them in a compact way, which can help applied researchers to more efficiently select an appropriate model. It is the first paper that systematically summarizes the methods to select a model that have been suggested in the literature. It can be used as a hands-on guide to select the appropriate discrete choice model. Although the paper compares the RPL and the LCL, the proposed methods can also be applied for other discrete choice models including hybrid discrete choice latent variable models [2], models combining RPL and LCL models (RPL-LCL) [17], error components models [19], multilevel models [20], and models simultaneously accounting for preference and scale heterogeneity [15,16]. In order to illustrate the procedures, I use DCE data from a survey on preferences for electricity supply attributes from private households in Hyderabad, India. To my knowledge, this is the only paper

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[2] More advanced models are available. Examples are the generalized multinomial logit model [15] and the scale adjusted latent class model [16], as well as the latent class random parameters model [17], which capture more complex patterns of heterogeneity including variance-scale heterogeneity.

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comparing the RPL and LCL that uses data from an emerging economy context.

2. Model description

2.1. Comparison of latent class logit and random parameters logit models

The LCL and the RPL are similar as they both incorporate unobserved heterogeneity in respondents' preferences on attributes. As Greene and Hensher [21] explain, the RPL is more flexible as it can induce nearly any behavioral assumption in terms of preference distribution, while the LCL benefits from its semi-parametric structure which does not require any assumption on the distribution of the parameters.

Several studies explicitly compare the RPL and the LCL for DCEs. Greene and Hensher [21], in a DCE on long-distance travel, analyze willingness to pay (WTP) values and choice probabilities and find small support for the LCL. The same conclusion is drawn by Birol et al. [22], who argue that apart from a better performance, the LCL is superior for welfare measures and interpretation in the context of wetlands restoration. Colombo et al. [23] use DCE data on public goods provision by agriculture and contrast three models, the RPL, the LCL and the covariance-heterogeneity model. Relying on statistical tests and welfare analysis, they find a small dominance of the LCL. Provencher and Bishop [24], in a DCE on recreational demand, find neither model dominating. Hynes et al. [25], also using DCE data on recreational demand, report similar results of the LCL and RPL in terms of welfare estimates but finally promote the LCL as the more informative one. Torres et al. [26] use Monte Carlo simulations to compare the LCL and RPL. They simulate preference heterogeneity based on a RPL and apply the data to a LCL and vice versa. Their findings imply that in case the RPL is the true model, the errors by using a LCL are rather small. In the opposite case, the errors are larger. Overall, they rate the performance of the RPL best. Hess et al. [27] use monte carlo simulations and an application to transport, concluding that the LCL is less computational demanding and able to capture more variants of preference heterogeneity. Beharry-Borg and Scapra [28] compare an RPL and a LCL using kernel density plots of individual WTP estimates for water quality improvements at the Caribbean coastal waters, finding some evidence that the RPL performs better.

The only study systematically comparing the two models in the field of energy is Yoo and Ready [29]. The authors focus on WTP for different types of renewable energy in Pensylvania, USA. In their approach, they use kernel density estimates of individual WTP and statistical goodness of fit measures to compare models. They compare the LCL and RPL models to the more advanced RPL-LCL model and include attribute-non-attendance in the latent class model by imposing restrictions on parameters. This approach allows to account for non-compensating behavior, e.g. when respondents ignore an attribute in their decision process [30]. Additionally, Yoo and Ready include socio-demographic interaction terms with the attributes to account for observed preference heterogeneity. They find that a RPL model with observed heterogeneity and the RPL-LCL model perform best, but note that all models provide valuable insights into preference heterogeneity. The study presented here differs from the approach of Yoo and Ready in two ways. First, I use data from an emerging economy where power supply is unstable and not continuously available. Economic development significantly depends on power supply and many private households are adversely affected by power cuts. Thus, the distribution of preferences in such countries can be expected to be very different from developed economies. Second, the present study does not focus on renewable energy only. It investigates further attributes including the organization of the electricity market and physical power quality. Both attributes are qualitatively different from renewable energy which is characterized by externalities and public good characteristics. Physical power quality, however, can be defined as a private good, and thus could imply a very different pattern of preference heterogeneity.

Summarized, most studies find a small dominance of the LCL. Further, the studies reveal that the differences of estimated parameters between the two models are large and may lead to different conclusions.

2.2. Models

In the following, I will briefly describe the models used in this application. I begin with the conditional logit (CL) model, which was first introduced by McFadden [31] and serves as the base model for the RPL and LCL. The CL is restricted by several assumptions such as the independence of irrelevant alternative assumption. Unlike the RPL and LCL, the CL is not capable to capture unobserved preference heterogeneity, and for this fact hardly used in applied work. I will then briefly outline the RPL and the LCL. Both models rely on the CL choice probability but relax the assumption of identical and independently distributed error terms. Ben-Akiva and Lerman [32] provide an introduction to the theoretical background of models for discrete choice.

2.2.1. Conditional logit model

Assume a randomly selected individual i who chooses repeatedly in t situations between several alternatives n. Each alternative accommodates attributes k with levels A_{iknt}. Assume indirect utility functions U_{int} for each alternative n, individual i in choice situation t to be linear in attribute levels A_{iknt}. For each alternative there are utility sensitive elements e_{int}. This formulation can be written as

$$U_{int} = V_{int} + e_{int} = \beta_1 A_{i1nt} + \beta_2 A_{i2nt} + \dots + \beta_k A_{iknt} + e_{int} \tag{1}$$

where V_{int} is the deterministic part of utility, A_{iknt} is the level of attribute k for alternative n in t and β_k are the corresponding utility parameters.

The CL choice probability is given by

$$Pr_{imt} = \frac{\exp(\beta_1 A_{i1mt} + \beta_2 A_{i2mt} + \dots + \beta_k A_{ikmt})}{\sum_{n=1}^{N} exp(\beta_1 A_{i1nt} + \beta_2 A_{i2nt} + \dots + \beta_k A_{iknt})} \tag{2}$$

2.2.2. The random parameters logit model

The RPL specification introduces a random component in the parameters as

$$\widetilde{\beta_{ik}} = \beta_k + \eta_{ik} \tag{3}$$

where η_{ik} is an error term with distribution $f(\eta_{ik})$ and mean 0 and variance ϕ^2. Hence $\widetilde{\beta_{ik}}$ is a random variable with distribution $f(\widetilde{\beta_{ik}})$ and mean β_k. The distribution of η_{ik} can be chosen by the researcher. Common distribution functions are ,for example, the normal, log-normal and triangular distributions. The unconditional RPL choice probability is given as a weighted average of all possible $\widetilde{\beta_{ik}}$ for the attribute parameters that are considered random.

$$\widetilde{Pr_{imt}} = \int_{\widetilde{\beta_{i1}}=-\infty}^{\infty} \int_{\widetilde{\beta_{i2}}=-\infty}^{\infty} \dots \int_{\widetilde{\beta_{ik}}=-\infty}^{\infty} Pr_{imt} f(\widetilde{\beta_{i1}}) f(\widetilde{\beta_{i2}}) \dots f(\widetilde{\beta_{ik}}) d(\widetilde{\beta_{i1}}) d(\widetilde{\beta_{i2}}) \dots d(\widetilde{\beta_{ik}}) \tag{4}$$

with

$$Pr_{imt} = \frac{\exp(\widetilde{\beta_{i1}} A_{i1mt} + \widetilde{\beta_{i2}} A_{i2mt} + \dots + \widetilde{\beta_{ik}} A_{ikmt})}{\sum_{n=1}^{N} \exp(\widetilde{\beta_{i1}} A_{i1nt} + \widetilde{\beta_{i2}} A_{i2nt} + \dots + \widetilde{\beta_{ik}} A_{iknt})} \tag{5}$$

2.2.3. The latent class logit model

The LCL can be regarded as a special case of the RPL with β_k taking a finite number S of values $\langle \beta_{k11}, \beta_{k12}, \dots, \beta_{kls} \rangle$ with corresponding

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