Combining data gathering efficiency with behaviourally realistic modelling

A case of park-and-ride facility choice data gathered with a Sequential Best Worst Discrete Choice Experiment and estimated with a Random Regret Minimisation model

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ABSTRACT

This research combines two relatively new additions to the field of discrete choice modelling: sequential best worst discrete choice experiments (SBWDCE) and random regret minimisation (RRM) modelling, with the hope of developing a more behaviourally realistic choice model. SBWDCEs are able to gather a larger number of stated choice observations from fewer respondents, while RRM models challenge the notion of fully compensatory behaviour implied by the traditional RUM model and suggest that consumers choose to minimise regret. According to image theory, best and worst choices are not made with the same kind of decision rule, so accounting for that variability using a μRRM model would produce a more realistic model with better model fit. Estimating the combined model proves that people do in fact use a compensatory decision rule when selecting the best alternatives and a semi- to non-compensatory decision rule when selecting the worst. The results also show that the way choice set size variation is accounted for can greatly impact the scale parameters, as these and the choice set size constants are inversely related. Although a better model fit was achieved, using best-worst tasks is contested and researchers also warn against the lower reliability of additional choices in the same choice set. Nevertheless, SBWDCEs provide great benefits in fields with small population sizes and can potentially help in obtaining higher quality prior parameter values for use in efficient experimental design generation.

Introduction

Discrete choice modelling (DCM) is a disaggregate method of analysing consumer preference, market share and future demand. It is used in a variety of sectors, including transportation, where the method was developed in the second half of the 20th century. The first applications of the model used only a simple logit model of binary mode choice, with alternatives described by travel time and travel cost (Ben-Akiva & Lerman, 1994). One of the first notable applications was for the Bay Area Rapid Transit (BART) system in the San Francisco area (McFadden, 2000). Over the years, choice models have been advanced and expanded to include multiple alternatives, socio-demographic characteristics of the respondents, preference and taste heterogeneity, use of different decision rules, latent classes etc. The applications of DCMs were also extended to the fields of telecommunications, healthcare, environment, energy etc. (McFadden, 2000).

Advancements of the initial first-choice random utility maximisation (RUM) multinomial logit (MNL) model have been developed as a response to the model lacking realistic behavioural representation for a certain aspect of user behaviour. Multinomial logit was introduced to accommodate more than two alternatives (Chorus, 2016). Preference and taste heterogeneity, modelled with the help of a mixed logit model, have allowed researchers to analyse how preferences and tastes differ within a sample (Chorus, 2016). A different approach of analysing variations of taste and preference are latent classes, where parameters do not vary. Instead, multiple classes with their own parameters are estimated and the parameters in each class can take up a different value, based on what the tastes and preferences of that class's members are (Hess, Ben-Akiva, Gopinath, & Walker, 2008). Different decision rules, such as the RRM challenge the notion of compensatory behaviour of respondents, assumed by the RUM model (Chorus, Arentze, & Timmermans, 2008).

These and many other advancements of DCMs make choice modelling more behaviourally realistic and provide insight into the decision-making process of consumers. With the objective of developing even more realistic choice models, the opportunity is taken to combine two relatively new advancements in the choice modelling field: sequential best worst discrete choice experiments (SBWDCE) and generalised random regret minimisation (RRM) modelling.

SBWDCEs are a more efficient data gathering technique, where respondents make multiple choices within the same choice set, providing a greater number of observations per choice set and per respondent. These choices are made by alternatingly selecting the best / worst alternative until the choice set is exhausted, meaning a single alternative remains. Asking respondents to make multiple choices within a single choice set can lead to successive choices being less reliable and taste parameters less intense, so the data should not be modelled without an additional scale parameter (Ben-Akiva, Morikawa, & Shiroishi, 1992).

There is reason to believe that best and worst choices are not made using the same decision rule. Image theory postulates that people use a two-step approach when making a choice: first evaluating the alternatives on their compatibility (removing all the alternatives performing below a certain threshold) and then maximising one's own profitability (selecting the best alternative from those remaining). While compatibility is a non-compensatory decision-making process, profitability is compensatory (Beach & Mitchell, 1987) (Meloy & Russo, 2004). In the case of best-worst choice tasks, best choices may be made in line with profitability and worst choices with compatibility.

By estimating SBWDCE data with a generalised RRM model, the hypothesis of different decision rules can be tested. Estimating the decision rule can be done with the help of the μRRM model (van Cranenburgh, Guevara, & Chorus, 2015), which includes a scale parameter that represent the rate of compensatory behaviour, where a value close to zero implies non-compensatory behaviour and a value above ten indicates fully compensatory decision-making.

The next section provides a further, more detailed analysis of both SBWDCEs and RRM modelling. The third section shows the exact models that are estimated and compared in this research. A description of the dataset and the experimental design generation are also given. Section four looks at the outcomes of the model estimations and compares the different models with various statistical tests. Finally, the conclusion provides a discussion of the results, the implications and limitations of the developed models and recommendations for future research.

Research methods

Sequential best worst discrete choice experiments and random regret minimisation modelling are two advancements of DCMs that have been introduced to the scientific community and have been a topic of further research in the last decade.

SBWDCEs are an efficient stated choice gathering technique that captures additional preference information, allowing a model with significant estimates to be obtained from a lower number of respondents (Louviere et al., 2008). The method was successfully applied on a larger scale in the healthcare domain for the treatment of cardiac arrest in public spaces (Lancsar, Louviere, Donaldson, Currie, & Burgess, 2013). How SBWDCEs work is they ask the respondents to not only select the alternative they prefer (like first-choice DCE), but to keep making choices, selecting best, then worst, then best and so on, until the choice set is exhausted, meaning a single alternative remains. In a choice set of five alternatives for example, this gives researchers four times as many observations from a single choice set. Asking respondents to make choices within the same choice set is also less burdensome than providing them with new choice sets, as they are already familiar with the choice set and need less cognitive effort to make a subsequent decision (Lancsar et al., 2013).

The gathered SBWDCE data is then analysed using either a rank ordered logit (ROL) which takes the implied rank of the alternatives (based on the choices made) or preferably a sequential best worst MNL (SBWMNL), which models the data in a way that is more similar to how the choices were made (Lancsar et al., 2013). Modelling worst choices is done the same as for best choices, but using negative utilities in the logit function, meaning that the alternative with the highest disutility is the most likely to be selected as the worst alternative.

Random regret modelling is a data analysis technique that contests the belief that people make choices in a fully compensatory manner (Chorus et al., 2008). Compensatory behaviour implies that decision-makers are willing to overlook an alternative performing poorly on one attribute, if the performance on another is superior to the same extent. Non-compensatory behaviour on the other hand, states that performing well on an attribute adds no value to the alternative, whereas performing badly on another reduces its attractiveness. Unlike RUM models, where alternatives are evaluated solely on their own performance, RRM models make binary comparisons among alternatives. The regret (analogous to utility) of each alternative is a summation of individual regrets when said alternative is compared to all other alternatives. A logit model is then used in the same way as in RUM models, with the negative value of regret being used in the calculation (Chorus et al., 2008).

A generalisation of the RRM model is the μRRM model, which includes a scale parameter (μ) that is freely estimated in the model, along with the taste parameters (van Cranenburgh, Guevara, et al., 2015). This scale parameter should not be mistaken for the scale parameter present in the variance of the error term in traditional RUM models, which is often associated with choice consistency (and fixed to one) (Train, 2009).

Based on the value the scale parameter takes up, a decision rule can be inferred. If the scale parameter approaches zero, the behaviour is non-compensatory. A value around one infers semi-compensatory behaviour, as in the regular RRM model (Chorus, 2010). For all values above ten (towards infinity), the decision rule can be assumed to be fully compensatory or RUM.

Model specification

The experimental design used in the survey was a Bayesian efficient design due to a level of uncertainty regarding the prior parameter values (Walker, Wang, Thorhauge, & Ben-Akiva, 2018). The experimental design was also constructed in a way that makes it more robust towards the underlying decision rule. By applying a novel technique, D-errors were calculated for both RUM and P-RRM decision rules and the design with the lowest composite D-error was selected for the survey (van Cranenburgh, Rose, & Chorus, 2018). The presented data gathering technique was used to obtain 108 responses on a topic of park-and-ride facility choice.

Each choice set contained five alternatives, described by five attributes with either three or two levels (Table 1).

Table 1. Attribute specification

Attribute	Var.	Levels
Travel time by car	Car	5, 15, 25 [min]
Travel time by public transport	PT	10, 20, 30 [min]
Trip cost	Cost	1, 5, 9 [€]
PT service headway	Head	5, 15, 30 [min]
Public transport mode	Mode	bus, train

The data was then estimated using a variety of models that were developed, along with three already proven DCMs: first-choice RUM model, first-choice μRRM model and the SBWMNL RUM. A total of five models were developed, with different numbers of scale parameters and different ways of accounting for choice set size variation. Because the choice set size decreases in successive choices in the same choice set, this needs to be accounted for, since in RRM models, the number of alternatives in a choice set influences the overall regret of alternatives. One way of accounting for this is to add to all but one of the choice set sizes an additional regret correction factor. The second option is very similar, except that it uses a single regret correction constant that is then adjusted with the choice set size (van Cranenburgh, Prato, & Chorus, 2015). While the former is less restrictive, the latter is more flexible with respect to applications in choice set sizes not modelled in the estimation process.

The three existing models are labelled as E.1, E.2 and E.3, with the five models developed in this research labelled from E.4 to E.8. The specification of each model is shown in Table 2. Models with two scale parameters model the best and worst choices separately, while the models with four scale parameters model each individual choice. Model E.4 with a single scale parameter, tests which decision rule is best if applied across all the choices.

Table 2. Specification of the developed models

	E.4	E.5	E.6	E.7	E.8
# of μ	1	2	4	2	4
# of Λ	3	3	3	1	1

In addition, model E.5 is also estimated with the scale parameters fixed to represent either a RUM (μ=10) or a P-RRM decision rule (μ=0,1). All four combinations are shown in **Error! Not a valid bookmark self-reference.**.

Table 4. Models with implied decision rules

	I.1	I.2	I.3	I.4
Best choices	RUM	P-RRM	RUM	P-RRM
Worst choices	RUM	P-RRM	P-RRM	RUM

Results

Analysing the models with implied decision rules (Table 4), the models with a RUM decision rule for best choices (I.1 and I.3) perform better than the other two models, with a log-likelihood that is 45 points higher. A Ben-Akiva and Swait test (Ben-Akiva & Swait, 1986) also proves this, as models E.2 and E.4 have a near zero probability of being the true models of the population. Comparing the better fitting models I.1 and I.3, the one assuming a RUM decision rule for worst choices (I.1) performed slightly better, with a log-likelihood that is only 0,08 points higher. Even the Ben-Akiva and Swait test showed that model I.3 has a 34% probability of being the true population model. This may indicate that the utilised decision rule is between fully and non-compensatory behaviour.

In the models with estimated decision rules, shown in Table 5 and Table 6, the highest model fit was achieved by both first-choice only models, significantly outperforming all the SBW models with a rho-squared almost two times higher.

In SBW models, several values needed to be fixed for the model to converge. For best choices, the scale parameter was often fixed to ten as the estimate was initially much higher and since there is virtually no difference between a scale parameter value of ten or higher, the model cannot converge. For models E.6 and E.8, the μWorst 2 was fixed to an arbitrary value of one, as only two alternatives are present, so the RRM

Table 3. Model outcomes of models with inferred decision rules

	I.1	I.2	I.3	I.4
μBest	10	0,1	10	0,1
μWorst	10	0,1	0,1	10
Null LL	-6204,59	-6204,59	-6204,59	-6204,59
Final LL	-5346,00	-5391,87	-5346,08	-5396,12
Rho-squared	0,1384	0,1310	0,1384	0,1303

Table 5. Model outcomes of models E.1, E.2, E.3 and E.4

	E.1		E.2		E.3		E.4	
	Estimate	p-val	Estimate	p-val	Estimate	p-val	Estimate	p-val
Car	-0,0874	0,00	-0,0350	0,00	-0,0581	0,00	-0,0371	0,00
PT	-0,0601	0,00	-0,0241	0,00	-0,0453	0,00	-0,0282	0,00
Cost	-0,2918	0,00	-0,1168	0,00	-0,2274	0,00	-0,1412	0,00
Head.	-0,0643	0,00	-0,0257	0,00	-0,0383	0,00	-0,0260	0,00
Mode	0,1875	0,00	0,0770	0,00	0,1864	0,00	0,1004	0,00
μ			53,50	0,00			[2] 10,00	
Λ 5							[2] 0,86	
Λ 4							0,61	[1] 0,00
Λ 3							1,00	[1] 0,95
Null LL	-2085,83		-2085,83		-6204,59		-6204,59	
Final LL	-1549,08		-1548,82		-5397,20		-5346,00	
Rho-sq.	0,2573		0,2575		0,1301		0,1384	

[1] p-value calculated for difference from 1, instead of 0
[2] value fixed based on prior estimation, which did not converge

Table 6. Model outcomes of models E.5, E.6, E.7 and E.8

	E.5		E.6		E.7		E.8	
	Estimate	p-val	Estimate	p-val	Estimate	p-val	Estimate	p-val
Car	-0,0367	0,00	-0,0366	0,00	-0,0368	0,00	-0,0369	0,00
PT	-0,0282	0,00	-0,0282	0,00	-0,0280	0,00	-0,0281	0,00
Cost	-0,1399	0,00	-0,1392	0,00	-0,1367	0,00	-0,1371	0,00
Head.	-0,0264	0,00	-0,0265	0,00	-0,0267	0,00	-0,0268	0,00
Mode	0,1023	0,00	0,1037	0,00	0,0954	0,00	0,0957	0,00
μBest (1)	[2] 10,00		[2] 10,00		[2] 10,00		[2] 10,00	
μWorst (1)	0,43	0,01	0,43	0,01	0,36	0,00	0,36	0,00
μBest 2			0,50	0,05			12,31	0,55
μWorst 2			[3] 1,00				[3] 1,00	
Λ					5,23	0,00	5,25	0,00
Λ 5	0,87	[1] 0,24	0,88	[1] 0,27				
Λ 4	0,70	[1] 0,00	0,71	[1] 0,00				
Λ 3	1,00	[1] 0,99	1,11	[1] 0,48				
Null LL	-6204,59		-6204,59		-6204,59		-6204,59	
Final LL	-5340,49		-5337,51		-5372,99		-5372,95	
Rho-sq.	0,1393		0,1397		0,1340		0,1340	

[1] p-value calculated for difference from 1, instead of 0
[2] value fixed based on prior estimation, which did not converge
[3] value fixed because in a choice set with 2 alternatives, RRM reduces to a RUM model

model reduces to a RUM model and all scale parameter values yield the same result. The p-values of the choice set size constants (Λ) are calculated with respect to their difference from one, as that would be the value if no choice set size constant is present.

All the developed models outperformed the SBWMNL RUM model. The best fit was achieved by model E.6, which also has the highest number of parameters. It is closely followed by model E.5, which uses two instead of four scale parameters. Using the likelihood ration test (LRT) to compare E.5 and E.6, the probability of E.6 achieving a better fit due to sample peculiarities is 0,05. This comes mostly from the second-best choice being made with semi- to non-compensatory behaviour instead of fully compensatory as implied in E.5.

If a single scale parameter is inferred across all choices, fully compensatory behaviour seems to be most accurate, as the scale parameter had to be fixed to ten after achieving a higher initial value in a non-convergent model. Interestingly, model E.4 outperformed even models E.7 and E.8, despite only using a single scale parameter.

Models E.7 and E.8 performed almost the same, with a difference of only 0,04 log-likelihood points. This is echoed in the LRT which states that E.8 achieving a better fit is almost entire due to sample peculiarities, with a p-value of 0,96. Comparing these models to E.4, E.5 and E.6, using a single Λ produces a worse model fit, regardless of the number of scale parameters. The multiple choice set size constants in models E.4, E.5 and E.6 do not follow a linear relationship, so forcing one onto the model resulted in lower model fit. As the scale parameters and choice set size constants are rooted in each other, restricting the constant to a single choice-set-size-adjusted value results in the model performance declining and it also influences the scale parameter, as the μBest 2 changes from 0,5 in E.6 to 12,31 in E.8.

It was observed that differences in model fit were smaller when switching between decision rules for each additional choice: switching between RUM and P-RRM made a big difference for the first-best choice (over 50 LL points) and less for the first-worst (5-10 LL points) and second-best (2-10 LL points). This explains why μBest 2 changed from RRM to RUM with a different specification for choice set size. It is also why in model E.4, where a single scale parameter value was used, converged to a RUM decision rule across all choices made.

Investigating the relationship between the scale parameter and choice set size constant reveals it is inverse: when one increases in value, the other will decrease. That is why μBest 2 changed so much, as the individual constant for a choice set size three was 1,11 in E.6, while in E.8 when adjusted for choice set size, it only had a value of 0,57. To compensate for this change, the scale parameter needed to increase in value.

The individual estimates and two inverse relationship curves are plotted in Figure 1, where the relationship can clearly be distinguished. Two different curves were plotted with the relationship either allowed to limit at an estimated value (f(x)=a/x + b) or limiting towards zero (g(x)=a/x). Function f(x) can be justified because the values of the scale parameter above ten can increase towards infinity with minimal change to the model outcome. Function f(x) achieved a very good fit of R^2=95,45%, while g(x) achieved R^2=61,73%.

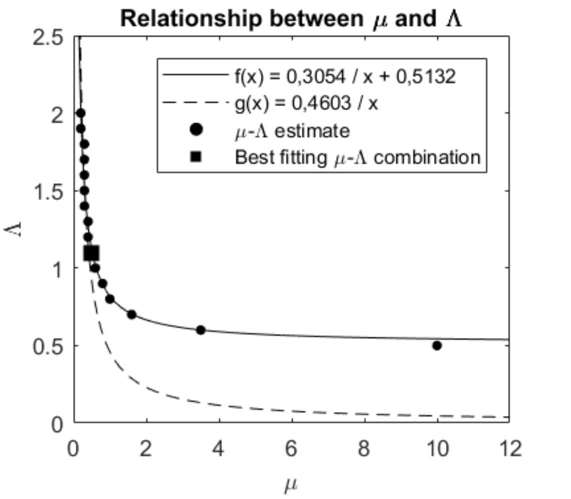

Figure 1. Relationship between the scale parameter and choice set size constant

Conclusions and recommendations

This research has shown that different decision rules are indeed utilised in best-worst choice tasks, with the decision rules for the most part being in line with image theory: best choices made using fully compensatory behaviour and worst choices using (mostly) non-compensatory behaviour. Because of this, models accounting for such variation performed better in terms of model fit and validation.

While image theory (Beach & Mitchell, 1987) may explain best / worst choice decision rules, it does not explain why the second-best choices were once compensatory and once not. This may be due to successive decisions being less reliable compared and the fact that taste parameters are liable to be less intense (Ben-Akiva et al., 1992) (Dyachenko, Reczek, & Allenby, 2014) and as these were the same across all choices, the scale parameter had to compensate for this. The inaction effect (Zeelenberg, van den Bos, van Dijk, & Pieters, 2002) may have also played a role in this, stating that when choosing not to act (which can be assumed when selecting worst or even second-best), respondents are more likely to experience regret and thus decide with anticipated regret in mind.

The use of best-worst style surveys is contentious, as although it offers far more observations from a lower number of respondents, it is criticised for being an unnatural way of decision-making (Dyachenko et al., 2014). Even some respondents of the survey commented on this issue. Each individual field of application may also be more or less suitable for best-worst tasks, with transport possibly falling under the less suitable. Best-worst tasks are widely applicable in healthcare (Flynn, Louviere, Peters, & Coast, 2007) (Zhang, Reed Johnson, Mohamed, & Hauber, 2015) and SBWDCE prove very useful in cases of very small populations to which certain surveys are relevant (a small group of patients suffering from a rare medical condition for example). An interesting potential for SBWDCEs is obtaining prior parameter values from a pilot survey. For efficient experimental designs, researchers need prior parameter values, which often cannot be obtained from literature. Surveys for obtaining priors are often much more limited compared to the main stated choice surveys. Using SBWDCE would therefore allow researchers to obtain significant prior parameter estimates from a small number of respondents.

Although providing more behaviourally realistic model outcomes, the developed models also have limitations. Introducing additional parameters results in models becoming more complex and the time needed to estimate results increases. Of the developed models, flexibility for application was also found to be an issue, as because the scale parameter and choice set size constant are linked, only one pair of the parameters can be used for each choice set size. This can be remedied to a certain extent by using a single choice set size constant, but this area of modelling requires further research. Another reoccurring issue is RRM models not being applicable for project appraisal in the same way as RUM models, due to their inability to determine the net welfare effect (the value of the whole choice set), although researchers have made progress in this field as well (Dekker, 2014) (Dekker & Chorus, 2018).

This research adds to the understanding of respondent behaviour in stated preference situations and in the field of SBWDCEs, showing that respondents do indeed utilise different decision rules, as is postulated in image theory. It also opens many new possibilities to be investigated. Given the specific nature of SBWDCEs, efficient experimental designs specifically for best-worst tasks should be analysed and a new / different D-error that incorporates all possible choices (not only the first-best) could be determined. Examining whether random errors are choice set specific, alternative specific or a combination of both would greatly improve the understanding of consumer behaviour and researches using synthetic data to evaluate models would benefit from it as well. The uncovered relationship between the scale parameter and choice set size constant also warrants further attention in the scientific community to better understand how models such as the ones used in this research should be carried out. As with many newly developed models, the μRRM SBWMNL model would benefit from further applications in a variety of fields. Making conclusions based on a single sample is not accurate and by applying it in a variety of different fields could help in either proving or rejecting the findings reported here.

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