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Random Regret Minimization for consumer choice modeling:

Assessment of empirical evidence

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Abstract

This paper introduces to the field of marketing a regret-based discrete choice model for the analysis of multi-attribute consumer choices from multinomial choice sets. This random regret minimization model (RRM), which has recently been introduced in the field of transport, forms a regret-based counterpart of the canonical random utility maximization paradigm (RUM). This paper assesses empirical results based on 43 comparisons reported in peer-reviewed journal articles and book chapters, with the aim of finding out to what extent, when, and how RRM can form a viable addition to the consumer choice modeler's toolkit. The paper shows that RRM and hybrid RRM-RUM models outperform RUM counterparts in a majority of cases, in terms of model fit and predictive ability. Although differences in performance are quite small, the two paradigms often result in markedly different managerial implications due to considerable differences in, for example, market share forecasts.

Keywords: Random Regret Minimization; Random Utility Maximization; Choice Modeling; Consumer Preferences.

Random Regret Minimization for consumer choice modeling: Assessment of empirical evidence

1. Introduction

For decades, discrete choice models have been among the most-used methods for empirical research in the broader field of marketing, retailing and consumer studies (e.g., Baltas & Doyle, 2001). They have been used to analyze and predict consumer choice behavior in a wide variety of contexts, such as related to shopping destination, store or channel choices and their choices between different products and product types (e.g., Timmermans et al., 1991; Volle, 2001; Kaplan et al., 2011; Oppewal et al., 2013) – to name just a few of the abundant body of available examples published in this journal. Practically without exception, these choice models are rooted in the Nobel-prize winning concept of Random Utility Maximization or RUM (McFadden, 1973; Ben-Akiva & Lerman, 1985; Train, 2009).

Recently, a discrete choice model based on premises of regret-minimization has been introduced in the travel behavior community (Chorus, 2010). This so-called Random Regret Minimization model or RRM-model is geared towards the analysis of choices made among multi-attribute alternatives in multinomial choice sets. It postulates that as long as alternatives are defined in terms of multiple attributes (which, as argued by for example Lancaster (1966) is usually the case in consumer choice settings), regret emerges from the process of trading off attribute-levels when making a decision. More specifically, the RRM-model states that regret emerges when a chosen alternative is outperformed by another alternative in terms of one or more attributes. As such, the RRM-model forms a regret-based counterpart of discrete (consumer) choice models that are based on the canonical Random Utility Maximization (RUM). Like

RUM models, the RRM model can be easily estimated (in either MNL, Nested Logit, Probit or Mixed Logit forms) using a range of (off-the-shelf) software packages.

Since its recent introduction, the RRM-model has received an increasing amount of attention from choice modelers in fields as diverse as transportation, urban planning, environmental economics and health economics (e.g., Chorus et al., 2011; Thiene et al., 2012; Kaplan & Prato, 2012; Beck et al., 2013; Guevara et al., 2013; Boeri et al., 2013; Hensher et al., 2013). The result of this increasing interest is a rapidly growing body of empirical and theoretical papers. To explore its merits most of these papers contrast the RRM model to the linear-in-parameters RUM specification that has dominated the field of choice modeling for decades[1]. Typically, differences across the two models are investigated in terms of model fit, predictive performance and/or managerial output. Results of these comparisons suggest that the RRM can be a valuable addition to the choice modeler's toolbox as it features a number of distinct and interesting behavioral properties (see Section 2).

The contributions of this paper are twofold. First, it introduces the RRM model to the marketing research community as an additional tool in their choice modeling toolbox. Second, and more importantly, the paper provides an assessment of the empirical literature on RRM modeling. More specifically, the recently developed body of literature in which RRM is compared with its RUM-counterpart is assessed to explore the potential and limitations of the RRM model as a consumer choice model. The overview presented in this paper consists of 43 comparisons that have been published (or are accepted for publication) in peer-reviewed international journals or scholarly books covering a wide variety of choice

[1] Note that the fact that we in this paper focus our attention on this most basic form of RUM-models is driven by pragmatic reasons in that – with only very few exceptions – the linear-in-parameters version of the RUM-model has been used in empirical comparisons with RRM. Of course, over time many more sophisticated RUM-models have been developed. Some of these models are discussed in the final section of this paper, and an important direction for further research would be to compare RRM with these more sophisticated RUM-models.

contexts, including – but not limited to – choices among travel alternatives, leisure activities, durable goods, dating profiles, and health care options.

Importantly, the aim of this paper is not to suggest in any way that the RRM model may replace the canonical RUM model as a model of consumer choice. In fact, our overview of results shows that differences in model fit and predictive performance between the RRM and RUM model are often small. Yet, irrespective of the differences in fit across the two specifications, we find that the managerial implications derived from both models may vary substantially. As such, the RRM model allows the choice modeler to describe and predict a different type of behavior – supporting the view that RRM is a valuable addition to the consumer choice modeler's toolbox.

Furthermore, it should be mentioned that the idea that anticipated regret plays an important role in (consumer) decision making is by no means new. Roughly speaking, two strands of related literature in the marketing research domain can be distinguished[2]: a first body of literature (e.g., Simonson, 1992; Taylor, 1997; Spears, 2006; Strahilevitz et al., 2012) develops conceptual models that usually take the form of a series of hypotheses, which are subsequently tested based on data collected by means of questionnaires or behavioral experiments. A second body of literature (Hey & Orme, 1994; Inman et al., 1997; Bleichrodt et al., 2010; Chen & Jia, 2012) adopts a more formal perspective as it proposes and empirically tests mathematical models of regret-based decision making, usually inspired by the seminal Regret Theory proposed in the early 1980s (Loomes & Sugden, 1982; Bell, 1982, Fishburn, 1982).

However, despite that the RRM-model is grounded in regret theory it differs in various ways from these previous approaches to model regret-based decision making. As will become clear in the next section,

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[2] An interesting finding that emerges from both bodies of empirical literature is that regret minimization is a particularly important determinant of decision making when choices are perceived by the decision maker as difficult, and important to him- or herself and/or to his or her relevant social peers (e.g. Zeelenberg & Pieters, 2007). It goes without saying that for many consumer choice situations, these conditions readily apply.

the RRM model predicts that the wish to minimize 'attribute-level' regret leads to semi-compensatory decision making and to preferences that are dependent on the composition of the choice set. As such, it makes more sense to view the RRM model as an addition to the literature on context-dependent discrete choice models (e.g., Kivetz et al., 2004; Rooderkerk et al., 2011) than as a new addition to the literature on regret-based decision making. This point is further highlighted in the Appendix, where we provide a conceptual comparison with the regret based model proposed by Inman et al. (1997).

The remainder of this paper is organized as follows. Section 2 introduces the RRM model. Next, Section 3 presents the overview of comparisons. After that, sections 4 to 6 provide respectively discussions on differences between RRM and RUM in terms of model fit, predictive performance, and managerial output. Section 7 draws conclusions and discusses how the RRM model can be used in the process of designing effective marketing strategies.

2. A Random Regret Minimization model of consumer choice

The RRM model (Chorus, 2010) has been designed to incorporate the notion of regret-based decision making in non-risky choice models. The RRM model hypothesizes that, when confronted with a choice set, the decision-maker chooses the alternative from the set that has minimum regret. The regret of alternative *i* is described by the sum of binary regrets where alternative *i* is compared to every other alternative in the choice task on each attribute (see Eq. 1). Regret arises when alternative *i* is outperformed by alternative *j* on attribute *m*. The left panel of Figure 1 depicts the binary regret function for $\beta_m = 1$. If alternative *i*'s relative performance on attribute *m* is sufficiently bad, a nearly linear regret function arises. More specifically, the right panel of Figure 1 shows how marginal regret converges to β_m as (x_{jm}-x_{im}) becomes sufficiently large. From Eq. 1 it can also be observed that the total anticipated regret is the sum of anticipated regrets across all *M* attributes. Overall regret is increasing with the number of attributes on which alternative *i* is outperformed as well as with the number of alternatives by which alternative *i* is outperformed (as denoted by the summation over *j≠i)*, and the importance of the attribute (as denoted by β_m).

$$RR_i = R_i + \varepsilon_i = \sum_{j\neq i}\sum_{m=1}^{M}\ln\left(1+\exp\left[\beta_m\cdot\left(x_{jm}-x_{im}\right)\right]\right) + \varepsilon_i \qquad \textbf{Eq. 1}$$

RR_i denotes the random (or: total) regret associated with a considered alternative i

R_i denotes the 'observed' regret associated with i

ε_i denotes the 'unobserved' regret associated with i

β_m denotes the estimable parameter associated with attribute x_m

x_{im}, x_{jm} denote the values associated with attribute x_m for, respectively, the considered alternative i and another alternative *j*

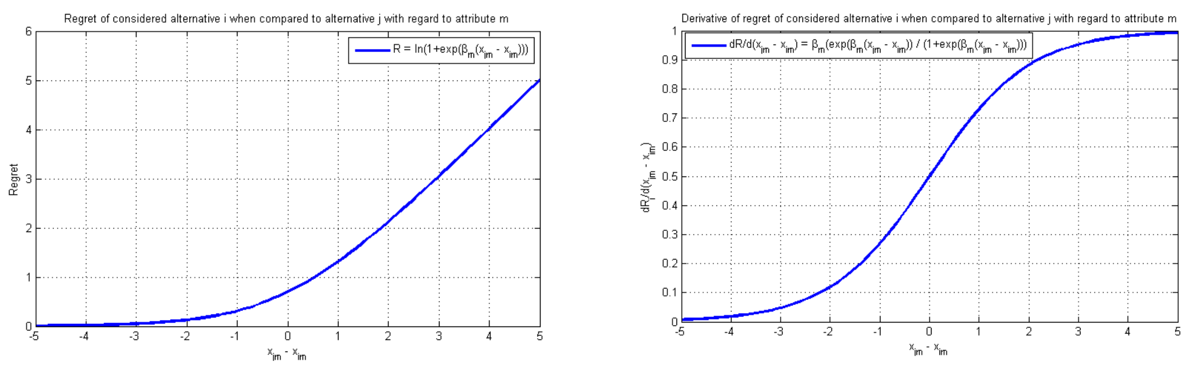

Figure 1: Regret and derivative of Regret of considered alternative *i* when compared to alternative *j* with regard to attribute *m* (in the situation where β = 1)

Figure 1 makes clear that marginal regret with respect to attribute *m* when considering alternative *i* approaches zero when $(x_{jm}-x_{im})<0$. Hence, the RRM-model postulates that when a decision maker considers alternative *i* as compared to alternative *j* he or she experiences (almost) no regret with regard to attribute *m* when in alternative *i* the *m*'th attribute performs considerably better. Note that since Eq. 1 is a smooth approximation[3] of $max\{0,\beta_m(x_{jm}-x_{im})\}$, binary regret is not immediately equal to zero when alternative *i's* performance is better than that of alternative *j*.

Similar to the RUM framework, the functional form of the choice probabilities changes as different assumptions on the random error term ε_i are imposed. When the negative of the errors is assumed to be i.i.d. Type I Extreme Value, the classical MNL-form is obtained[4] and choice probabilities are written as in Eq. 2.

$$P(i) = \frac{\exp(-R_i)}{\sum_{j=1..J} \exp(-R_j)} \qquad \textbf{Eq. 2}$$

Similar to the linear-additive RUM-model, the RRM-model features a smooth, differentiable and globally concave[5] likelihood function. Therefore, it is allows for easy estimation and implementation in existing software packages. However, it is important to note that the independence of irrelevant alternatives (IIA) axiom no longer holds in the RRM framework, since attribute levels of all other alternatives enter the regret function of alternative *i*. In addition, just as under the RUM framework, flexible specifications

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[3] A previous version of the RRM-function (Chorus et al., 2008) featured a combination of two max-operators. That model postulated that regret *equals* (rather than approaches) zero when a considered alternative outperforms a competing alternative on a given attribute. While behaviorally intuitive, this model suffered from the fact that due to the max-operators' discontinuities the resulting likelihood function was not globally differentiable. This implied that the model could only be estimated using custom-made code, and that elasticities and willingness to pay measures could not be obtained. The regret function proposed in Chorus (2010) and put forward in the current paper forms a smooth approximation of the 2008-model, while circumventing the econometric issues mentioned directly above.

[4] Note that one can also derive closed form expressions for RRM-choice probabilities under the assumption that the error terms itself, rather than their negatives, are distributed Extreme Value Type I. This would reframe the RRM-model as a so-called reverse discrete choice model (Anderson & de Palma (1999)). However, while still closed form, the resulting choice probability formulations are less tractable than the MNL-ones and the resulting choice models are less compatible with standard discrete choice software packages. Therefore, in this paper the assumption is maintained that the *negatives* of the errors are distributed Extreme Value Type I.

[5] Under linear-additive MNL specification.

of the error term can be used to capture correlation structures in the data. This translates into well-known model forms like the Nested Logit model, Error Components model and the Probit model.

Given space limitations and in the light of the fact that previous publications provide more in-depth discussions of the properties of the RRM model (e.g., Chorus, 2010, 2012a), we choose to limit ourselves to a brief discussion of the arguably most important model property for consumer choice modelers: the RRM model features a particular type of semi-compensatory behavior which results in preferences for compromise alternatives.

Due to the convexity[6] of the regret-function, the RRM model imposes that improving an alternative in terms of an attribute on which it already performs well relative to other alternatives generates only a small decrease in regret ($dR/dx_{im} < \beta/2$). However, deteriorating to a similar extent the performance on another equally important attribute, on which the considered alternative has a poor relative performance, may generate a substantial increase in regret ($dR/dx_{im} \approx \beta$). As a consequence, the RRM model predicts that improving an attribute does not necessarily compensate for an equally substantial deterioration of another, equally important, attribute. This behavior, which is embodied in the functional form of the regret function and illustrated by Figure 1, implies that, contrary to the linear-additive RUM model, the implied attribute-tradeoffs are no longer constant: they are to a large extent dependent on the composition of the choice set. Under a RRM framework, attribute-tradeoffs crucially depend on the performance of the alternative *and* its competition in terms of the attributes, relative to other alternatives in the choice set.

RRM's ability to accommodate a preference for compromise alternatives follows directly from the above mentioned semi-compensatory behavior: RRM-models postulate that it is effective (in terms of avoiding

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[6] Note that $d^2R/dx^2>0$ for all x.

regret) to select a compromise alternative. Even when such a compromise alternative fails to have a strong performance on any of the attributes (relative to the other alternatives in the set), RRM-models predict that it will still only generate modest levels of regret as long as it does not have a particularly poor performance on any of the attributes. In other words, it is efficient – in terms of avoiding regret and gaining market share – for an alternative to avoid a poor performance on any attribute, even when this implies that the alternative does not have a very strong performance on any attribute as well.

By conceptually comparing the RRM model with what is perhaps the most prominent regret based choice model in the marketing literature: the Inman-Dyer-Jia-model – or IDJ-model from here on (Inman et al., 1997)[7], it is clear that the RRM model is a new addition to the choice modelling literature, rather than an extension or adaptation of previous regret based models. Such a conceptual comparison between the two models is reported in the Appendix.

3. An overview of empirical comparisons between RRM and RUM models

We focus on empirical studies that report comparisons between RRM and RUM and have been published in, or are (conditionally) accepted for publication in, peer-reviewed scientific journals or books. Twenty-one of such publications (co-authored by in total 28 authors) emerged over the last three years. These 21 publications encompass a total of 43 empirical comparisons between RRM and RUM: for example, one publication may estimate MNL- as well as Mixed MNL specifications of both the RUM and RRM models, and do so in the context of two different datasets. This would result in four comparisons. Table 1 presents these 43 comparisons.

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[7] It should be noted that Inman et al.'s (1997) model was actually developed as a post choice valuation model. However, the Appendix of the paper explains how the model can be recast in terms of a choice model.

The columns present from left to right: the comparison identifier (which is used in the remainder of this article as a reference); the name of the authors; year in which the article is (to be) published; type of data (Stated Preference or Revealed Preference); model specification (MNL or Mixed MNL, the latter including random parameter logit and error component logit); best model fit; best predictive ability (two different metrics); and choice type or context. The last row provides column totals.

The overview of comparisons in Table 1 provides some interesting insights. Firstly, looking at the far right column we see that choice types in which RRM and RUM are compared are quite diverse, albeit the majority refers to mobility and freight transport related choices. This is of course to be expected given that the RRM-model originates from the transportation community. Choice types closest to the marketing domain include choices among durable goods (car types) and shopping destination choices. Secondly, it appears that most of the reported comparisons are based on SP-data: only five out of 43 use RP data. Thirdly, the majority of comparisons are done in the context of estimation of MNL-models. Only seven comparisons concern error component mixed logit models to accommodate panel and nesting effects, and four comparisons report a random parameter mixed logit model to accommodate random taste heterogeneity[8].

Rather than conducting a formal statistical meta-analysis using the reported comparisons in the overview, the next 3 sections discuss findings on differences between RRM and its RUM counterparts in terms of model fit, predictive performance and managerial implications. Although some may argue that the number of comparisons (43) may be just sufficient to perform such a formal statistical meta-analysis, we feel that for the results of such an analysis to be reliable, robust and meaningful, a larger sample and a larger degree in variation across choice types (e.g. more non-transportation choice contexts) and

[8] Note that Prato (2014) reports estimation results of MNL-models as well as a variety of non-MNL models. However, these non-MNL models are specifically designed to control for possible bias caused by route overlap and are as such of less relevance in consumer choice contexts. Therefore, the current paper only focuses on the MNL-results of Prato (2014).

characteristics of choice situations (e.g., number of alternatives, attributes per alternative) is needed. Especially in light of the fact that (as will be elaborated below) differences in model fit and predictive performance between RUM and RRM are (very) small, we feel that a larger number of studies is needed before any reliable conclusions can be drawn from a meta-study.

4. RRM versus RUM: differences in model fit

To evaluate whether RRM or RUM outperforms the other in terms of model fit, we need a statistical test. Since neither model can be seen as a special case of the other model (even though both models consume the same number of parameters) a test for non-nested models needs to be used. Most studies contrast the fit of the RUM and RRM model using the Ben-Akiva and Swait test (1986). This test generates an upper limit for the probability that, given that the log-likelihood associated with model A is higher than that of model B, model B actually provides the best representation of the data-generating process. For studies not reporting the Ben-Akiva and Swait test statistic, we carried it out *ex post* based on the reported estimation results. The conclusions are as follows:

As can be seen in Table 1, at a significance level of 95%, in 15 cases the RRM model fits the data significantly better than the RUM model, while in also 15 cases the RUM model fits the data significantly better. In 13 cases, there is a statistical tie (at the 95% significance level). Arguably more important than the statistical significance of the differences in model fit is the size, and therefore relevance, of these differences; it appears that in almost all cases the differences are small (see further below for discussion of a notable exception).

One of the key questions is whether there is a pattern in when one model structurally outperforms the other. For instance, it might be expected that contextual factors, such as time pressure or importance of the decision, may be important determinants for the decision process. The consumer-psychological literature provides a starting point for an analysis of the role of contextual factors as a determinant of the differences in model fit between the RRM and the RUM: a series of empirical studies have shown that the minimization of anticipated regret especially plays an important role when a particular choice is either considered difficult and/or important for the decision makers and/or when they anticipate having to be able to defend their choice to others. Having this information in mind, it is not surprising to find that comparisons in the context of e.g. car type choices, policy choices of politicians, choices between dating profiles, and choices of goods transporters in general show a better fit for RRM, whilst choices between e.g. leisure time activities and car-drivers' routes choices in general show a better fit for RUM. Also in line with the above mentioned psychological evidence is the finding that RRM outperforms RUM in the context of stated car type-choices made by households and by individuals in households that shoulder a high degree of responsibility for their choice (Beck et al., 2013), while RUM and RRM perform equally well in the context of the same stated choices, but made by individuals in the household that do not shoulder a high degree of responsibility for the choice (Beck et al., 2013).

Another seemingly structural impact on the relative differences between model fits of RUM and RRM models is caused by the use Mixed MNL models. Several studies (e.g., Hess et al., 2014; Boeri & Masiero, 2014) report that differences in fit between the two models in MNL-form become more amplified when re-estimated in Mixed MNL form. The intuition behind this finding is clear: if there is a preferred behavioral mechanism underlying the data (either RRM or RUM), a more sophisticated treatment of the error term reduces the amount of 'white noise' that is left uncaptured in the model. As such it helps bring to the front any differences in model fit related to differences in assumed decision rule.

As noted, although generally significant, model fit differences between RRM and RUM vary between very small and modest. A notable exception however, is the situation where, in the context of stated choice-experiments, a so-called ‘opt out’ or ‘no choice’ option exists. A recent study (Hess et al., 2014 – comparisons 38-41 in Table 1) found that when this option is framed as ‘none of these’ (or a variant thereof), the regret model is likely to perform much worse than its utilitarian counterpart in terms of model fit, and might even produce biased parameters. But when the ‘opt out’ is framed as ‘I am indifferent’ (or a variant thereof), the regret model is likely to perform much better than its utilitarian counterpart, the latter generating biased parameters. As explained in that paper, these substantial differences in performance in the context of different formulations of the ‘opt out’ option, can be directly and unambiguously related to the differences in behavioural premises underlying the two model types: in short, the ‘none of these’ frame corresponds well with the meaning of an opt out-constant in a RUM model (but poorly with the meaning of an opt out-constant in an RRM model). The opposite holds for the ‘I am indifferent’ frame. However, note that Chorus & Rose (2012), using other data, found that even in the context of a ‘none of these’ opt out, the RRM-model achieved a better fit than its RUM counterpart (albeit the difference, in favour of RRM, was much bigger when the opt out was not taken into account). More research is hence needed to find out to what extent these findings related to the impact of opt out-formulations on the performance of RUM and RRM models, can be generalized.

Besides the comparison of RRM and RUM models, a number of comparisons – e.g., 13, 20, 21, 30-37) as well a manuscript not included in Table 1 (Greene, 2012) – also involve so-called hybrid RUM-RRM models. These hybrid models (see Chorus et al., 2013a for an in-depth introduction) assume that the decision maker processes some attributes following the RRM model and others using the linear-additive RUM model.

Testing all possible RUM-RRM attribute combinations[9] in terms of model fit shows that the hybrid model often performs better than a model that assumes the same rule of behavior (RRM or RUM) for each attribute. More specifically, a hybrid model outperforms full RUM and RRM models in about two-thirds of cases. Differences are again small but mostly statistically significant at conventional levels. When we incorporate hybrid models in our over-all model fit comparison, it appears that in a substantial majority of cases a model that is (partly or fully) based on regret minimization provides a significantly better model fit than a model fully based on utility maximization.

Another kind of hybrid RUM-RRM model has been recently proposed by Hess et al. (2012): these authors assume – in contrast with the hybrid specification presented above – that all attributes are processed using one and the same decision rule (e.g. RUM or RRM). However, they propose that the assignment of decision rules to individuals can be modeled as a probabilistic process; as such the authors allow for heterogeneity in decision rules across individuals. Using a latent class specification, the authors show that such a hybrid RUM-RRM form (using the Chorus et al. (2008) version of the RRM-model) provides important gains in model fit compared to models that assume that all individuals use the same decision rule. See also Hess & Stathopoulos (2014) and Boeri et al. (2014) for somewhat similar latent class applications, but now working with the Chorus (2010)-version of RRM, and using random parameter-Mixed MNL models within each class.

5. RRM versus RUM: differences in external validity

[9] When alternatives encompass *M* attributes, there exist 2^M possible RRM-RUM attribute combinations. However, it should be mentioned here that the estimation of hybrid models is facilitated in the software package NLOGIT 5, which provides the option of indicating per attribute whether it should be processed as a 'RUM-' or a 'RRM-attribute'.

To explore differences in external validity between RRM and RUM, we look at two measures of predictive power on hold-out data: likelihood of the hold-out data given the estimated model, and hit rate. In total, eight out of the 43 comparisons mentioned in Table 1 reported one or both measures. Seven of these comparisons reported a measure based on the likelihood of the hold-out data given the estimated model. This concerns the so-called mean-likelihood, which calculates for each observation (observed choice) from the hold-out data the probability of that observation given the estimated model, and from that calculates the average. Only two comparisons reported a so-called hit rate or 'percentage correctly predicted'. The hit rate was calculated ex post by the authors for five other comparisons while not being reported in these publications themselves. Below we provide an overview of the differences between RRM and RUM in terms of all these published and unpublished results.

As far as the mean-likelihood is concerned, the performance of the RRM-model is found to be slightly better than that of the RUM-model: in four cases hold out data are more likely given the RRM-model than the RUM-model, while in two cases the two models perform equally well. Only one case reports a better performance of the RUM model. However, it should be noted that these differences between RUM and RRM are, without exception, small.

The RRM-model also performs slightly better than the RUM-model as far as the hit rate is concerned: in three of the seven cases the RRM-model produces a higher hit rate; in two cases the hit rate of the estimated RUM-model is higher and in the other two cases both models perform equally well. The differences in hit rates are somewhat more substantial than differences in mean-likelihood, although never larger than a few percentage points. However, this is a direct consequence of the fact that the hit rate translates a probabilistic measure into a deterministic choice. Overall, the results in terms of external validity are comparable to those in terms of model fit.

Interestingly, it appears that differences in model fit and external validity between RUM and RRM are not necessarily consistent when compared across measures: that is, some comparisons report a higher model fit for one of the two models, in combination with a worse out of sample predictive ability.

6. RRM versus RUM: differences in managerial implications

Even though most (consumer) choice modelers are very much interested in the performance of models in terms of model fit and external validity, it is clear that consumer choice models need to ultimately serve a 'higher' goal: the quantitative support of marketing management. Therefore it is important to examine the differences between RUM and RRM in terms of the managerially relevant output both models produce (such as estimates of willingness to pay, demand elasticities, and market share forecasts). Of the 43 comparisons, about one third present some form of managerially relevant output. For reasons of succinctness we do not discuss all forms of managerial relevant output that have been reported. Instead, we focus on only an illustrative sub-sample consisting of four comparisons (in the context of elasticities and market share forecasts, respectively): 7, 12, 14, and 22.

Comparison 7 (Thiene et al. 2007) focuses on itinerary route choices of visitors to a natural area in the Dolomites. Demand elasticities are calculated (for RRM and RUM models) for attributes such as the presence of way-markers and possible access fees. For most of the attributes the RRM-elasticities were greater than the RUM-counterparts – in most cases the differences were about 10%. The extent to which the market share of a route was influenced by imposing access fees was also examined. For the chosen variant the effect predicted by the RUM model (3.10% decrease in the market share) was greater than the effect predicted by the RRM (2.06% decrease in market share).

Comparison 12 (Chorus et al. 2013) analyzed preferences of company car users in terms of alternative fuel vehicles. Despite that the estimated RUM and RRM models achieved a very similar fit with the data, when both models were used to predict market shares of different alternatives in a hold-out sample, differences between RUM and RRM in terms of predicted market shares were often large: in 26% of the cases the difference between the market share predicted by RRM and RUM was larger than 5 percentage points and in about 4% of the cases it was 10 percentage points or more. In about 7% of choice situations, the RRM and RUM model identified different car-types as the 'winner' in their choice set.

Comparison 14 (Chorus and Bierlaire 2013) focuses on route choices of Dutch commuters (routes being specified in terms of travel times, costs, percentage of travel time in congestion, and travel time variability. In this study particular attention was given to the possible presence of a compromise effect. Estimated demand elasticities for RUM and RRM models hardly differ, with the exception of the travel time elasticity which is nearly 10% greater for the RRM model than for the RUM model. In addition, estimated models were used to predict market shares for alternative routes. In line with theoretical expectations (Chorus, 2010, 2012a – see also Section 2 of the current paper) the RRM model (27%) predicted a substantially and significantly higher choice probability than the RUM model (23%) for a 'compromise' route.

The focus of comparison 22 (Hensher et al. 2013) was on the preferences of consumers for cars which use alternative fuels. The authors calculated elasticities based on the estimated RUM and RRM models and concluded that the differences between the two model types was substantial – up to 19%. Without exception, price elasticities based on RRM turned out to be greater than the RUM counterparts.

Taken together, and also including results from other comparisons not discussed in depth in this section, it can be concluded that despite the fact that differences between the two model forms in terms of model fit and external validity are often very small the differences between RUM and RRM in terms of managerially relevant output (such as elasticities, market shares) are sometimes quite substantial. The next section considers the question of what implications this somewhat paradoxical combination (i.e., the combination of a generally very similar empirical performance and a sometimes quite large difference in managerially relevant output) has for the possible role of the RRM model in supporting marketing management strategies.

7. Conclusions and discussion

The results presented in the three preceding sections trigger the question to what extent and in what ways the recently introduced Random Regret Minimization (RRM) model can be most effectively implemented as an alternative for or in combination with the canonical Random Utility maximization (RUM) model, to assist marketers to develop robust and effective marketing strategies. The choice between the two model types is not an easy one: on many datasets either one or the other model (RRM or RUM) is statistically preferred over the other in terms of model fit; however, we find that differences are nearly always small. Besides that, we find that it is sometimes the case that a model type that has a better model fit than the other model type for a certain dataset scores less well than the competing model type in terms of predictive ability on hold out data. Yet, we also find that the two models can lead to markedly different managerially relevant output, such as predicted market shares for products or services. The choice of model form (RUM vs. RRM) can therefore have a substantial practical impact.

This means that there are at least two options left to determine the role of RRM for supporting the design and selection of marketing strategies. A first option is to apply RRM in the situations where it has shown to perform better than RUM, for example in terms of model fit with relevant data. Whether or not this approach is appropriate is debatable, given the small differences between the two models in terms of model fit. However, strictly speaking there is a case for estimating both RUM and RRM models on a given dataset and then, in case of statistically significant differences in fit, choosing the best fitting of the models for further analyses and the derivation of managerially relevant output.

Another option is not to choose for either of the two models, but to implement them both simultaneously and then, based on the outcomes, to set up a number of 'behavioral scenarios' using either a RUM, RRM or hybrid RUM-RRM model (for example, one scenario based on RUM-elasticities and another scenario based on RRM and/or hybrid RUM-RRM elasticities). Similarly, a 'behavioral confidence interval' can also be created, using both the RUM and the RRM outcomes. Using this type of approach, marketing strategies can be developed and/or selected which score relatively well from both a regret minimization and utility maximization perspective (for example in terms of the expected effects of the demand for a product or service). In other words: by jointly using outcomes from RUM and RRM / Hybrid RUM-RRM models, marketing strategies can be developed and/or selected which are *robust from a behavioral perspective:* the selected measures have been shown to score relatively well, regardless of the assumed behavioral premises (regret minimization or utility maximization). To the authors, this second option seems to be the most fruitful one.

For instance, in the marketing field it would particularly be interesting to use the RRM model specifically in situations where choice set composition effects (such as the compromise effect) are expected to play an important role. Since regret exists as a result of the comparison between competing alternatives, the RRM model by definition predicts that the regret of an alternative can be influenced by changing the composition of the choice set (without altering the alternative itself). As such, the RRM model offers the possibility of examining the potential of marketing strategies aiming composing choice sets in a way that is optimal for a certain marketing strategy. In such a context the RRM model can provide managerially relevant information which complements the information generated by linear-additive (and context-independent) RUM models.

Finally, it is clear that (much) more work is needed before the potential of the RRM model in the context of consumer choice and marketing research can be fully understood and realized. Important directions for future research include:

- estimation of RRM models on consumer choice data (so far, most datasets focused on transportation, leisure and health related choices);
- estimation of more sophisticated RRM model forms allowing for, e.g., random heterogeneity in terms of both tastes and scale (so far, the majority of RUM-RRM comparisons focused on the rather simple MNL-model form);
- identification of possible structural differences in the relative performance of RRM and RUM across different types of choice situations and socio-demographic segments.
- comparisons between RRM and non-linear-in-parameters utility models[10].

This final bullet deserves some additional attention: the marketing science and consumer behavior research community in particular have been very active in developing utility-models that relax the rather strict behavioral assumptions represented in the linear-in-parameters model form. Some notable examples include the Contextual Concavity Model (Kivetz et al., 2004) which captures reference dependency and decreases in sensitivity by means of a locally concave utility function; the Relative Advantage Model (Tversky & Simonson, 1993) which incorporates loss aversion and decreasing sensitivity by means of a non-linear advantage/disadvantage function; the Elimination-by-Aspects model (Tversky, 1972), which assumes that decision makers randomly select attributes (more important attributes have a higher chance of being selected), and eliminate alternatives which do not perform well enough on the attribute; the Lexicographic model (e.g., Saelensminde, 2006) which can be considered a

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[10] We know of only two papers that provide comparisons between RRM and non-linear-in-parameters utility-models (Leong & Hensher, 2014; Chorus & Bierlaire, 2013). In light of this very small number of studies involved, we refrain from drawing generic conclusions from these comparisons.

special case of an Elimination by Aspects model in that it assumes that decision makers only consider one attribute when choosing, and select the best performing (on that attribute) alternative; the Satisficing model recently proposed by Stüttgen et al. (2012), which postulates that decision makers randomly select alternatives and pick the first alternative that performs 'good enough'; and the generic context dependent model (Rooderkerk et al., 2011) which simultaneously incorporates compromise, attraction and similarity effects. Each in their own way, these models deviate from the linear-in-parameters RUM model by allowing for non-IIA behavior, choice set composition effects, reference dependency and asymmetry of preferences. It is of crucial importance that in future research the RRM model is also empirically compared with these more advanced utility based choice models, as opposed to only (or mainly) with the most basic RUM model – the linear-in-parameters model.

Notwithstanding these and other important knowledge gaps, we believe – based on the results reported in this paper – that the evidence that has so far accumulated in fields adjacent to marketing research suggest that RRM may in time become a viable addition to the toolkit of consumer choice modelers.

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Appendix: comparison of the RRM model (Chorus, 2010) and the IDJ-model (Inman et al., 1997)

The IDJ-model can be denoted as follows (our notation; in line with Inman et al. (1997), we focus on the single attribute, binary choice set case):

$$EV_i = \beta \cdot \sum_s P_s \cdot x_{is} + \sum_s P_s \cdot \left[\beta_{rej} \cdot \max\{0, x_{is} - x_{js}\} + \beta_{reg} \cdot \max\{0, x_{js} - x_{is}\} + \beta_{ela} \cdot \max\{0, x_{is} - \sum_s P_s \cdot x_{is}\} + \beta_{dis} \cdot \max\{0, (\sum_s P_s \cdot x_{is}) - x_{is}\}\right]$$

Here,

EV_i = expected utility of alternative *i*

P_s = probability of state of the world *s*

x_{is}, x_{js} = quality of alternatives *i* and *j* given state of the world *s*

β = parameter for context free quality

β_{rej} = rejoice-parameter

β_{reg} = regret-parameter

β_{ela} = elation-parameter

β_{dis} = disappointment-parameter

A conceptual comparison between the two models can now be made along a number of dimensions.

Choice set size: the IDJ-model is derived in the context of binary choice sets, containing two alternatives. In contrast, the RRM-model reduces to linear-additive RUM in the context of binary choice sets; it is designed to capture choice set composition effects in multinomial choice sets. Extending the IDJ-model towards multinomial choice sets is not trivial. For example, the analyst must decide whether to include comparisons with all competing alternatives (as is the case in the most recent version of the RRM-model), or to include comparisons only with the best of the non-chosen alternatives (as has been advocated by, for example, Quiggin (1994)).

Smooth or non-smooth regret: the ‘regret-part’ of the IDJ-model is non-smooth (i.e., it has a kink around zero). This implies that standard procedures for maximum-likelihood estimation cannot be used to estimate the IDJ-model, precluding the use of most standard software packages. Also, the derivation of willingness to pay measures and elasticities is hampered by this non-smoothness. In contrast, the regret function of the RRM model is smooth and globally differentiable (see also Footnote 3).

Number of attributes: the IDJ-model is presented in the context of a single-attribute[11] comparison between choice options, although it is mentioned that the model can in principle be extended towards capturing multi-attribute comparisons. In contrast, the RRM-model is designed for multi-attribute comparisons. As mentioned above, it is the multi-attribute nature of comparisons that generates the semi-compensatory behavior and choice set composition effects that are key character traits of the RRM model.

Choice context: the IDJ-model explicitly focuses on risky choices. Regret emerges due to the fact that the decision-maker is not certain about the quality of different choice options at the time of choosing (this riskiness is captured by means of appropriately specified probability distributions over states of the world). In contrast, the RRM model explicitly focuses on riskless choices, where quality of different products is known beforehand. Potential regret emerges due to the fact that the decision-maker has to make tradeoffs between different attributes (quality-dimensions).

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[11] Actually, IDJ use the term ‘attribute’ differently from how we use that term in this paper. In this paper, the term ‘attribute’ corresponds with what IDJ call a ‘performance dimension’.

Beyond regret: besides regret, the IDJ-model also incorporates rejoice (the opposite of regret), as well as disappointment and its opposite (elation). The latter two terms are computed by comparing an alternative's quality with *a priori* expectations. In addition, the IDJ-model includes a reference-free utility term, which represents the valuation of product quality independent of comparisons with non-chosen alternatives and expectations. In contrast, the RRM-model is less generic than the IDJ-model, as it only considers regret[12].

Number of parameters: the full IDJ-model contains five estimable parameters (per attribute) – one for reference-free utility, two for regret, respectively rejoice, and two for disappointment, respectively elation. When symmetry is assumed for regret/rejoice and for disappointment/elation, this number drops to three. In contrast, the RRM-model only features one parameter per attribute. This implies an advantage in parsimony for the RRM-model compared to the IDJ-model, which however comes at the cost of a loss in completeness and in flexibility. The loss in flexibility relates to the fact that the RRM model imposes a particular functional form to represent convexity in regret, while the IDJ-model allows for estimation of the degree of convexity (by estimating the (relative) size of regret- and rejoice parameters).

Together, the above discussion shows that the RRM-model (Chorus, 2010) and the IDJ-model (Inman et al., 1997) are two quite different models, both in terms of behavioral conceptualizations, scope, and mathematical formalization.

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[12] Strictly speaking, the RRM-model can also incorporate rejoice: when a 'correction term' of size ln(2) is subtracted from all attribute-regrets (note that this does not change choice probabilities), the attribute-regret function goes through the origin and equals zero when the considered alternative performs equally well as a competing alternative; that is, the corrected regret function results in zero regret when comparing two equally good alternatives. This also implies that when the considered alternative outperforms a competing alternative in terms of the attribute, there is rejoice. By definition however, convexity of the regret function adopted in the RRM-model implies that rejoice plays a minor role compared to regret.