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Preference heterogeneity for renewable energy technology

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ABSTRACT

This study explores heterogeneity in individual willingness to pay (WTP) for a public good using several different variants of the multinomial logit (MNL) model for stated choice data. These include a simple MNL model with interaction terms between respondent characteristics and attribute levels, a latent class model, a random parameter (mixed) logit model, and a hybrid random parameter-latent class model. The public good valued was an increase in renewable electricity generation. The models consistently show that preferences over renewable technologies are heterogeneous among respondents, but that the degree of heterogeneity differs for different renewable technologies. Specifically, preferences over solar power appear to be more heterogeneous across respondents than preferences for other renewable technologies. Comparing across models, the random parameter logit model and the hybrid random parameter-latent class model fit the choice data best and did the best job capturing preference heterogeneity.

1. Introduction

Random utility models (McFadden, 1974) have a wide range of application in the analysis of choice data including recreational demand choice (Boxall and Adamovicz, 2002; Scarpa and Thiene, 2005; Train, 1998), stated choice valuation (Borchers et al., 2007; Revelt and Train, 2000; Scarpa and Willis, 2010), transportation choice (Greene and Hensher, 2003; Shen, 2010), and marketing (Swait and Adamowicz, 2001). Analyzing choice data with random utility models is often done by estimating a simple Multinomial Logit Model (MNL), which assumes that preferences are homogeneous across the population. The assumption of homogeneous preferences, however, is problematic since each person is unique in terms of habit, education background, characteristics, and income level, which might be correlated with preferences over non-market goods. Failure to incorporate the unique nature of each consumer in estimating discrete choice models would mask heterogeneity in preferences and could lead to biased estimates of average preferences over the population.

Several different extensions of the MNL discrete choice model have been developed that can accommodate consumer preference heterogeneity for non-market goods. Some of these also relax the IIA (Independence of Irrelevant Alternatives) assumption. The simplest and most commonly used approach is to interact attribute levels with measured individual characteristics to see whether people with different characteristics exhibit different preferences within the MNL model. This approach retains the unrealistic assumptions of the MNL model such as IIA and uncorrelated unobserved error over time. The IIA property assumes that the choice of alternatives A and B is not influenced by the addition or exclusion of the third choice, C. In general, this may not be a realistic assumption and create a problem of leading a model to erroneously predict the probability of choosing one alternative over the other. Also, assumption of uncorrelated errors might be problematic when using a panel data because a person's choice might be correlated across repeated choice through learning or fatigue effects. Two models that allow for preference heterogeneity and that relax the IIA assumption and/or uncorrelated error terms are the random parameter logit (RPL) model (Greene and Hensher, 2003; McFadden and Train, 2000; Train, 1998), also known as the mixed logit model, and latent class models (LCM) (Boxall and Adamovicz, 2002; Milon and Scrogin, 2006; Scarpa and Thiene, 2005; Swait and Adamowicz, 2001), also known as finite mixture models. Each model has strengths and weaknesses. LCM models are less flexible than RPL models, but have an advantage when it comes to computational simplicity. The continuous representation of preference variation in the RPL might be

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inappropriate when the sample consists of discrete groups with different group-specific tastes. The discrete representation of preference variation in the LCM cannot capture within-class heterogeneity. Using either of these models could oversimplify the taste variation of the sampled respondents (Allenby and Rossi, 1998; Bujosa et al., 2010; Wedel et al., 1999). A hybrid model that combines both continuous and discrete representation of taste variation was first proposed by Bujosa et al. (2010). They find that this hybrid model fits best in terms of statistical goodness-of-fit.

In this research, we estimate several different discrete choice models that accommodate preference heterogeneity. These models include the MNL model with interactions between choice attributes and respondent characteristics, a LCM, a RPL model, and a hybrid RPL–LCM. These models are compared in terms of how well they fit the data and their ability to identify heterogeneity in WTP. This research includes two advances over previous studies that have explored preference heterogeneity in discrete choice data. First, the LCM developed here places specific restrictions on parameter values for certain latent classes. These restrictions are motivated by previous research that shows that some respondents, when faced with a complex choice task, focus their attention on a restricted set of attributes, and ignore other attributes that are less salient to them (Blamey et al., 2001). We extend Scarpa et al. (2009) model of attribute non-attendance in our LCM. Second, following Greene and Hensher (2010), our hybrid RPL–LCM is estimated in a way that accounts for the panel nature of stated choice data, but extends their hybrid model by incorporating the same types of restrictions on the preference parameters for certain latent classes. Finally, this is the first study to compare all of the above mentioned models based on their ability to capture heterogeneity in individual WTP, and therefore represents an extension of what Beharry-Borg and Scarpa (2010) did.

This study, specifically, estimates Pennsylvania residents' preference over different renewable electricity production technologies and their willingness to pay (WTP) for an increase in renewable electricity production. Our results build on previous studies that have estimated WTP for increased renewable energy production (Borchers et al., 2007; Farha, 1999). We explore both the mean WTP for each of several different generation technologies and the degree of heterogeneity among respondents' individual for each technology.

Information on mean WTP for individual renewable technologies is important from a policy perspective. Currently, Pennsylvania has in force an Alternative Energy Portfolio Standard (AEPS) to promote renewable energy production. The current AEPS policy specifies a minimum for the amount of electricity that must come from renewable and alternative sources, setting minimum standards for renewable content. The AEPS includes a carve-out (technology-specific minimum) for solar, but does not set individual requirements for other renewable technologies such as wind, hydroelectric power and biomass. If Pennsylvania residents prefer some renewable technologies over others, that preference could be reflected in differential requirements in the AEPS. If Pennsylvania residents have negative views toward some renewable energy technologies, the current AEPS could force them to pay for technologies that they do not want.

It is equally important to know how WTP varies across the population, which is the main focus of this research. We find that mean WTP for some renewable technologies is positive, but that WTP exhibits heterogeneity such that an important proportion of the population has negative WTP for the technology. This result suggests that, while the average resident would support a policy that increases renewable energy production, an important proportion of residents could oppose such a policy. Policy makers in Pennsylvania should consider the entire distribution of preferences, rather than focusing only on the mean preference.

The paper is organized as follows. Section 2 reviews previous literature on two topics: comparisons of LCM and RPL models and attribute non-attendance behavior. Section 3 presents the models that will be estimated in this study, followed by descriptions of the goods being valued and of the survey methodology. Section 4 discusses the results and Section 5 presents a summary and discusses implications of the research.

2. Literature review

2.1. Previous studies on the RPL, LCM, and RPL–LCM models

Both the RPL and LCM models relax some of the restrictions of the MNL model, but they do so in different ways. Since MNL is nested within both of these two models,[2] comparisons between MNL and RPL and between MNL and LCM are feasible using likelihood ratio tests. Many recent studies (Beharry-Borg and Scarpa, 2010; Greene and Hensher, 2003; Kosenius, 2010; Shen, 2010) conclude that the LCM and the RPL both improve statistical fit relative to MNL. One exception is Provencher and Bishop (2004). However, a direct comparison between RPL and LCM cannot be made based on a likelihood ratio test, because one model is not nested within the other. In order to compare these two models, different approaches have been developed.

Greene and Hensher (2003) compare LCM and RPL models by looking at choice elasticities for a change in travel times, mean willingness-to-pay estimates, and choice probability plots,[3] and find that respondents' behavioral sensitivity to an attribute (changes in travel time) is reduced in the LCM relative to the RPL, although other measures such as choice probability plots and willingness to pay valuations yield similar patterns for both models. Shen (2010) adds a non-nested test[4] and prediction success indices to investigation of the choice probabilities, WTP valuations, and choice probability plots to test which model is better. She finds that the LCM is superior to the RPL in terms of these two measures. Shen (2010) and Greene and Hensher (2003) show that LCM fits better than RPL based on statistical goodness-of-fit.

Kosenius (2010) investigated consumer's preference heterogeneity for water quality attributes using RPL and LCM. In order to compare the two models, the author presents WTPs for 3 potential future nutrient reduction scenarios. Rather than focusing on statistical measures, Kosenius focused on the heterogeneity of WTP of a representative respondent. They conclude that a LCM was indisputably superior in terms of capturing the relative importance order of each attribute within different classes. However, the sample in that study was not representative of the population. They conclude that the RPL is better than the LCM when the sample is weighted to correct for sampling bias. Although their study was the first attempt to explore aspects of RPL and LCM other than statistical goodness-of-fit, the heterogeneity of individual WTP was not considered in their study.

Beharry-Borg and Scarpa (2010) were the first study to compare LCM and RPL based on individual WTP. They use 2 sub-samples, snorkelers and non-snorkelers, in a study valuing quality change in Caribbean coastal waters. They found that an LCM outperformed a RPL model for the snorkeler sample, but that the LCM did not behave well for the non-snorkeler sample. They did not directly compare RPL and LCM based on individual WTP within each subsample.

[2] In RPL, if a distribution of random coefficient is degenerate, then the integral term will vanish leaving a simple logit form behind. In LCM, if coefficients across different classes are the same, then the latent class model is reduced to the MNL. In that sense, MNL is a special form of both LCM and RPL (MNL is nested within LCM and RPL).

[3] Greene and Hensher (2003) plotted choice probabilities under LCM and RPL for each alternative and investigated the relationship between choice probabilities for RPL and those for LCM via OLS. They found that there is a weak relation between two models.

[4] Shen's non-nested test is based on an AIC proposed by Ben-Akiva and Swait (1986). The test procedure is as follows: Suppose there are 2 models (model 1 and model 2) and K_1 and K_2 represent the number of parameters in model 1 and model 2, respectively. Also define L_0, L_1 and L_2 represent the likelihood value for constant-only model, the likelihood value at convergence for model 1, and likelihood value at convergence for model 2, respectively. Then, fitness measure for model j is expressed as: $\rho_j^2 = 1 - \frac{L_j - K_j}{L_0}$. An upper bound for probability that model 1 is chosen as the true model despite model 2 being true is then given by $\Pr\left[\rho_2^2 - \rho_1^2 > z\right] \le \Phi\left[-\left(-2zL_0 + (K_1 + K_2)\right)^{\frac{1}{2}}\right]$, where z represents the difference between ρ_2^2 and ρ_2^2.