Annex C: Mixed Logit or Latent Class Logit

Two main families of models can incorporate unobserved preference heterogeneity into random utility functions: the mixed logit model (MXL) and the latent class logit model (LCL). The MXL assumes that the unobserved preference coefficients follow continuous distribution functions; the LCL assumes that they follow discrete distribution functions, i.e. the population can be divided into homogeneous classes of preferences. For each approach, an assumption is not based on a theoretical foundation and is left to the modeller's selection (Greene and Hensher, 2003): the functional form of the distributions (MXL) or the number of classes (LCL). There are no clearly defined rules for choosing between the two types of models. A recent review of the literature suggested there is no clear winner between the two types of approaches (Sagebiel, 2017) and proposed a set of indicators and procedures to decide empirically the best modelling formulation for a given data set. We discuss the choices we made in terms of modelling approach using measures of fit (Table 1) and the conditional willingness to pay values (Figure 1), as proposed in Sagebiel (2017).

We compared three models: a conditional logit (CL, for reference), a mixed logit model with an error component MXL-EC, and a latent class model with two classes (LC2). We used a LCM with two classes, because models with more than two classes identified classes in which the coefficients had very large standard errors that were not considered interpretable. We attributed this in part to the relatively small data set.

The measures of fit showed that both MXL-EC and LC2 fitted the data better than the CL model. However, they did not give a clear indication for choosing between MXL-EC and LC2. The pseudo R^2 and AIC give a slight advantage to the MXL-EC formulation, while the BIC and percentage of correctly predicted choices gave a slight advantage to LC2. Lastly, the comparisons of conditional WTPs for the two types of models showed that the LC model suggested bimodal distributions for the attributes Labour and Lower Fertility, which was less apparent when using a MXL-EC model, since MXL models can only use unimodal distributions. However, in the case of the "Lower Fertility" attribute, it was not completely clear whether this difference emanated from our difficulty in estimating a model with 3 latent classes, as the three peaks for the distribution of the parameters under the MXL formulation would suggest.

In the absence of a clear advantage of the LCM over the MXL-EC, and the greater flexibility allowed by the MXL formulation (given our small sample), we opted for a MXL approach. Moreover, the MXL also allowed us to test the possible different preferences for the "No-change" alternative using the additional Error Component.

Table 1: Measures of fit

	CL	MXL-EC	LC 2 Classes	Const Only
LL	-578.03	-532.59	-539.7	-777.86
Parameters	7	21	17	1
Pseudo R2	0.257	0.315	0.306	
Adj Pseudo R2	0.248	0.288	0.284	
AIC	1172.100	1107.20	1113.40	
AIC/N	1.628	1.54	1.546	
BIC	1208.70	1203.30	1191.30	
BIC /N	1.679	1.671	1.655	
Chi Sq Test	399.66	490.54	476.32	
Chi Sq Crit Value	12.591	31.41	26.29	
P Chi Sq	0.00	0.00	0.00	
Correct Pred	0.63	0.66	0.72	

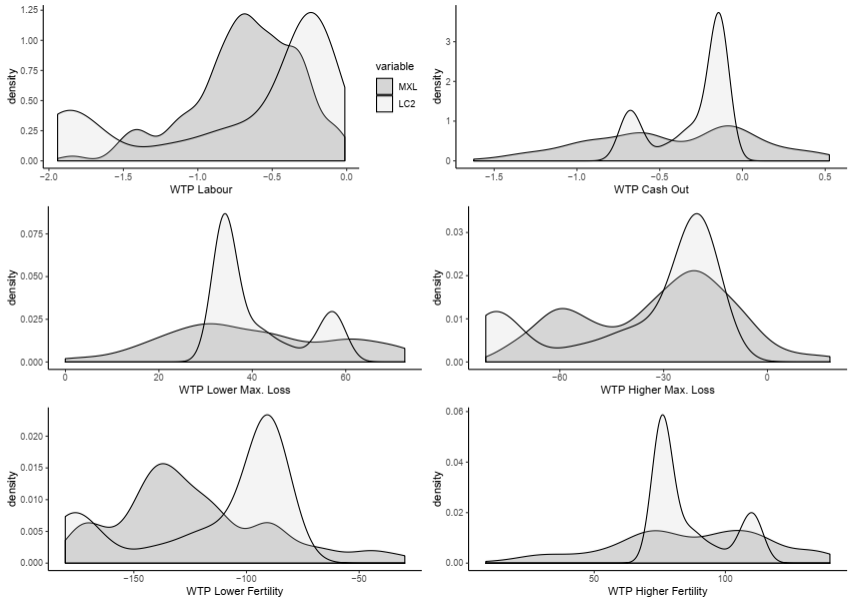

Figure 1: Conditional Willingness to Pay

References:

Greene, W. H., Hensher, D. A., 2003. A latent class model for discrete choice analysis: contrasts with mixed logit, Transport Res. B-Meth. 37 (8), 681-698.

Sagebiel, J., 2017. Preference heterogeneity in energy discrete choice experiments: A review on methods for model selection, Renewable and Sustainable Energy Reviews 69 (804-811.