11. Selecting a date: a matter of regret and compromises

Caspar G. Chorus and John M. Rose

1. INTRODUCTION

The past decade has seen a large and growing interest in the study of mate preferences (see Hitsch et al., 2010 for a recent contribution including a very useful review of past work). Various studies have attempted to derive mate preferences by means of the estimation of choice models on observed (stated or revealed) choices. Estimated choice models are generally built on the premises of utility-maximization: i.e., the decision-maker is postulated to select a mate (or a date) from which he or she expects to derive the highest utility. In these studies, often a (variant of the) well-known multinomial logit (MNL) model is estimated, which is founded in random utility maximization (RUM) theory (e.g., Fisman et al., 2006; Banerjee et al., 2009; Hitsch et al., 2010). Although it goes without saying that this utilitarian approach to modeling mate preferences has resulted in many valuable insights, it leaves open the important question to what extent mate selection processes are in fact adequately represented by a utilitarian framework.

Motivated by this question, this chapter compares utility-maximization based choice models with equally parsimonious counterparts that are based on regret-minimization premises. The focus on regret-based choice models is inspired by the notion put forward throughout the social sciences, that regret-minimization is an important determinant of choice behavior.[1] To cite just one example, Coricelli et al. (2005), using neuroimaging techniques, show that the area of the human brain that is active when decision-makers experience regret after having made a (poor) choice, is also highly active seconds *before* they make a choice. In their words "anticipating regret is a powerful predictor of future choices". More specifically, findings from the field of behavioral decision-making (e.g., Zeelenberg and Pieters, 2007) 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, mate- and date-selection processes intuitively fit these conditions very well.

Recently, the idea that minimizing anticipated regret co-determines choices has been translated into a generic discrete choice model: this random regret minimization (RRM) approach (Chorus, 2010) is developed for the econometric analysis of risky as well as riskless[2] choices in multinomial and multi-attribute contexts. It allows for the estimation, based on observed choices, of parameters reflecting decision-makers' valuation of alternatives and their attributes. RRM-models feature closed form logit-type choice probabilities, are equally parsimonious as their linear-additive utilitarian counterparts and can be easily estimated using conventional discrete-choice software packages. They have been found to perform well empirically in the context of modeling various types of mobility choice-behavior (e.g., Chorus, 2010; Chorus and de Jong, 2011; Boeri et al., 2012; Hensher et al., in press; Kaplan and Prato, in press). This chapter presents the first application of RRM in the context of date selection decisions. The comparability of the RRM- and the RUM-based approaches (see Section 2 for details) allows us to test empirically which behavioral premises (utility-maximization versus regret-minimization) better fit observed choice patterns. We use data from a stated choice experiment involving hypothetical choices that mimic the process of online data selection. As a second contribution we empirically test expectations, formulated in earlier work (Chorus, 2010) in the context of numerical examples, concerning differences in predicted choice probabilities between RRM- and RUM-model specifications.

The remainder of this chapter is structured as follows: Section 2 presents the RUM- and RRM-based approaches to discrete choice modeling. Section 3 introduces the data collection effort. Empirical analyses are presented in Section 4, while Section 5 presents conclusions and discusses potential avenues for future research.

2. RANDOM REGRET MINIMIZATION VERSUS RANDOM UTILITY MAXIMIZATION

Assume the following choice situation: 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 focus is on predicting the choice probability for an alternative i from this set. Before introducing the new RRM model, note as a reference point that a conventional, linear-additive utilitarian specification would assign the following deterministic utility to alternative *i*:

$$V_i = \sum_{m=1..M} \beta_m x_{im}.$$

Adopting the classical random utility maximization (RUM) paradigm (that is: adding i.i.d. extreme value type I-distributed errors to the deterministic utilities of all alternatives to represent heterogeneity in unobserved utility) implies the following MNL formulation of the resulting choice probability (McFadden, 1974):

$$P_i = \exp(V_i) / \sum_{j=1..J} \exp(V_j).$$

Note that we leave out the scale factor in this and following equations – it will be normalized to 1 in our empirical analyses.

The RRM model postulates that when choosing between alternatives, decision-makers aim to minimize anticipated random regret. The level of anticipated random regret that is associated with the considered alternative *i* is composed out of an i.i.d. random error ε_i which represents unobserved heterogeneity in regret and whose negative is extreme value type I-distributed, and a systematic regret R_i. Systematic regret is in turn conceived to be the 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:

$$R_i = \sum_{j \neq i} R_{i \leftrightarrow j}.$$

The level of binary regret associated with comparing the considered alternative with another alternative *j* is conceived to be the sum of the regrets that are associated with comparing the two alternatives in terms of each of their *M* attributes:

$$R_{i \leftrightarrow j} = \sum_{m=1..M} R^m_{i \leftrightarrow j}.$$

This attribute level regret in turn equals

$$R^m_{i \leftrightarrow j} = \ln(1 + \exp[\beta_m \cdot (x_{jm} - x_{im})]).$$

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.

Systematic regret can then be written as:

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

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 well-known multinomial logit formulation: the choice probability associated with alternative i equals

$$P_i = \exp(-R_i) \Big/ \sum_{j=1..J} \exp(-R_j).$$

Note that the obtained choice model can be easily coded and estimated using standard discrete choice-software packages like NLOGIT (version 5) and BIOGEME.

The correspondence of the proposed RRM model with the linear-additive RUM-based MNL model is striking: apart from the fact that both result in logit-choice probabilities, both models are equally parsimonious. Each parameter estimated for a RRM model has a counterpart in a linear-additive MNL model and when choice sets are binary, the proposed RRM model generates the same choice probabilities as RUM's linear-additive binary logit model. Apart from these similarities, the two modeling approaches exhibit a number of important differences (see Chorus, 2010, 2012 for a more in-depth discussion of these differences, using numerical examples).

First, the RRM model does not exhibit the so-called Independence from Irrelevant Alternatives (IIA) property even when error terms are i.i.d. distributed. That is, the ratio of choice probabilities of any two alternatives i and j depends on the performance of these alternatives relative to one another as well as relative to each other alternative k in the set. This follows directly from the specification of the regret function, which postulates that the regret associated with any alternative in the set is a function of its performance relative to each of the other alternatives available.

Second, the RRM model implies semi-compensatory behavior. That is, the extent to which a strong performance on one attribute can make up for a poor performance on another attribute depends on the relative position of each alternative in the set. More specifically, the RRM model predicts that deterioration of an attribute on which an alternative already has a poor performance relative to other alternatives in the set cannot be compensated by an equally large improvement of an equally important attribute on which the alternative has a relatively strong performance. This results from the fact that the deterioration of the former attribute generates a substantial level of additional regret, while the improvement of the latter attribute only reduces regret to a limited extent. This is a direct consequence of the convexity of the regret function.

3. DATA COLLECTION

The data were collected from an internet panel (The Online Research Unit http://www.theoru.com/) in June 2010. Twelve hundred respondents were sampled from a potential panel of 300,000 with only currently single individuals eligible to participate in the survey. As part of the study, respondents were randomly assigned to one of 15 different experimental designs involving having to answer nine choice tasks with either two alternatives plus a no-choice alternative or three alternatives plus a no-choice alternative. For this study, we use only part of the data, concentrating solely on respondents who faced three alternatives plus a no-choice alternative drawn from eight of the fifteen underlying experimental designs. Data collected on respondents facing two dating contacts was omitted as the binary case of RRM theory reduces to the RUM model (Chorus, 2010, appendix 2). Although the inclusion of the no-choice alternative alongside the two SP alternatives theoretically renders the choice task as a multinomial choice, the method works best with at least three non no-choice alternatives. The resulting sample consists of 661 respondents and 5,949 choice observations.

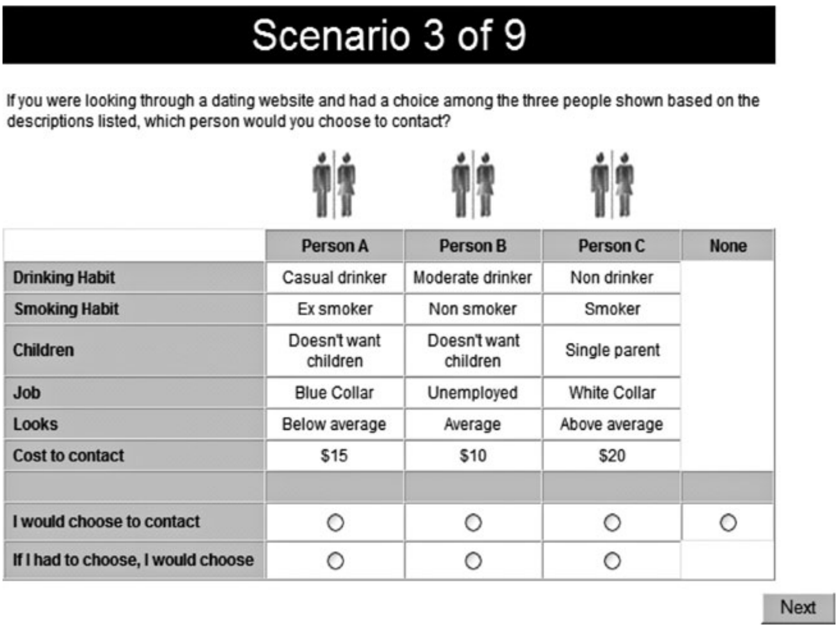
For each choice task, respondents were asked to assume they were reviewing three potential dates on a dating website and to select which candidate they would most likely select to contact, if any. A second choice question was also asked that required respondents to choose from amongst the three candidates if they originally answered that they would contact none of the candidates shown (these 'forced' choices were not used in our analyses). Each potential contact was described on six attribute dimensions which are described in Table 11.1 alongside the attribute levels each attribute could take. An example choice screen is shown in Figure 11.1.

At the conclusion of the survey, respondents were also asked to describe themselves based on the same attributes and attribute levels used in the choice tasks (Figure 11.2). Table 11.2 shows the percentage of respondents in the sample who reported themselves as taking a particular level. The majority of the sample claim to be casual drinkers who

Table 11.1 Attributes and levels used in the choice experiment

Attribute	Level 1 (coded 0)	Level 2 (coded 1)	Level 3 (coded 2)
Drinking habit	Non drinker	Casual drinker	Moderate drinker
Smoking habit	Non smoker	Ex smoker	Smoker
Children	None currently	Single parent	Doesn't want children
Job-type	Unemployed	Blue Collar	White Collar
Looks	Below average	Average	Above average
Cost to contact*	$10	$15	$20

Note: * The actual levels for the price attribute were retained as opposed to using the levels 0, 1, 2.



Scenario 3 of 9

If you were looking through a dating website and had a choice among the three people shown based on the descriptions listed, which person would you choose to contact?

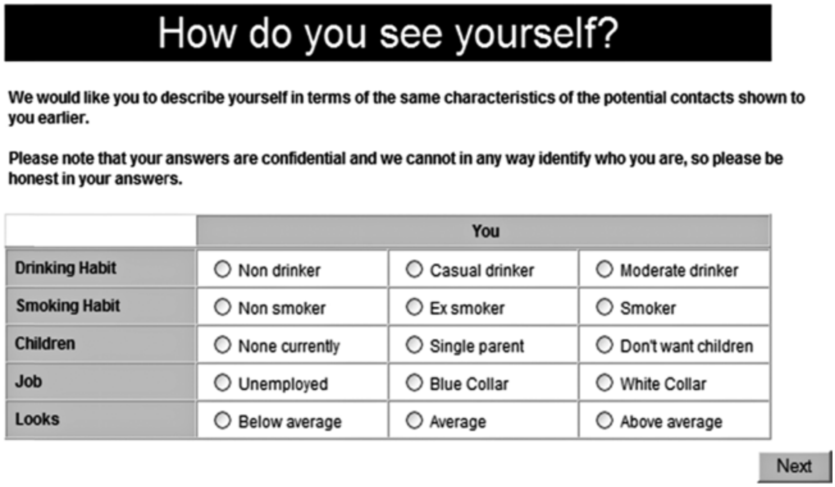
	Person A	Person B	Person C	None
Drinking Habit	Casual drinker	Moderate drinker	Non drinker	
Smoking Habit	Ex smoker	Non smoker	Smoker	
Children	Doesn't want children	Doesn't want children	Single parent	
Job	Blue Collar	Unemployed	White Collar	
Looks	Below average	Average	Above average	
Cost to contact	$15	$10	$20	
I would choose to contact	○	○	○	○
If I had to choose, I would choose	○	○	○	

Next

Figure 11.1 Example choice screen

do not smoke, have no children currently, are white collar workers and of average looks.

The median age of the sample was 50 years with 38 percent of respondents being female. The final sample had a median income level of Au$40,000 per year.



How do you see yourself?

We would like you to describe yourself in terms of the same characteristics of the potential contacts shown to you earlier.

Please note that your answers are confidential and we cannot in any way identify who you are, so please be honest in your answers.

	You		
Drinking Habit	Non drinker	Casual drinker	Moderate drinker
Smoking Habit	Non smoker	Ex smoker	Smoker
Children	None currently	Single parent	Don't want children
Job	Unemployed	Blue Collar	White Collar
Looks	Below average	Average	Above average

Next

Figure 11.2 Respondent self report questions

Table 11.2 Self reported attribute levels (%)

	Level 1 (coded 0)	Level 2 (coded 1)	Level 3 (coded 2)
Drinking habit	18.76	61.57	19.67
Smoking habit	51.59	26.78	21.63
Children	51.74	26.32	21.94
Job-type	25.42	21.18	53.40
Looks	5.45	76.10	18.46

4. MODEL ESTIMATION AND EMPIRICAL ANALYSES

4.1 Model operationalization

Based on preliminary analyses,[3] the following coding scheme was adopted: for attributes 'looks', 'job-type' and 'contacting costs', the original coding (see above) was used. For attributes 'drinking behavior', 'smoking behavior' and 'number of children' the deviation from the decision-maker's own characteristics was used. For example: for 'drinking behavior', "0" stands for no difference in drinking habit (e.g., the decision-maker considers herself to be a casual drinker and is confronted with a potential date of the casual drinker-type), "1" stands for a moderate difference (e.g., the decision-maker considers herself to be a moderate drinker and is confronted with a potential date of the casual drinker-type) and "2" stands for a large difference (e.g., the decision-maker considers herself to be a non-drinker and is confronted with a potential date of the moderate drinker-type). Based on this coding scheme, we expect positive parameters for attributes 'looks' and 'job-type', and negative parameters for all other attributes. Since all attributes except 'contacting costs' have a similar range (consisting of the values 0, 1 and 2), we can directly compare parameter estimates in terms of their magnitude (being a measure of the relative importance of the attribute).

4.2 Estimation results and empirical analyses

Table 11.3 presents estimation results (obtained via BIOGEME (Bierlaire, 2003, 2008)). All estimated parameters are highly significant and have the expected sign in both the utility-based and regret-based model specifications. Also the order of relative importance of non-cost attributes (relative importance being measured by the absolute value of parameter estimates) is the same for both models.[4] It is worth noting at this point, that the data has a panel structure, in the sense that each individual made multiple choices. In Table 11.3 we compute and report both conventional and robust *t*-values to get an idea of the appropriateness of our cross-sectional MNL specification which assumes no correlation between different choices made by the same individual. More specifically, we use the

Table 11.3 Estimation results

	Utility-based model			Regret-based model		
	Beta	*t*-value	Robust *t*-value	Beta	*t*-value	Robust *t*-value
Smoking behavior	−0.764	−22.32	−16.37	−0.534	−21.10	−15.64
Job-type	0.626	27.48	22.40	0.460	27.57	21.23
Looks	0.559	24.48	20.17	0.402	24.86	19.23
Children	−0.459	−13.08	−10.01	−0.308	−12.30	−9.43
Drinking behavior	−0.394	−14.54	−11.31	−0.276	−14.42	−11.28
Contacting costs	−0.0368	−8.20	−7.09	−0.0280	−8.91	−7.27
Constant	−0.0950	−1.19	−0.86	−8.14	−278.6	−126.4
Number of obs.	5949			5949		
Null-LL	−8247			−8247		
Final-LL	−7139			−7127		
ρ^2	0.13			0.14		

approach outlined in Daly and Hess (2011) and Daly et al. (chapter 4, this book) which considers the sequence of choices when computing the sandwich estimator. The fact that for most attributes the difference between conventional and robust *t*-values is not very substantial, signals that the MNL model form – notwithstanding the fact that our model does not contain any socio-demographic variables – is a fairly appropriate approximation in the context of our data.

The final log-likelihood of the regret-based specification is 12 points higher than that of the utility-based model, implying a significantly better model fit with the data. More precisely: using the Ben-Akiva and Swait test (1986) for non-nested models,[5] the null-hypothesis that the utility-based model describes the data better than the regret-based model can be rejected at a 1 percent significance level. Although the difference in model fit remains small, this result can be considered to be in line with our hypothesis that the process of selecting a date is driven more by regret-minimization than utility-maximization premises.

To see how these estimation results translate into differences between choice paradigms when it comes to making relative 'market share' predictions, we use the following example: the choice situation depicted in Figure 11.1 is taken, and we vary person B's job-type and looks between 0, 1 and 2 (implying the full ranges from *unemployed* to *white collar work* and from *below average looks* to *above average looks*, respectively). Our fictitious respondent is a moderate drinker and non-smoker who doesn't want children. Table 11.4 presents relative market shares for Person B (i.e., the predicted choice probability that someone picks person B, given that the individual chooses one of the three dating options), as a function of his or her job-type and looks (RRM probabilities in italic). Although

Table 11.4 Predicted choice probabilities as a function of job-type and looks (%)

Choice probability person B	Below average looks	Average looks	Above average looks
Unemployed			
RUM	19	29	41
RRM	*17*	*28*	*41*
Blue collar			
RUM	30	43	57
RRM	*31*	*45*	*60*
White collar			
RUM	44	58	71
RRM	*47*	*62*	*75*

predictions appear to be roughly similar for the two models, differences are found, of up to 4 percentage points.

Two more specific observations can be made, when inspecting Table 11.4: firstly, it appears that the RRM model is more sensitive than RUM to a simultaneous poor performance on the two attributes (job-type and looks), as well as to a simultaneous strong performance on the two attributes. That is, RRM predicts (ceteris paribus) a lower choice probability than RUM for an unemployed person with below average looks, but a higher choice probability than RUM for a white collar worker with above average looks. The difference between RRM and RUM is largest for the situation where a simultaneous strong performance is present. These results are completely in line with theoretical expectations formulated recently (Chorus, 2010) based on inspection of the RRM model's properties in the context of numerical examples.

Secondly, it appears that RRM predicts a higher choice probability than RUM for a blue collar worker with average looks; in the consumer psychology literature, such an option with intermediate performance on relevant attributes is called a compromise alternative (e.g. Simonson, 1989; Wernerfelt, 1995; Kivetz et al., 2004). Studies in that field (including the ones cited above) have repeatedly shown that decision-makers tend to favor these compromise alternatives over alternatives with a strong performance on some attributes, and a poor performance on others. This behavioral effect is known as the compromise effect. Again, RRM's potential to exhibit a compromise effect has been suggested earlier, based on theoretical derivations and numerical examples (Chorus, 2010); this, however, is the first time this relation is shown empirically in the context of actual choice data.

We proceed by testing how the two model paradigms compare across different segments of the sample. It appears that the relative goodness of fit of the regret-based versus the utility-based approach is relatively stable across different age groups, but that it differs relatively substantially between the subsample of males (N=410, implying 3,690 observations) and that of females (251, implying 2,259 observations). More specifically, while the RRM model fits the data better than its RUM counterpart on the subsample of males (RRM-ρ^2 = 0.154, RUM-ρ^2 = 0.150; p = 0.000), both models fit the data equally well (when employing a 5 percent significance level) for the subsample of females (RRM-ρ^2 = 0.133, RUM-ρ^2 = 0.134; p = 0.079). In sum: although the regret-based and utility-based models appear to be equally good in terms of explaining choice behavior of females, we find that males' choice behavior is governed more by regret-minimization than by utility-maximization premises.

5. CONCLUSIONS AND DISCUSSION

In this paper, regret-based discrete choice models are estimated to explore the determinants of online data-selection decisions. This contrasts with earlier work on this topic, which has predominantly used utility-based modeling approaches. Our general finding that the regret-based model has a better empirical performance in the context of these data is in line with suggestions from the field of behavioral decision-making that date selection-decision contexts are particularly likely to trigger regret-minimization behavior.

More specifically, we find that, in line with previously formulated expectations, the regret-based model predicts lower (higher) choice probabilities than its utilitarian counterpart when choice options have a simultaneous poor (strong) performance on multiple attributes. In addition, also in line with expectations formulated in earlier work, we show how the regret-based model predicts higher choice probabilities than its utilitarian counterpart for choice options that perform reasonably well on each attribute rather than having a strong performance on some attributes and a poor performance on other attributes (so-called compromise options). The degree of importance of regret-minimization as a determinant of choice behavior is relatively high for males.

In our view, the most important direction for future research would be to study whether (or to what extent) our findings can be replicated on other datasets concerning date selection, or other decisions having an important social dimension. This relates to our general finding that regret-based choice models may have an empirical edge over their utility-based counterparts in the context of these decisions, but also to more specific findings such as the relative importance of regret anticipation for young males.

Another potentially fruitful research avenue would be to include more direct measurements of anticipated regret in the choice experiment (for example in the form of questions to be answered using Likert-scales, or even neuroimaging techniques). Such measurements would allow us to test whether found differences in terms of empirical performance between RRM and RUM models on different subsets of the data are in line with more direct measurements of the relative importance of regret in various decision contexts, and for various categories of decision makers. Finally, it appears worthwhile to investigate how both the RRM and RUM models compare (in the context of dating choices as well as other choice types) with respect to more elaborate models of semi- or non-compensatory behavior, such as the model proposed by Swait (2001) and Tversky's Elimination-by-Aspects model (Tversky, 1972).

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NOTES

1. Examples can be found in many sub-fields of the social sciences, including marketing (e.g., Simonson, 1992; Zeelenberg and Pieters, 2007), microeconomics (e.g., Loomes and Sugden, 1982; Starver, 2008), psychology (e.g. Zeelenberg, 1999; Connolly and Reb, 2005) and the management sciences (e.g., Savage, 1954; Bell, 1982).
2. It is important to note here that, 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 – which is the case in our choice-experiment. 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).
3. We tested which coding scheme provided the best results in terms of model fit (final log-likelihood) for the utility-based MNL-model. These analyses showed that while for some attributes ('looks', 'job-types' and 'contacting cost') the absolute level of the attribute matters, for other attributes ('drinking behavior', 'smoking behavior' and 'number of children') it is the deviation from one's own profile that counts.
4. Note that all non-cost attributes have the same scale, so that a mutual comparison in terms of relative importance becomes meaningful, while the cost-unit (AUSD) implies a fundamentally different scale.
5. The Ben-Akiva and Swait test gives an upper bound for the probability that, when some model A achieves a lower log-likelihood than some other (non-nested) model B, A is still the correct model of the data-generating process. This upper bound can therefore be considered a conservative proxy for the significance (or p-value) of a difference in model fit between two non-nested models A and B.

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