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Random regret minimization or random utility maximization: An exploratory analysis in the context of automobile fuel choice.

By

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ABSTRACT: Interest in alternative behavioural paradigms to random utility maximisation (RUM) has existed ever since the dominance of the RUM formulation. One alternative is known as random regret minimisation (RRM), which suggests that when choosing between alternatives, decision-makers aim to minimise anticipated regret. Although the idea of regret is not new, its incorporation into the same discrete choice framework of RUM is very recent. This paper is the first to apply the RRM-model framework to model choice among durable goods. Specifically, we estimate and compare RRM- and RUM-models in a stated choice context of choosing amongst petrol, diesel and hybrid fuelled vehicles (associated with specific levels of fuel efficiency and engine capacity). The RRM-model is found to achieve a marginally better fit (using a non-nested test of differences) than its equally parsimonious RUM-counterpart. As a second contribution, we derive a formulation for regret-based elasticities, and compare utility- and regret-based elasticities in the context of stated vehicle-type choices. We find that in the context of our choice-data, mean estimates of elasticities are different for many of the attributes and alternatives.

KEY WORDS: ***Random regret; random utility; automobile choice; stated choice experiment; elasticities.***

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1. Introduction

There is a growing interest in attribute processing heuristics that allow for non- and semi-compensatory decision making in traveller behaviour research (see Hensher 2010 for a review). The majority of the decision rules are developed within a random utility maximization (RUM) framework in which parameter estimates attached to alternative-specific attributes represent the marginal (dis)utility of an attribute, conditioned as appropriate on an attribute processing rule. Examples include attribute addition or parameter transfer under a common metric (e.g., Layton and Hensher 2010, Hensher and Layton 2010), attribute cut-off thresholds (e.g., Swait 2001), and attribute non-preservation (e.g., Scarpa et al. 2009, 2010).

An alternative behavioural framework that has been recently promoted in the travel choice literature by Chorus and his colleagues (Chorus et al. 2008, 2009, and Chorus 2010) is random regret minimization (RRM) in which the chosen alternative depends on the anticipated performance of non-chosen alternatives. Specifically, RRM assumes that an individual's choice amongst a finite set of alternatives is influenced by the wish to avoid the situation where one or more non-chosen alternatives perform better than the chosen one, on one or more attributes – which would cause regret. This behavioural choice rule translates into one in which an individual is assumed to act as if they are minimising anticipated regret in contrast to maximising utility. This rule is applicable when the alternatives have attributes that matter in common, which is typically the case in many choice applications.

The notion that anticipated regret influences behaviour is not new. Rather, as some have argued, regret is "the emotion that has received the most attention from decision theorists" (Connolly and Zeelenberg 2002). There is an extensive and growing literature in experimental psychology and neurobiology that shows that anticipated regret influences decision-making (e.g., Kahneman and Tversky 1982; Zeelenberg 1999; Corricelli et al., 2005). Although generally the notion of regret is associated with risky choices in particular, it is also readily applicable to riskless choices, as long as alternatives are defined in terms of multiple attributes. This follows from the idea that the process of making tradeoffs between different attributes of different alternatives implies that – in most situations – one has to decide to live with a suboptimal performance on one or more attributes in order to achieve a satisfactory outcome on other attributes. It is this situation which can be postulated to cause regret at the level of specific attributes (see Section 2 for a more formal and detailed exposition of this argument).

The RRM-approach is the first operationalization –in a discrete choice context– of the notion that anticipated regret influences choice-behaviour. Its most recent version (Chorus, 2010), which is the focus of this paper, is estimable using conventional discrete-choice software packages. It is equally parsimonious as conventional RUM-based logit models, but it allows for semi-compensatory choice behaviour. So far, estimation results show a strong performance of RRM-models, also when compared to its RUM-counterparts (Chorus, 2010).

This paper pushes the envelope of RRM-based choice modelling along two dimensions: first, it is the first application of RRM in a durable goods-context. While previous applications have focused on operational travel choices such as route-choices (Chorus, 2010), this paper compares RRM and RUM in the context of strategic/tactical choices. Our exploration of RRM's potential in the context of vehicle type-choices is motivated by findings from the field of behavioural decision-making (e.g., Zeelenberg and Pieters, 2007), which suggest that minimization of anticipated regret is a particularly important factor when choices are perceived as difficult and important, and when the decision-maker believes that choices are important to significant others in their social network. Clearly, vehicle type-choices intuitively fit these conditions very well. As a second contribution, we derive RRM-elasticities and compare RUM- and RRM-elasticities in the context of our data. By providing these two contributions –one empirical, one theoretical, this paper aims at exploring and increasing the potential of RRM as a discrete choice-model.

This paper is part of the body of research published in this journal that is promoting new ways of studying travel choice (e.g., Park et al. 2010 and Shir-mohammadli et al. (2011).

The next section introduces the RRM-model and derives a formulation for RRM-elasticities. Subsequently, the data collection effort is described, followed by the presentation of estimation results (including the comparison of RRM- and RUM-elasticities).

2. The RRM-model

A decision-maker faces a set of J alternatives, each being described in terms of M attributes x_m that are comparable across alternatives. The RRM-model postulates that when choosing between alternatives, decision-makers aim to minimize anticipated random regret, and that the level of anticipated random regret that is associated with a considered alternative i is composed out of a systematic regret R_i and an i.i.d. random error ε_i which represents unobserved heterogeneity in regret and whose negative is Extreme Value Type I-distributed with variance $\pi^2/6$.

Systematic regret is in turn conceived to be sum of all so-called binary regrets that are associated with bilaterally comparing the considered alternative with each of the other alternatives in the choice set[1]. The level of binary regret associated with comparing the considered alternative i with another alternative j equals the sum of the regrets that are associated with comparing the two alternatives in terms of each of their M attributes. This attribute level-regret in turn is formulated as follows: $R_{i\leftrightarrow j}^{m} = \ln\left(1+\exp\left[\beta_m \cdot \left(x_{jm} - x_{im}\right)\right]\right)$. This formulation implies that regret is close to zero when alternative j performs (much) worse than i in terms of attribute m, and that it grows as an approximately linear function of the difference in attribute-values in case i performs worse than j in terms of attribute m. In that case, the estimable parameter β_m (for which also the sign is estimated) gives the approximation of the slope of the regret-function for attribute m. See Figure 1 for a visualization.

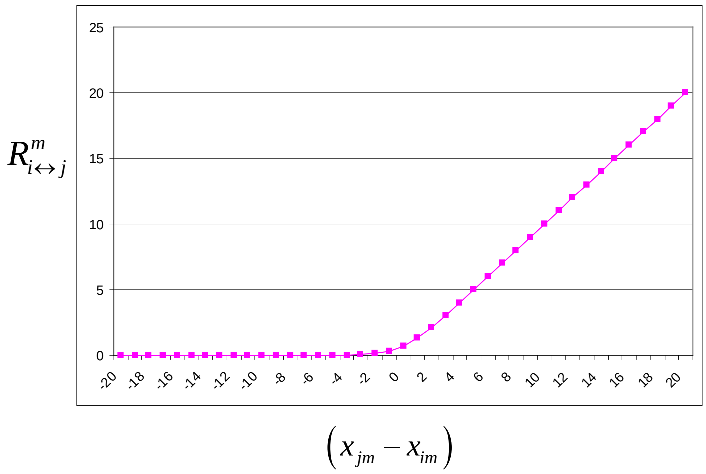

Figure 1: A visualization of attribute level-regret (for β_m = 1)

[1] This heuristic across alternatives has similar behavioural properties to the parameter-transfer rule advocated by Hensher and Layton (2010) within an alternative. Furthermore, the symmetrical form devised initially by Quiggin with regret and rejoice has similar properties to the best-worse (BW) processing rule that focuses on contrasts between alternatives (see Marley and Louviere 2005)

In combination, this implies the following formulation for systematic regret: $R_i = \sum_{j \neq i} \sum_{m=1..M} \ln\left(1+\exp\left[\beta_m \cdot \left(x_{jm} - x_{im}\right)\right]\right)$. Acknowledging that minimization of random regret is mathematically equivalent to maximizing the negative of random regret, choice probabilities may be derived using a variant of the multinomial logit-formulation[2]: the choice probability associated with alternative *i* equals $P_i = \exp\left(-R_i\right) \Big/ \sum_{j=1..J} \exp\left(-R_j\right)$.

The parameters estimated within a RRM-framework, have a different meaning than those estimated within a RUM-framework. The RUM parameters represent the contribution of an attribute to an alternative's utility, whereas the RRM parameters represent the *potential* contribution of an attribute to the regret associated with an alternative. An attribute's actual contribution to regret depends on whether an alternative performs better or worse on the attribute than the alternative it is compared with. As a result, in contrast with linear-additive utilitarian choice-models, the RRM-model implies semi-compensatory behaviour. This follows from the convexity of the regret-function depicted in Figure 1: improving an alternative in terms of an attribute on which it already performs well relative to other alternatives generates only small decreases in regret, 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. Therefore, the extent to which a strong performance on one attribute can compensate a poor performance on another depends on the relative position of each alternative in the set.

As a result of the conceptual difference between RUM- and RRM-based parameter estimates, the best way to establish the behavioural implications of RUM vs. RRM is not through interpretation of the parameter estimates but through the direct choice elasticities. Direct choice elasticities derived in the RUM as well as in the RRM context provide a measure of the relationship between a one percentage change in the level of the attribute and the percentage change in the probability of choosing the alternative characterized by that specific attribute. Importantly, RRM-based direct elasticities associated with a change in an alternative's attribute depend on the relative performance of *all* the alternatives in the choice-tasks, rather than depending only on the performance (choice probability) of the specific alternative. This follows directly from the behavioural premise, underlying the RRM-approach, that the regret associated with an alternative's attributes depends on its performance on these attributes relative to the performance of other alternatives on these attributes. We formally derive the formulae for direct elasticity which has not been derived or implemented in previous papers on RRM. The definition of R_i is

$$R_i = \sum_{j \neq i} \sum_{m=1}^{M} \ln\{1+\exp[\beta_m (x_{jm} - x_{im})]\} \tag{1}$$

To simplify (1) for ease of manipulation, we add back and then subtract the *i* term in the outer sum. This gives us (2).

$$R_i = \left\{ \sum_{j=1}^{J} \sum_{m=1}^{M} \ln\{1+\exp[\beta_m (x_{jm} - x_{im})]\} \right\} - M \ln 2 \tag{2}$$

[2] Note that, as has been formally shown in Chorus (2010), the two models (RRM and RUM) give identical results when choice sets are binary. A referee asked whether the findings would be sensitive to six alternatives in contrast to three alternatives used herein. We are unable to provide a definitive response since it will depend on a number of considerations, including whether the differences in attribute levels between pairs of alternatives are likely to vary significantly or not. This is an area of relevance in future research.

By definition,

$$\mathrm{P}_i = \frac{\exp[-R_i]}{\sum_{j=1}^{J}\exp[-R_j]} \tag{3}$$

To differentiate the probability, we use the result $\partial P_i/\partial x_{lm} = P_i \partial lnP_i/x_{lm}$. Then,

$$\begin{aligned}
&\ln \mathrm{P}_i = -R_i - \ln \Sigma_{j=1}^{J}\exp(-R_j), \text{ so,}\\
&\frac{\partial \ln \mathrm{P}_i}{\partial x_{lm}} = \frac{-\partial R_i}{\partial x_{lm}} - \frac{\partial \ln \Sigma_{j=1}^{J}\exp(-R_j)}{\partial x_{lm}}\\
&\qquad = \frac{-\partial R_i}{\partial x_{lm}} - \frac{\Sigma_{j=1}^{J}\partial \exp(-R_j)/\partial x_{lm}}{\Sigma_{j=1}^{J}\exp(-R_j)}\\
&\qquad = \frac{-\partial R_i}{\partial x_{lm}} - \frac{\Sigma_{j=1}^{J}\exp(-R_j)\partial(-R_j)/\partial x_{lm}}{\Sigma_{j=1}^{J}\exp(-R_j)}\\
&\qquad = \frac{-\partial R_i}{\partial x_{lm}} - \sum_{j=1}^{J} P_j \frac{\partial(-R_j)}{\partial x_{lm}}\\
&\qquad = \left(\sum_{j=1}^{J} P_j \frac{\partial R_j}{\partial x_{lm}}\right) - \frac{\partial R_i}{\partial x_{lm}}
\end{aligned} \tag{4}$$

We still require $\partial R_i/\partial x_{lm}$, which is given in (5);

$$\begin{aligned}
&\frac{\partial R_i}{\partial x_{lm}}(where\ \mathrm{l} \neq \mathrm{i}) \;=\; \beta_m \frac{\exp[\beta_m(x_{lm}-x_{im})]}{1+\exp[\beta_m(x_{lm}-x_{im})]} = \beta_m q(l,i,m),\\
&\frac{\partial R_i}{\partial x_{im}}(i.e., where\ \mathrm{l} = \mathrm{i}) = -\beta_m \sum_{j\neq i}^{J} \frac{\exp[\beta_m(x_{jm}-x_{im})]}{1+\exp[\beta_m(x_{jm}-x_{im})]} = -\beta_m \sum_{j=1}^{J} q(j,i,m),\\
&where\ \mathrm{q(j,j,m) = 0.}
\end{aligned} \tag{5}$$

$$\frac{\partial \ln P_i}{\partial x_{lm}} = \beta_m\left[\left(\sum_{j=1}^{J} P_j q(j,i,m)\right) - q(l,i,m)\right] \tag{6}$$

Combining terms, the first part of (4) is common to both $l = i$ (own elasticities) and $l \neq i$ (cross elasticities), while the second term in (4) involves either the second or the first term in (5), respectively. The elasticity, $\partial lnP_i/\partial lnx_{lm}$, is then a simple multiplication of (4) or (6) by x_{lm}. One oddity, unfortunately, is that the sign results that hold for the MNL are not ensured here. The elasticities appear to be reasonably well behaved, however, some peculiar sign reversals can occur.

3. The survey approach: A stated choice experiment

The data used to investigate differences between RUM and RRM is drawn from a larger study undertaken in Sydney on the demand for alternative-fuelled automobiles. Full details including the properties of the design experiment are given in Beck et al. (2010) and Hensher et al. (2010). The data was collected over a four month period in 2009. The final sample used in model estimation herein comprises 3,172 observations related to households who had purchased a vehicle in the previous two years. We briefly describe the study herein, focussing on the stated choice experiment which is the key input for the model estimation.

The universal finite choice set comprises three alternatives based on fuel type: petrol, diesel or hybrid. The hybrid alternative reflects a vehicle option that is cleaner with respect to emission levels. The vehicle type, broken down into six variants: Small, Luxury Small, Medium, Luxury Medium, Large and Luxury Large, was done so that the experiment would have adequate attribute variance over the alternatives, particularly with respect to price, whilst still having a manageable number of alternatives for the design.

Nine attributes were included in the choice experiment, which were refined via review of the literature on vehicle purchasing, as well as through a pilot survey and preliminary analysis of secondary data sets. The typical monetary costs involved in purchasing and operating a car are included in the design. These are purchase price of the vehicle, the fuel price and the cost of registration (including compulsory third party insurance). Fuel efficiency of a vehicle is an important attribute, given that this is the link to which level of emissions surcharge will be set. The remaining attributes, seating capacity, engine size, country of manufacture, were selected to give respondents a realistic and varied set of alternatives such that cars of differing types could be evaluated and traded against within the choice experiment. Table 1 displays the levels that have been selected for each attribute. The purchase price for the hybrid alternative is $3,000 higher at each level in order to recognise that hybrid technology is more expensive than conventional engine technology.

Table 1: Attribute levels for stated choice experiment

Purchase Price	*Small*	$15,000	$18,750	$22,500	$26,250	$30,000
	Small Luxury	$30,000	$33,750	$37,500	$41,250	$45,000
	Medium	$30,000	$35,000	$40,000	$45,000	$50,000
	Medium Luxury	$70,000	$77,500	$85,000	$92,500	$100,000
	Large	$40,000	$47,500	$55,000	$62,500	$70,000
	Large Luxury	$90,000	$100,000	$110,000	$120,000	$130,000
Fuel Price	*Pivot off daily price*	-25%	-10%	0%	10%	25%
Registration	*Pivot off actual purchase*	-25%	-10%	0%	10%	25%
Fuel Efficiency (L / 10km)	*Small*	6	7	8	9	10
	Medium	7	9	11	13	15
	Large	7	9	11	13	15
Engine Capacity (cylinders)	*Small*	4	6			
	Medium	4	6			
	Large	6	8			
Seating Capacity	*Small*	2	4			
	Medium	4	5			
	Large	5	6			
Country of Manufacture	*Random Allocation*	Japan	Europe	Sth Korea	Australia	USA

The final two attributes relate to the mechanism via which vehicle emissions charges will be implemented, a surcharge that is paid annually, and a variable charge that is a function of how much the vehicle is used. Both charges are a function of a vehicles' fuel efficiency given that better fuel economy is strongly associated with lower levels of vehicle emissions. The levels chosen for the annual and variable surcharges are given in Table 2. Both of the surcharges are determined by the type of fuel a vehicle uses and the fuel efficiency of that vehicle. For a given vehicle, if it is fuelled by petrol it would pay a higher surcharge than if it was fuelled by diesel, which is in turn more expensive than if it was a hybrid. Once the car has been specified in terms of fuel type and efficiency, there are five levels of surcharge that could be applied.

Table 2: Levels for annual emissions surcharge ($)

		Fuel Efficiency (litres used per 100km)									
Petrol		**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Level	**1**	0	0	0	0	0	0	0	0	0	0
	2	90	105	120	135	150	165	180	195	210	225
	3	180	210	240	270	300	330	360	390	420	450
	4	270	315	360	405	450	495	540	585	630	675
	5	360	420	480	540	600	660	720	780	840	900
		Fuel Efficiency (litres used per 100km)									
Diesel		**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Level	**1**	0	0	0	0	0	0	0	0	0	0
	2	75	87.5	100	112.5	125	137.5	150	162.5	175	187.5
	3	150	175	200	225	250	275	300	325	350	375
	4	225	262.5	300	337.5	375	412.5	450	487.5	525	562.5
	5	300	350	400	450	500	550	600	650	700	750

Table 3: Levels for variable emissions surcharge ($/km)

		Fuel Efficiency (litres used per 100km)									
Petrol		**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Level	**1**	0	0	0	0	0	0	0	0	0	0
	2	0.06	0.07	0.08	0.09	0.10	0.11	0.12	0.13	0.14	0.15
	3	0.12	0.14	0.16	0.18	0.20	0.22	0.24	0.26	0.28	0.30
	4	0.18	0.21	0.24	0.27	0.30	0.33	0.36	0.39	0.42	0.45
	5	0.24	0.28	0.32	0.36	0.40	0.44	0.48	0.52	0.56	0.60
		Fuel Efficiency (litres used per 100km)									
Diesel		**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Level	**1**	0	0	0	0	0	0	0	0	0	0
	2	0.05	0.06	0.07	0.08	0.09	0.09	0.10	0.11	0.12	0.13
	3	0.10	0.12	0.14	0.15	0.17	0.19	0.20	0.22	0.24	0.26
	4	0.15	0.18	0.2	0.23	0.26	0.28	0.31	0.33	0.36	0.38
	5	0.20	0.24	0.27	0.31	0.34	0.37	0.41	0.44	0.48	0.51

A reference alternative is included to add relevance and comprehendability of the attribute levels being assessed (see Rose et al., 2008); however it was not included in the set of alternatives that were ranked (see Figure 1). In the process of building the experiment design, there were a number of conditions on the interaction of the attributes and alternatives:

1. The annual and variable surcharge that is applied to an alternative is conditional on the type of fuel used and the fuel efficiency of the vehicle in question.
2. If the reference alternative is petrol (diesel), the petrol (diesel) fuelled alternative must have the same fuel price as the reference alternative.
3. The annual and variable surcharge for the hybrid alternative cannot be higher than that of another vehicle when the alternative vehicle has the same fuel efficiency rating or is more inefficient than the hybrid.
4. To ensure that respondents faced a realistic choice set, given the size of the reference alternative, one of the remaining alternatives was restricted to be the same size as the reference, another was allowed to vary plus/minus one body size, and the third was allowed to vary freely. The condition was applied to the alternatives at random.

As part of designing an efficient experiment (see Rose and Bliemer 2008), the design is optimised over the values in the reference alternative. As we do not know, a priori, the exact specifications of the vehicle that each respondent has most recently purchased, it is not possible to present each respondent with a fully optimised design. However, an approximate method was used whereby all recent purchases were defined as being one of six different body sizes (small, small luxury, medium, medium luxury, large, large luxury) and one of two fuel types (petrol or diesel). Consequently, each respondent received choice sets from one of twelve possible designs, depending on what category their most recent purchase belongs to. In calculating each design an analytical approach was used whereby the asymptotic variance-covariance matrix was derived via the second derivatives of the log-likelihood function of the model to be estimated. To optimise this design, different combinations of attributes are trialled, and the design with the minimised d-error after repeated iterations is used. The iterations were allowed to run uninterrupted for 72 hours.

The internet based survey with face to face assistance of an interviewer was completed by pairs of individuals. The survey is unique in its composition and the method of completion. Some sections of the survey require respondents to complete questions together on one computer (but with data recorded for each individual); and other sections required respondents to work individually. The information is pooled for model estimation.

The logistics of survey participation of relevance to that part of the larger data set used in this paper are as follows. First individuals complete the survey as a pair on one computer, providing details of the vehicles within the household, and details of the most recent (or a potential) purchase. Then four choice sets are provided (see an example in Figure 2) and they are asked to review the alternatives, decide which attributes are relevant[3], and then indicate their preferred joint outcome as well an indication of which alternatives are acceptable and what is the certainty of actually making the choice if it were available now in a real market. Each individual in the group is then asked to indicate which alternative they individually preferred, which may or may not diverge from the group choice. We focus herein on the individual responses (see Beck et al. 2010 and Hensher et al. 2010 for analyses of groups).

[3] The survey is programmed so that respondents can click on various rows, columns and cells within a choice scenario if they find that attribute, alternative, or level to be ignored or irrelevant. This information is stored so that for each and every choice set completed by every respondent, data is collected on what information was important in making a decision and what information was discarded.

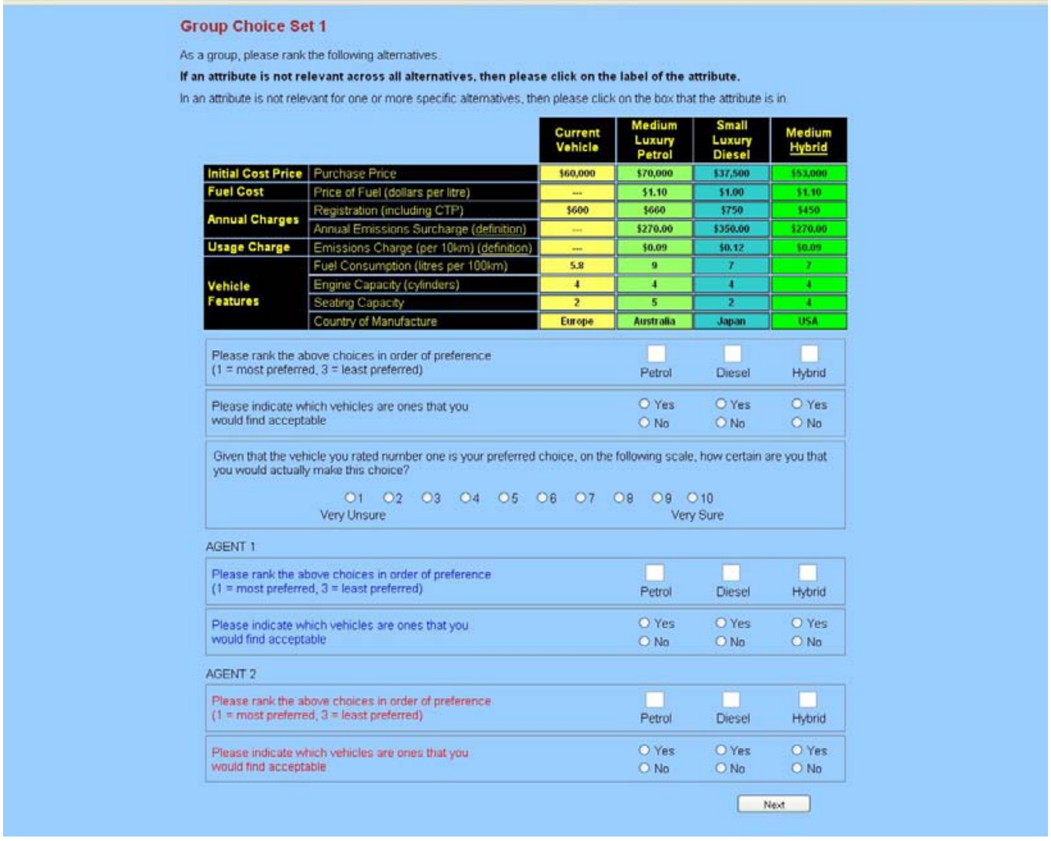

Figure 2: Illustrative stated choice screen

3.1 Empirical results

The random regret and random utility models are estimated as multinomial logit. The findings are summarised in Table 4[4]. We undertook extensive investigation into the possible influence of socioeconomics characteristics and found statistically significant interactions of respondent age, full time employment dummy, and personal and household income with vehicle price but not with other attributes of the alternatives.

RUM and RRM are on nested models, and are generally assessed by means of a selection criteria, such as Akaike's (1973) information criterion, based on the Kullback-Leibler Information Criterion (KLIC). Under KLIC, when two models are compared, minimization of the criterion only depends on the maximum likelihood of the two competing models. The Akaike Information Criterion (AIC) penalizes the log likelihood of each model by a quantity equal to the number of its parameters. The Akaike criterion for model selection simply consists in comparing the AIC values for the two models. If the value is positive the first model is chosen, otherwise the second will be deemed best. On the AIC test, the random regret minimization model (RRM) is marginally superior on statistical fit to the RUM model. All parameters have the expected sign and are statistically significant at the 95 percent confidence level except for registration fee. The fuel-specific constants show a preference for petrol vehicles, after controlling for the observed attributes.

[4] A referee asked whether '…the RRM model has a higher requirement on the reliability of the SP data (depending on whether respondents seriously consider all alternatives in the SP game) because it uses the unchosen alternatives as well in estimation'.We believe that although the information on attributes of alternatives is used in a different way in RRM compared to RUM, the very same issues in relation to how information on attributes is processed is present under RUM. Indeed there are a number of studies under RUM that investigate deviations from a reference or status quo alternative that involve using data in a differencing manner (see for example, Hess et al. 2008).

Table 4: Summary of model results

T-values in brackets

Attribute	Alternatives	RUM	RRM
Vehicle price ($)	All	-0.01583 (-5.50)	-0.0096 (-5.47)
Fuel price ($/litre)	All	-0.4504 (-7.23)	-0.2970 (-7.36)
Annual emissions surcharge ($)	All	-0.00067 (-8.61)	-0.00044 (-8.79)
Variable emissions surcharge ($/km)	All	-0.3716 (-3.57)	-0.2344 (-3.53)
Petrol specific constant	Petrol	0.0753 (2.00)	0.0494 (2.03)
Registration Fee ($ per annum)	All	-0.00013 (-1.63)	-0.000088 (-1.68)
Fuel efficiency (litres per 100km)	All	-0.0174 (-3.15)	-0.0123 (-3.46)
Engine Capacity (# cylinders)	All	-0.0274 (-2.47)	-0.0179 (-2.54)
Seating Capacity	All	0.2554 (18.5)	-0.1712 (20.4)
Vehicle price interacted with:			
Age of respondent	All	-0.0002 (-3.53)	-0.00015 (-4.21)
Full time employed (1,0)	All	-0.0069 (-4.07)	-0.0052 (-5.07)
Personal income ('000s)	All	0.0000445 (2.02)	0.000035 (3.34)
Household income ('000s)	All	0.000029 (3.49)	0.000021 (4.17)
Korean manufactured (1,0)	All	-0.1354 (-4.11)	-0.0880 (-4.19)
Diesel specific constant	Diesel	-0.3235 (-8.65)	-0.2137 (-9.22)
Gender (male=1)	Hybrid	-0.1546 (-3.33)	-0.1014 (-3.45)
Model Fit:			
Log-likelihood at zero		-10636.764	
Log-likelihood at convergence		-9,484.028	-9,472.694
Info. Criterion: AIC		1.9624	1.9602
Sample Size		9,682	

Figures 3 to 6 depict the RUM (ProbRUM) and RRM (ProbRRM) probability distributions across the sample overall, and for each of the alternative fuel types, as well as the differences (ProbDif) between RUM and RRM. The most notable evidence is the narrower range and more peaked distribution for RRM compared to RUM suggesting greater heterogeneity in predicted probabilistic choice under RUM. The incidence of greater observation frequency around the mean and median is most stark under RRM compared to RUM, despite overall model fits being relatively similar. There are clear differences in the choice probabilities associated with each respondent as highlighted in the ProbDif graphs. This suggests that the implied elasticities associated with one or more attributes are likely to differ given their dependence on the choice probabilities (see below).

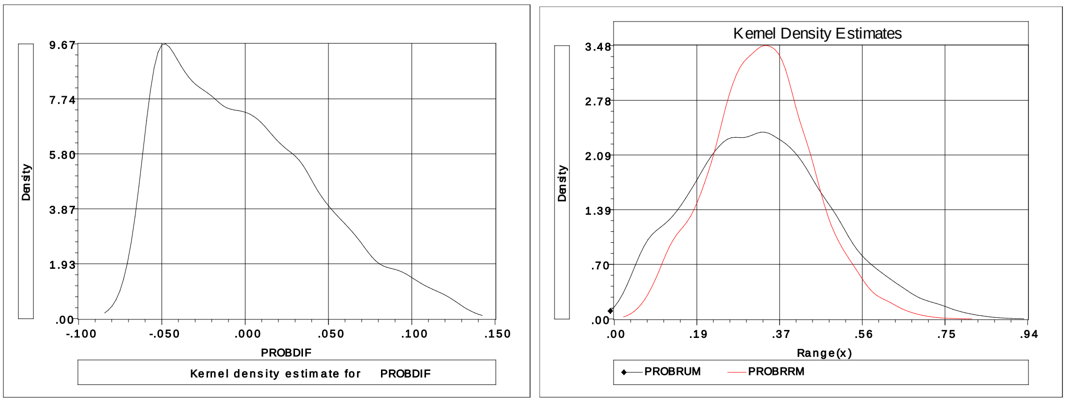

Figure 3: Profile of choice probabilities for RUM and RRM

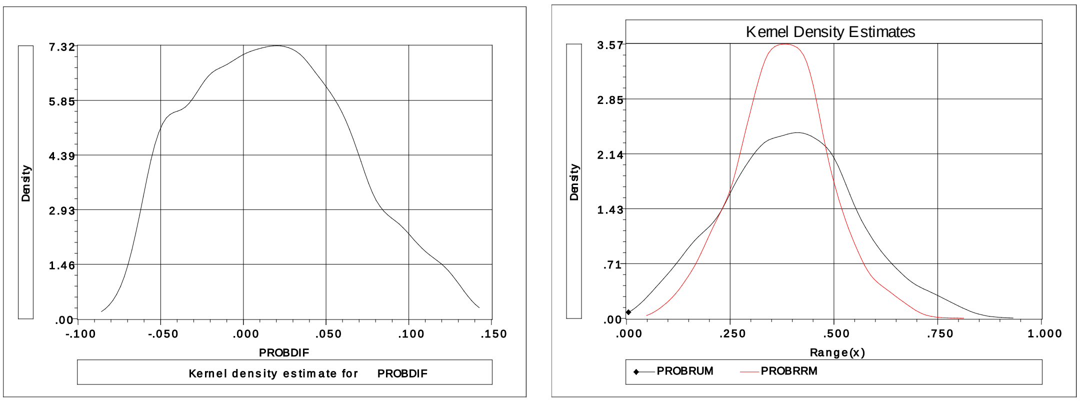

Figure 4: Profile of petrol choice probabilities for RUM and RRM

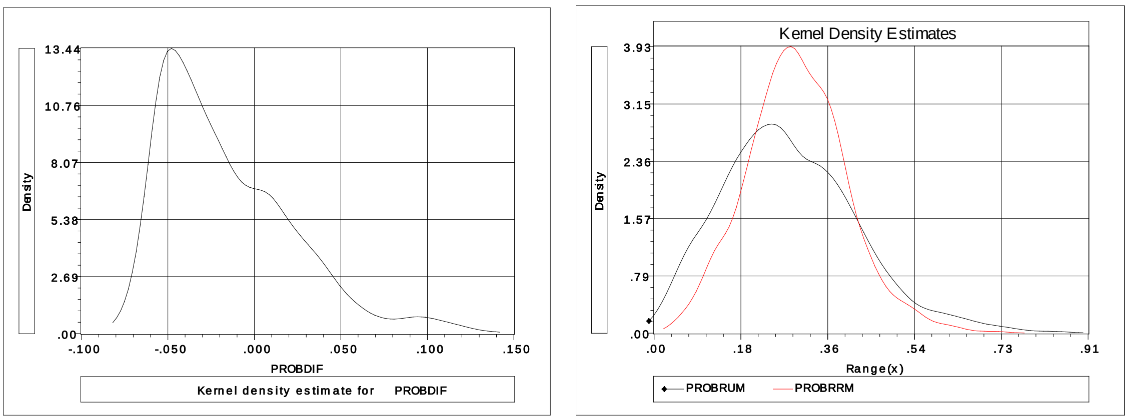

Figure 5: Profile of diesel choice probabilities for RUM and RRM

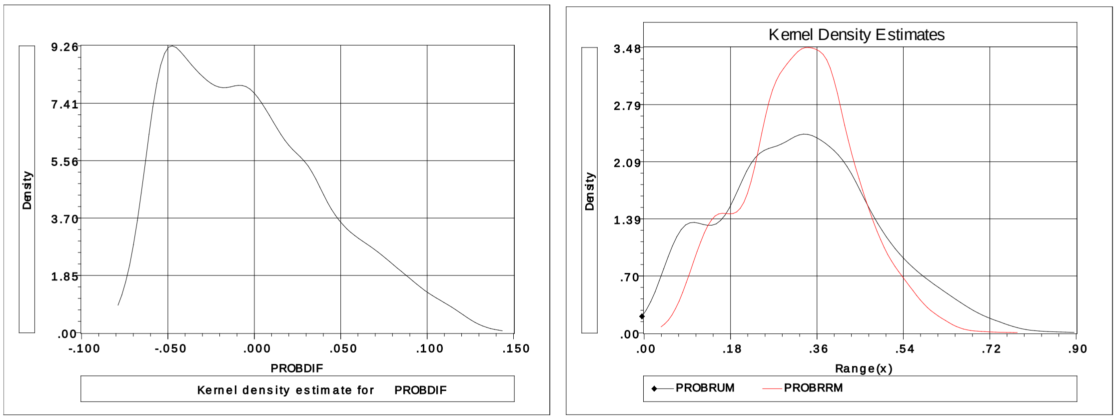

Figure 6: Profile of hybrid choice probabilities for RUM and RRM

All the mean[5] elasticities obtained from the RUM and RRM models are summarised in Table 5. Although the absolute magnitudes appear at first glance to be relatively similar with some exceptions such as vehicle price, many of the elasticities are quite different in percentage terms (varying between 1.21 and 18.95 percent). The vehicle price elasticities for RRM are greater than for RUM by between 4.22 and 12.39 percent, for fuel price they are greater by between 1.21 and 9.5 percent, for fuel efficiency they are higher by between 5.31 and 18.95 percent, and for annual emissions surcharge they are higher by between 1.90 and 10.2 percent. These differences are substantial, and they suggest varying behavioural responses to a given change in a specific policy instrument across the three fuel types. All attributes are relatively inelastic, with the exception of vehicle price for diesel and hybrid fuels, with the direct elasticity associated with vehicle price being the most (in)elastic, and the vehicle emissions surcharge per kilometre being the least inelastic (the latter expected given it relates to a kilometre of travel).

To illustrate the way that the evidence is interpreted, in the RUM model a ten percent increase in the price of a petrol vehicle results, on average, in a 9.31 percentage reduction in the probability of choosing a petrol vehicle, given the choice amongst petrol, diesel and hybrid, holding all other influences constant; however this ten percent increase in the price of a petrol vehicle in the context of the RRM model takes into account the level of the vehicle price associated with the diesel or hybrid alternative. More specifically, the 9.87 percent reduction in the probability of choosing the petrol vehicle in RRM explicitly accounts for the levels of vehicle price in the set of available alternatives, in recognition of regret that one may have chosen the wrong alternative. It is 6.02 percent higher than the RUM behavioural response, suggesting that accounting for the possibility that the wrong choice may have been made amplifies the behavioural response that one would normally attribute to a RUM-based elasticity.

[5] Mean elasticities are obtained from probability weighting the respondent-specific elasticities, where the probability weight relates to the probability of choosing a particular alternative in a choice set setting.

Table 5: Direct elasticity contrasts

Attribute	RUM			Random Regret		
	Petrol	Diesel	Hybrid	Petrol	Diesel	Hybrid
Vehicle price ($)	-0.931	-1.089	-1.227	-0.987	-1.135	-1.379
Fuel price ($/litre)	-0.303	-0.358	-0.331	-0.319	-0.392	-0.327
Annual emissions surcharge ($)	-0.105	-0.102	-0.049	-0.107	-0.104	-0.054
Variable emission surcharge($/km)	-0.041	-0.04	-0.019	-0.043	-0.039	-0.021
Registration Fee ($ p a)	-0.062	-0.074	-0.069	-0.068	-0.075	-0.072
Fuel efficiency (litres per 100km)	-0.095	-0.113	-0.104	-0.113	-0.119	-0.118

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Attribute	Absolute Difference (RUM-Random Regret))			Percent Difference		
	Petrol	Diesel	Hybrid	Petrol	Diesel	Hybrid
Vehicle price ($)	0.056	0.046	0.152	-6.02%	-4.22%	-12.39%
Fuel price ($/litre)	0.016	0.034	-0.004	-5.28%	-9.50%	1.21%
Annual emissions surcharge ($)	0.002	0.002	0.005	-1.90%	-1.96%	-10.20%
Variable emission surcharge($/km)	0.002	-0.001	0.001	-4.88%	2.50%	-5.26%
Registration Fee ($ p a)	0.006	0.001	0.003	-9.68%	-1.35%	-4.35%
Fuel efficiency (litres per 100km)	0.018	0.006	0.014	-18.95%	-5.31%	-13.46%

The absolute mean elasticities associated with annual and variable emissions surcharges and annual registration fee are much more similar for RUM and RRM (except for hybrid vehicle for annual emissions surcharge) than are the other attribute elasticities (with the exception of registration fees for diesel fuelled vehicles)[6].

Overall the mean differences are such that the RUM model is not a good approximation to the RRM model if random regret is a preferred representation of behavioural response, as is the case in this empirical study. This raises the important question of which elasticity estimates should policy advisers use? This bears some close thought; however regret estimates may be more appropriate for actual potential loss (for example, being involved in an accident) or significant potential gains (for example, in winning a lottery)?

4. Conclusions

The RRM-model (Chorus 2010) offers an alternative semi-compensatory way of accounting for the role of the anticipated performance of non-chosen alternatives in an individual's choice amongst a finite set of alternatives. Specifically, it is not unreasonable to assume that the choice amongst a set of discrete and mutually exclusive alternatives is not always based on identifying the alternative that yields the maximum utility, but on ensuring that one rejects alternatives in the process of arriving at a preferred alternative that minimises the regret associated with the decision.

In this paper we have estimated multinomial logit models based on RUM and RRM using data from a study of the choice of automobile purchases from the available three types of fuel sources (petrol, diesel and hybrid). This constitutes the first application of RRM (and: the first comparison of RRM and RUM) in the context of strategic choices (choices between durable goods). Both RUM and RRM models result in plausible influences of attributes of choice, although the overall model fit is better for the RRM model.

[6] It is important to note that an elasticity calculation has a number of estimates embedded in them of parameters and probabilities (see equation 6), and hence it is extremely complex (if not practically impossible) to derive standard errors that are required in testing a hypothesis about the elasticity. The delta method or Krinsky-Robb tests could be implemented to do that, but for elasticities, even from a simple multinomial choice model, it is extremely complex to program, if it could be done at all. On the other hand, we would not trust an hypothesis test for an elasticity even if the standard errors were computed by the delta method.

Furthermore, this paper has set out for the first time, as far as we are aware, the elasticity formulae for the random regret model. We have been unable to find any papers that have focussed on interpreting the elasticities from a random regret model, even though it is well known what the underlying parameter estimates for each attribute actually mean. We find that in the context of our choice-data, implied mean direct elasticities are quite different for many of the attributes and alternatives. RRM is an appealing alternative approach to RUM and has unlimited application potential in traveller behaviour studies, including the capability to be jointly estimated with RUM to establish the extent to which each approacj contributes to explaining choice responses.

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