Information and choice paradigms when exploring preferences for renewable energy

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Outline of the Presentation

- The effect of information on Choice Experiments
- Random Utility Maximisation
- Random Regret Minimisation
- Results
- Conclusions

Discrete Choice Experiments

In a **Discrete Choice Experiment** (DCE) survey, respondents are asked to choose between different goods or services described by a set of **attributes** (Louviere et al, 2000).

Stated preference method.

Goods differ by the **level** that two or more attributes take.

Respondents trade-off the levels of the attributes of the goods, one of which is usually cost, allowing to infer the **willingness to pay** for the good and the implicit value of each attribute.

How is regret important in energy?

The idea is not new and is well established theoretically and empirically in many fields.

How is regret important in energy?

Regret-minimization has been found to be particularly important when:

a) choices are perceived as important (much can be "lost" or "gained") and difficult;
b) the decision-maker expects to receive feedback about chosen and non-chosen options;
c) when choice sets are evaluated in terms of their desirability (+ compromise).

(psychology literature Zeelenberg and Pieters, 2007).

Regret: some features

- **Semi-compensatory behaviour**:
  - Improving an alternative in terms of an attribute on which it already performs well relative to other alternatives generates only small changes in regret (if any), whereas deteriorating to a similar extent the performance on another equally important attribute on which the alternative has a poor performance relative to other alternatives may generate substantial increases in regret.
- **Compromise effect**:
  - Alternatives with an 'in-between' performance on all attributes, relative to the other alternatives in the choice set, are generally favoured by choice-makers over alternatives with a poor performance on some attributes and a strong performance on others.

Random Utility Multinomial Logit Model

1) $$U_{ni} = V(\beta, X_{ni}) + \varepsilon_{ni}$$

2) $$Pr_{nit}^{RU} = \frac{e^{\mu V_{nit}}}{\sum_{j=1}^{J} e^{\mu V_{njt}}},$$

$$\text{where } V_{nit} = \beta' x_{nit}.$$

n = respondent
i = alternative in the choice set *j*
X = vector of *m* attributes,
β = vector of parameters to be estimated
ε = i.i.d. error term

Random Regret Multinomial Logit Model

$$R_i = max_{j \neq i}\left\{ \sum_{m=1...M} max\left\{0, \gamma_{m(x_{jm}-x_{im})}\right\}\right\}$$

(Chorus, 2008)

$$R_i = \sum_{j \neq i} \sum_{m=1..,M} \ln\left(1 + e^{\gamma_m\left(x_{jm}-x_{im}\right)}\right)$$

(Chorus, 2010)

$$R_{nit} = \sum_{j \neq i} \sum_{m=1..,M} \ln\left(1 + e^{\frac{\theta_m}{\lambda}(x_{jm} - x_{im})}\right)$$

(Van Cranenburgh et al. 2015)

$$R_i^{P-RRM} = \sum_m \beta_m x_{im}^{P-RRM} \qquad where\ x_{im}^{P-RRM} = \begin{cases} \sum_{j \neq i} \max\left(0, x_{jm} - x_{im}\right) if\ \beta_m > 0 \\ \sum_{j \neq i} \min\left(0, x_{jm} - x_{im}\right) if\ \beta_m < 0 \end{cases}$$

(Van Cranenburgh et al. 2015)

$$Pr_{nit}^{RR} = \frac{e^{\lambda(-R_{nit})}}{\sum_{j=1}^{J} e^{\lambda(-R_{njt})}}$$

Identifying the drivers of choice behaviour

We use a ‘behavioural latent class approach’ (Hess et al. 2012; Boeri et al, 2014), to investigate the determinants of class—and hence of choice behaviour. We define a two class latent class model in which the choice probability within each class is defined by one of the two choice paradigms under consideration:

$$\Pr(y_{Tn}|X_{nit}) = \prod_{t=1}^{T} \left(\pi_V \, Pr_{nit}^{RU} + (1 - \pi_V) \, Pr_{nit}^{RR} \right)$$

$$\pi_V = \frac{\exp(\alpha_c + \gamma_c^{'} z_n)}{\exp(\alpha_c + \gamma_c^{'} z_n) + 1}$$

The case study

Case study: hypothetical renewable energy program

Attribute	Level 1	Level 2	Level 3	Level 4	Status quo
Annual reduction in greenhouse gas emissions due to renewable energy increase (3 levels)	1%	2%	3%	-	no additional greenhouse gas emissions reduction
Annual length of electricity shortages in minutes (3 levels)	30	60	120	-	no change in current levels of black out
Change in number of employees in the electricity sector (3 levels)	+1000	-1000	0	-	no employment change in the energy sector
Increase in electricity bill in £ (4 levels)	6	16	25	38	no price increase in the electricity bill

Example of DCE

Suppose you are asked to choose between hypothetical programs for promoting renewable energy. These programs are described in terms of the effect they have on greenhouse gas emission, black-outs, employment in the energy sector and energy bills...

Characteristics	**Policy A**	**Policy B**	**Neither**
Greenhouse Gas emissions	3% reduction per year	1% reduction per year	no additional greenhouse gases emissions reduction
Black-outs	30 min per year	60 min per year	no change in current levels of black outs
Employment	0 new jobs	-1,000 jobs	no employment change in the energy sector
Electricity bill increase	£25 per quarter	£6.5 per quarter	no price increase in the electricity bill
Which policy would you choose?	☐	☐	☐

Sampling and sample

300 in-person interviews

Respondents intercepted in shopping areas, public parks and other central areas of Bath, England, in July and August **2005** by professional interviewers.

To create the pairs of alternative hypothetical policies, we opted for a **fractional factorial design** (Louviere et al, 2000).

We then selected two of these alternatives, but discarded pairs containing dominated or identical alternatives and prepared six different versions of the questionnaire with six choice tasks each.

Results: descriptive statistics

Variable (acronym used in regressions)	Observations	Sample average or percent (Standard deviation)
Age	300	35.75 (12.52)
Annual Income in £	300	37,687.29 (26528.63)
Electricity bill in £ (BILL)	197	70.86 (38.78)
Dummy variables		
Male	300	51.33%
Have a college degree (UNIVERSITY)	300	22.66%
Married (MARRIED)	300	28.67%
Have children	300	25.66%
Member of environmental organizations (ENV_ORG)	300	22.00%
Use green electricity (GREEN_ELECTRICITY)	300	12.00%
Did not state the electricity bill (NOBILL)	300	34.33%
Answered DCE questions as best for society (SOCIETY_ CHOICE)	300	75.67%
Answered DCE questions as best for the individual	300	24.33%
Received the additional information on black-outs (BLACKOUT_INFO)	300	44.00%
Electric heating	300	30.33%

Results: RU-MNL and RR-MNL

	RU-MNL		RR-MNL		μRR-MNL	
Attribute	**Coeff**	**t-stat**	**Coeff**	**t-stat**	**Coeff**	**t-stat**
BLACK-OUT	-0.001	9.17	-0.007	9.71	-0.006	8.40
GREENHOUSE GASES REDUCTION	0.928	13.00	0.751	14.76	0.727	14.48
JOBS	0.0007	9.79	0.0005	11.61	0.0004	9.28
PRICE	-0.013	2.42	-0.015	4.36	-0.012	3.60
λ					0.393	2.39
Log-likelihood (LL)	-1535.497		-1512.959		1508.409	
Parameters	4		7		8	

Results: RU-RPL and RR-RPL

	RU-RPL		RR-RPL		μRR-RPL		PRR-RPL	
Attribute	**Coeff**	**t-stat**	**Coeff**	**t-stat**	**Coeff**	**t-stat**	**Coeff**	**t-stat**
BLACK-OUT	-0.0162	9.70	-0.0118	10.29	-0.0123	10.12	-0.0121	9.91
GREENHOUSE GASES REDUCTION	1.39	11.69	1.45	11.52	1.53	12.03	1.49	11.74
JOBS	0.0011	8.94	0.0008	10.49	0.0008	10.29	0.0008	10.42
PRICE	-0.0221	3.27	-0.0320	7.02	-0.0313	7.62	-0.0304	7.32
λ					0.12	1.15		
Standard deviations								
BLACK-OUT	0.0124	5.87	0.0078	4.70	0.00854	5.41	0.00984	5.85
GREENHOUSE GASES REDUCTION	0.759	9.12	0.748	9.11	-0.825	-9.1	-0.896	10.13
JOBS	0.0012	10.27	0.0007	10.04	0.00065	9.67	0.00073	10.16
Log-likelihood (LL)	-1413.100		-1381.615		-1367.912		-1370.022	
Parameters	7		7		8		7	

The effect of information on DCE

The information respondents receive before answering the DCE questions may affect their answers.

Arrow et al. 1993, NOAA Panel on Contingent Valuation:

“It is important to provide respondents facing a stated preferences questionnaire with a <u>detailed and accurate description of the proposed scenario</u>, so that they know what they are being asked to evaluate and can make an informed decision”

The effect of information on DCE

From the previous example, let's consider the 'black-out' attribute:

"As the demand for electricity increases, it is likely that we will experience an increase in the number and in the length of black-outs since the grid might not be able to satisfy the total demand. ***Having black-outs means that there is no electricity. As a consequence, we would have no light at home, the fridge would not work, so wouldn't the lifts, etc. Also the industrial production would suffer.*** Using renewable sources, we increase the number of the sources from which we can produce electricity, which lowers the risk associated with the dependence of foreign energy suppliers so that the disruption of one of the sources will have smaller effects on the total energy supply."

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The effect of information on stated preferences studies

- Boyle, 1989, Land Economics
- Rolfe et al., 2002, Australian Journal of Agricultural and Resource Economics
- Bergstrom et al. 1990, American Journal of Agricultural Economics
- Spash and Hanley 1995, Ecological Economics
- Ajzen et al. 1996, Journal of Environmental Economics and Management
- Gao, Z. and Schroeder, T. C., 2009, American Journal of Agricultural Economics

The effect of information in RU

	RU-MNL		RU-RPL	
specification	**LL**	**K**	**LL**	**K**
pooled model (info and not) no scale	-1535.497	4	-1413.100	7
scaled model	-1534.634	5	-1412.888	8
only not added info	-871.174	4	-604.140	7
only additional info	-661.825	4	-804.547	7
TEST under RU-MNL model	**TEST MNL**	**χ at P = 0.10**	**P = 0.05**	**P = 0.01**
H1a (D.G.F. = 9)	3.27	14.68	16.92	21.67
H1b (D.G.F. = 1)	1.73	2.71	3.84	6.63
TEST under RR-MNL model	**TEST RPL**	**χ at P = 0.10**	**P = 0.05**	**P = 0.01**
H1a (D.G.F. = 15)	8.40	25.00	30.58	37.70
H1b (D.G.F. = 1)	0.42	2.71	3.84	6.63

The effect of information in RR

- Estimating scaled RR MNL models we find that the subsample with less info has scale = 0.

- When accounting for heterogeneity (RPL) scale is not significantly different from zero in both subsamples (as in the full sample).

- So no real impact of the changed info in either RU and RR.

Results: Latent Class model

	RU-MNL-class		RR-MNL-class	
Attribute	**Coeff**	**|t-stat|**	**Coeff**	**|t-stat|**
BLACK-OUT	-0.017	6.90	-0.0077	7.35
GREENHOUSE GASES REDUCTION	1.81	7.72	0.713	12.52
JOBS	0.00032	1.78	0.00086	11.59
PRICE	-0.0196	1.61	-0.0275	6.97
Membership probability model	45.59%		54.41%	
INTERCEPT	-2.75	1.78		
BLACKOUT_INFO	0.261	0.91		
SOCIETY_CHOICE	0.0331	0.1		
BILL[a]	-0.0035	0.75		
NOBILL	-0.312	0.69		
AGE	0.11	1.53		
AGE_SQUARED	-0.001	1.14		
MARRIED	-0.211	0.62		
ENV_ORG	0.846	2.49		
Log-likelihood (LL)	-1,394.238			
Number of parameters	17			

Conclusions

- We have estimated MNL (4 models – RUM, RRM, μRRM, PRRM), RRM performs better than RUM. Scale in μRRM significantly different from 0 and from 1.

- Then we have estimated RPL (again 4 models – RUM, RRM, mRRM, PRRM) again RRM good.
  - Note the scale in the RRM tends to zero!
  - P-RRM (truncated distributions) is the best model in terms of model fit.

- No impacts of different information on 1 attribute black-outs either on scale for RUM or RRM (nor in the hybrid…).

Conclusions

- We have estimated latent class (hybrid) models with no preferences heterogeneity and with preference heterogeneity.

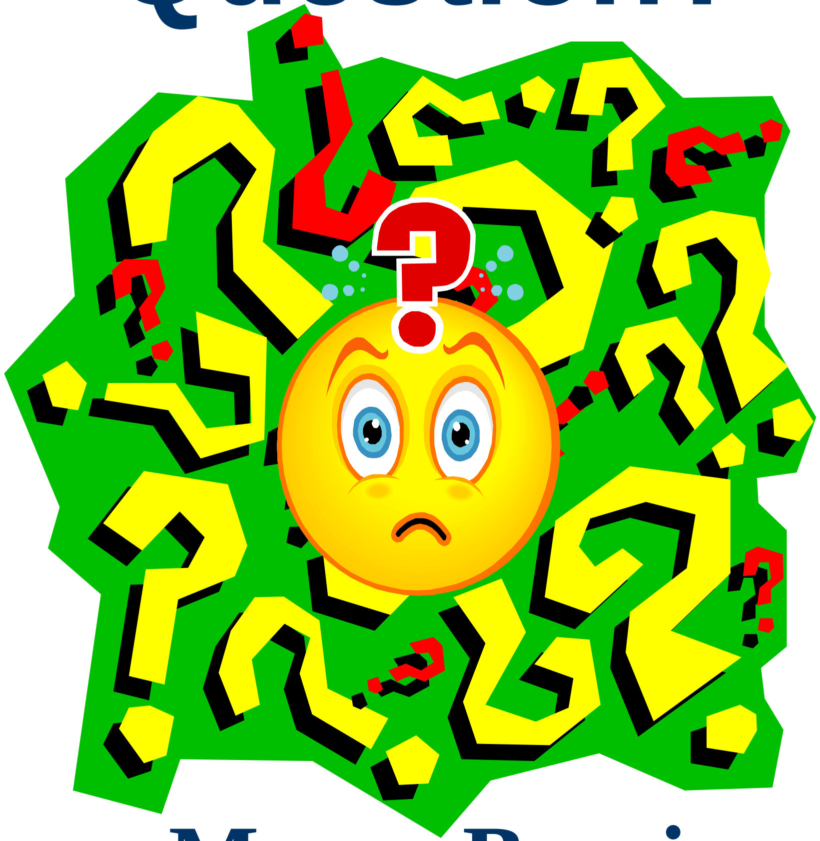
No preference heterogeneity

- When looking at 3 classes μRRM completely free, we get one class with scale = 0 (pure RRM) and one with scale very high (RUM) plus a third class with scale not significantly different from zero (and with very low membership probability).
  - We note that these models are not identifiable (numerical problem when scale = 0 – or very high).
  - we suggest to recode the class with scale = 0 with a pure RR model and the class with very high scale with a RUM model.

Preference heterogeneity,

- hybrid models are not identifiable and all classes scale = 0, suggesting the best model is the P-RRM, with truncated distributions.

Question?



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