Regret aversion in riskless choice contexts:

A formal model of choice behavior and morally problematic choice architectures

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Abstract

This Chapter presents a mathematical model of regret-based decision making in riskless contexts; regret emerges when, in a multi-attribute and multinomial choice set, a chosen alternative is outperformed in terms of one or more attributes by one or more non-chosen alternatives. The model is used to formalize the notion of choice set regret, which is the amount of regret imposed onto a decision maker when choosing from a set of alternatives. Using this formalized notion of choice set regret, I show how morally problematic choice sets can be identified; choice architects may use the proposed formalizations to avoid triggering unwarranted levels of regret among decision makers.

1. Introduction

The notion of regret aversion has a rich tradition in the Economic sciences. Prominent examples of microeconomic models of regret based decision making include the minimax regret framework (Savage, 1951) and regret theory (Loomes and Sugden, 1982; Bell, 1982). What these frameworks and models have in common, is that they postulate that when choosing between options, the decision maker aims to avoid the situation where a non-chosen option turns out to perform better than the chosen one. Indeed, there is ample empirical evidence from the field of psychology and the neurosciences, that the phenomenon of regret aversion plays an important role in decision making (e.g., Coricelli et al., 2005; Zeelenberg and Pieters, 2007). A commonality between the regret based theories, frameworks and models presented in Economics, Psychology, and other fields, is that they refer to so-called risky decision making[ii]. That is, the decision maker does not know in advance the performance of each of the options in her choice set. The classical example being that of a

lottery: one does not know in advance if the lottery ticket is a winning one, and regret based models assume that when considering buying a lottery ticket, the decision maker contemplates the anticipated regret that will be experienced when not winning[iii]. It goes without saying that the scope of (regret based models of) risky decision making is much broader than lotteries; regret based models are routinely used to model decision making in all sorts of contexts including health, transportation, and financial decision making (insurance, investment decisions); see Section 5 in Bleichrodt & Wakker (2015) for a recent review of applications of regret theory for risky decision making. Crucially, by design and by definition, regret based models of economic decision making construe regret as resulting from – and inexorably bound to – imperfect knowledge; in a world of perfect information and optimal decision making, there would be no regret.

In this Chapter, I will argue that this perspective on regret minimization is incomplete, and that regret aversion also plays a role in so-called riskless situations where the decision maker has full advance knowledge of the performance of all options in her choice set, in terms of all relevant criteria. First, I will present a formal model of regret based decision making in riskless choice contexts. This so-called random regret minimization model (RRM from here on) has been recently introduced in the domain of Transportation (Chorus et al., 2008; Chorus, 2010, 2014a; van Cranenburgh et al., 2015; Jang et al., 2017), and has since been applied in a wide variety of decision making contexts within and well beyond that domain[iv]. Subsequently, I will use this model to explore why some choice sets (or: choice architectures) are morally problematic as they generate high levels of – anticipated – regret on the side of the decision maker. By taking these steps, I connect the notion of regret aversion in riskless choice contexts to the literature on nudging and choice architectures[v], which is rapidly gaining attention among researchers in marketing, health, transport and environment, behavioral economics and ethics (e.g. Selinger and Whyte, 2011; Johnson et al., 2012; Thorndike et al., 2012; Avineri, 2012; Thaler et al., 2014; Sunstein, 2015).

Section 2 presents the RRM model. A measure of 'choice set regret' is derived in Section 3, where it is also explained that choice set regret is a function of the specific composition (i.e., architecture) of the choice set; in that section I will also argue why some choice set compositions or architectures may be considered morally problematic as they trigger disproportionally high regret-levels among decision makers.

2. A Random Regret Minimization (RRM) Model of Riskless Decision Making

Before presenting the RRM model in mathematical notation, I give a behavioral introduction and interpretation. Consider a choice situation where a decision maker makes a choice from a finite set of discrete and mutually exclusive options (called alternatives); each option being described in terms of a number of dimensions or criteria (called attributes). The RRM model postulates that a decision maker, when making a choice from this set, aims to minimize regret, by means of choosing the alternative from the set with minimum regret. From the analyst's perspective, a considered alternative's regret is composed out of a random part and a systematic part. The random part contains all factors unobservable by the analyst but relevant to the decision maker. The systematic part contains the influence of all observable factors (i.e., attributes of the alternative[vi]). This *systematic regret* of a considered alternative is postulated to equal the sum of all so-called binary regrets which arise from bilaterally comparing the considered alternative with each competitor alternative. This *binary regret* in turn is specified as the sum of all so-called attribute regrets which arise from comparing the considered alternative with a particular competitor in terms of each attribute. This *attribute regret* is an increasing function of the product of the attribute difference and the taste parameter (decision weight) associated with the attribute. In other words: attribute regret increases 1) as the extent to which the competitor alternative outperforms the considered alternative in terms of a particular attribute increases, and 2) as the importance, to the decision maker, of the attribute increases. Crucially, attribute regret is postulated to be a *convex* function of attribute differences and decision weights: the regret which is caused by a deterioration of a considered alternative's relative (i.e., compared to a competitor) performance on a particular attribute is larger than the reduction in regret which is caused by an improvement of equal size.

To make this more concrete, I present a running example which will return in various shapes and forms in the remainder of this Chapter. Consider the situation where the decision maker is moving to a new town for work, and is considering a set of three residential alternatives (House A, B, and C) offered by her real estate agent. Each house is described in terms of a number of attributes, such as the size of the garden, number of rooms, commute time to work, price, etc. The decision maker is assumed to compare house A with house B and with house C in terms of the size of the garden, number of rooms, etc. Consider the comparison of A with B in terms of the attribute 'size of garden': assume that the decision maker prefers a larger garden over a smaller one. Now, if house A has a smaller garden than house B, this

generates attribute regret (‘garden regret’). The more important the size of the garden is to her, and the bigger the difference between sizes of A’s garden and B’s garden (in favor of the latter), the larger the amount of generated ‘garden regret’. If house A has a bigger garden than house B, the comparison of A with B in terms of the attribute ‘size of garden’ generates ‘garden rejoice’ (rejoice being the somewhat awkward term used by economists to describe the opposite of regret). Rejoice, just like regret, becomes larger when the attribute becomes more important and when the difference between the garden sizes increases (in favor of house A). Crucially however, the regret which is associated with a given difference in garden size in favor of house B, is larger than the rejoice which would be associated with the same difference in garden size if it were in favor of house A. Likewise, A is compared to B, and with C, on all other attributes; all these resulting attribute regrets are summed to obtain the full systematic regret associated with house A. The same is done for house B and C, to obtain systematic regrets for all three alternatives. Adding random errors to all three systematic regrets (in order to represent ‘noise’ in the decision-making process and the presence of attributes which are omitted in the model), leads to so-called total regrets for all three houses. The decision maker is subsequently assumed to choose the house with lowest total regret.

In mathematical notation, in its most generic form, the total regret of a considered alternative is written as follows:

$$RR_i = R_i + \upsilon_i = \sum_{j \neq i} \sum_m \mu \cdot \left[\ln\left(1 + \exp\left[\frac{\beta_m}{\mu} \cdot \left(x_{jm} - x_{im}\right)\right]\right) - \ln(2) \right] + \upsilon_i \qquad (1)$$

RR_i, denotes the total regret associated with considered alternative i.

R_i denotes the systematic regret associated with i.

υ_i denote the error terms associated with i; If it is assumed that its negative follows an i.i.d. Extreme Value Type I distribution, practical Logit type choice probabilities (P) are obtained: $P(i) = \frac{\exp(-R_i)}{\sum_{j=1..J} \exp(-R_j)}$.

β_m denotes the taste parameter (decision weight) associated with attribute x_m.

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

μ is a regret aversion parameter. If μ approaches 0, only regret matters and its behavioral counterpart, 'rejoice' is irrelevant. If $\mu \gg 0$, regret and rejoice are equally important. In that case, the RRM model reduces to a classical, linear in parameter multi-attribute utility maximization rule. Although μ can be allowed to vary across attributes, in this Chapter I will assume that it is generic.

Note that subtraction of the term $\ln(2)$ is merely cosmetical, and is done for reasons of ease of exposition: it ensures that no regret nor rejoice is generated by a comparison between two alternatives in terms of an attribute on which both alternatives have the same value, i.e., where $(x_{jm} - x_{im}) = 0$. In other words, subtracting this term implies that attribute regret functions always go through the origin (see Figure below). From the perspective of the analyses performed in this paper, this is inconsequential: it merely shifts the regret function downwards without affecting its shape, or regret differences between alternatives. As such, (not) subtracting the constant $\ln(2)$ does not affect choice behavior, as explained in more detail in Chorus (2014c) and in Chorus & van Cranenburgh (2018).

Figure 1 visualizes the shape of the attribute regret function, for different values of μ and β. The focus is on a comparison between a considered alternative i, and one competitor alternative j in terms of attribute x. For simplicity of notation, I denote $x_j - x_i$ by Δx. Note that the right hand side of each panel (i.e., the part of the domain where Δx is positive), represents the situation where the competitor alternative outperforms the considered alternative, leading to regret. The part of the domain where Δx is negative represents the situation where the considered alternative performs better than the competitor, leading to 'rejoice' (or: negative regret).

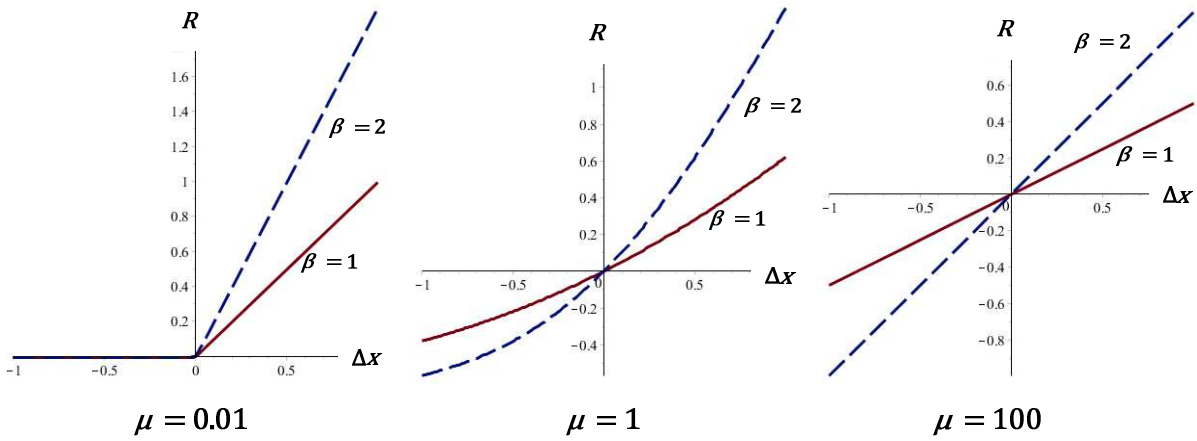

Figure 1:

Attribute regret $\mu \cdot \left[\ln\left(1 + \exp\left[\frac{\beta_m}{\mu} \cdot \left(x_{jm} - x_{im}\right)\right]\right) - \ln(2)\right]$, for different values of μ, β

The Figure clearly illustrates the key behavioral properties of the attribute regret function, as presented at the beginning of this Section. The left hand side panel represents extreme regret aversion. If a chosen alternative performs better than a competitor ('rejoice'), the extent to which it performs better is assumed to be irrelevant to the decision maker; the only thing that matters to her, is to avoid the situation where the chosen alternative performs worse. In the context of our running example: if house A has a smaller garden than house B, comparing house A with B in terms of the size of their gardens will generate regret. The larger the difference in size (represented by Δx), and the more important the attribute (represented by β), the more 'garden regret' is generated. However, if house A has a larger garden than house B, comparing house A with B in terms of the size of their gardens will not generate 'garden rejoice', irrespective of the magnitude of the difference and the importance of the attribute.

The right hand side panel represents the behavioral complement of the regret-only model: performing better than a competitor (rejoice) is now equally important as avoiding a worse performance (regret). In the housing choice example: the regret associated with house A having a garden which is Δx units smaller than B's garden is equally large as the rejoice that would be associated with house A having a garden which is Δx units larger than B.

The middle panel represents the intermediate position where there is mild regret aversion, i.e. a mild overweighting of regret relative to rejoice. This implies that while it is somewhat

important to the decision maker that the considered alternative performs better than a competitor in terms of the attribute, it is considerably more important to her to avoid the situation where the chosen alternative performs worse than a competitor in terms of the attribute. Table 1 further illustrates this RRM model with moderate regret aversion (i.e., with $\mu = 1$) in the context of the running example of house A being compared to house B in terms of the size of their respective gardens (assuming that garden size is measured in acres). The values presented in Table 1 may be directly compared to the plot (middle panel) presented in Figure 1.

Table 1:

Illustration of attribute regret ($\mu = 1$) in the context of the housing choice example

$$\ln\left(1 + \exp\left[\beta \cdot \left(x_{jm} - x_{im}\right)\right]\right) - \ln(2)$$

Values correspond to the middle panel of Figure 1	$\beta = 1$ *(per acre)*	$\beta = 2$ *(per acre)*	*regret / rejoice*
Garden A is 1 acre *smaller* than Garden B	0.62	1.43	regret
Garden A is 0.5 acre *smaller* than Garden B	0.28	0.62	
Garden A is 0.5 acre *larger* than Garden B	-0.22	-0.38	negative regret, i.e., rejoice
Garden A is 1 acre *larger* than Garden B	-0.38	-0.57	

As postulated in the model, an increase in attribute importance (i.e., a shift from $\beta = 1$ to $\beta = 2$) results in an increase in regret and rejoice levels. Furthermore, regret aversion (i.e., overweighting of regret compared to rejoice) is also clearly visible.

In the remainder of this paper, I will focus on the RRM model where $\mu = 1$ (visualized in the middle panel of Figure 1). This is done for reasons of ease of exposition, and without loss of generic applicability of results. The resulting model specification is known as the conventional (or 'classical') RRM model; this specification was introduced by Chorus (2010) and is currently the most widely used version of RRM. It has been incorporated in various Econometrics software packages (Greene, 2012; Vermunt & Magidson, 2014), is extensively covered in a recent Econometrics textbook (Hensher et al., 2015), and is taught in several

choice modeling courses. As can be seen above, this RRM model specification postulates moderate levels of regret aversion.

A particularly important behavioral property of the RRM model is worth highlighting here: the RRM-model implies *reference dependent* and *semi-compensatory* behavior. This is a direct result of the reference dependency and convexity of the attribute regret-function which was introduced earlier: improving an alternative in terms of an attribute on which it already performs well (relative to a competitor alternative) 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 a competitor alternative) generates more substantial increases in regret. This can be easily verified by looking at Figure 1 (middle panel): when the initial situation is positioned more to the right of the vertical axis (i.e., more deeply in the regret domain), the additional regret of a further deterioration of the attribute generates more additional regret. As a result, the extent to which a strong performance on one attribute can compensate for a poor performance on another depends on the relative 'position' (in terms of the performance with respect to relevant attributes) of each alternative in the set. When a choice alternative is deteriorated in terms of an attribute on which it already performs poorly, this deterioration is very difficult to compensate by improving another attribute of the alternative, especially when the alternative already performs well on the improved attribute.

It is instructive at this point to observe the relation between the behavior implied by the RRM model, and the notion of Loss Aversion in riskless choice as was put forward by Tversky and Kahneman (1991). The two models (LA and RRM) both postulate that reference points matter for decision making, and that losses with respect to that reference point loom larger than gains of equal size. A crucial difference between the two models is the choice of reference point: whereas the LA model uses the status quo as a reference point, the RRM model uses the attributes of other alternatives in the choice set as reference points. Take again the situation where the decision maker is moving to a new town, and is considering a set of houses offered by her real estate agent. The LA model postulates that she will compare each house *with her current house* (e.g. in terms of the size of the garden, commute time to work, mortgage payments, etc.); in contrast, the RRM model postulates that she will compare each house *with all other houses in the choice set* (in terms of all relevant attributes). Notwithstanding these differences in terms of reference point definitions, both the LA and RRM models have in common that they postulate that the decision maker will put a penalty

on houses that perform worse than her reference point on a particular attribute, and that this penalty is larger than the reward associated with a house that performs better than her reference point on a particular attribute. The RRM model's premise that reference points consist of attributes of competing alternatives make that model particularly suitable for the analysis of choice architectures. That topic will be further explored in the next Section.

But before I move on to the derivation of a measure of choice set regret, one final comment is in place. Up until this point, this Chapter has presented the RRM model as a *theoretical* model of decision making; its properties have been illustrated with preset values for relevant parameters (i.e., regret aversion parameter μ and taste parameters β). However, the RRM model is above all an *empirical* model of choice behavior, designed for the econometric analysis of observed choices. That is, the model has been developed within the so-called discrete choice theory (DCT) tradition (McFadden, 1973; Ben-Akiva & Lerman, 1985; Train, 2009). DCT aims to identify taste parameters in a Maximum-Likelihood based process of model estimation, and subsequently aims to use the estimated choice model to forecast choice behaviors of individuals, and market shares for products and services. DCT is nowadays routinely used in various sub-fields of the Social Sciences, earning its main developer the Nobel Prize in Economic Sciences (McFadden, 2001). Within the DCT framework, the RRM model is developed as a counterpart of the so-called linear in parameters Random Utility Maximization (RUM)-model which is the *de facto* model for the empirical analysis of choice behavior. Notwithstanding the immense popularity of linear in parameters RUM, it is well known that its behavioral realism may in some situations be compromised by its implicit assumptions of 1) absence of reference point effects, and 2) fully compensatory behavior. Inspired by the success of so-called Behavioral Economics research, various models have been proposed to overcome these potential behavioral limitations of RUM – see Leong & Hensher (2012) for an overview. In recent years the RRM model has become one of the most popular behavioral alternatives for RUM[vii]. There is now a very considerable amount of evidence of a strong empirical performance (in terms of model fit and predictive ability) of RRM models, also when compared to conventional RUM models (although it should be noted that the relative performance of RUM and RRM models is highly data set specific). Comparisons have been documented in various applications including Transport (e.g. Kaplan & Prato, 2012), Health (e.g., Chaugule et al., 2015), Marketing (e.g., Lim & Hahn, 2016), Energy & Environment (e.g. Thiene et al., 2012), Tourism (e.g. Boeri et al., 2012), and Anthropology (Nielsen et al., 2015). See also a relatively recent empirical overview paper

(Chorus et al., 2014), reviewing 43 empirical comparisons reported in international peer reviewed scholarly journals, and a more recent overview (van Cranenburgh et al., 2015) focusing on the most generic RRM model as presented in Equation (1). The remainder of this Chapter will be based on the premise that while the RRM model may not necessarily be the best available choice model on each and every dataset, it does have a strong empirical performance in general, making it a viable and relevant framework from which to study choice behavior.

3. A Measure of Choice Set Regret And Morally Problematic Choice Architectures[viii]

3.1. A Measure Of Choice Set Regret

Equation (1) serves to define the level of regret which is associated with choosing a particular *alternative* from a choice set. In principle, by combining these equations with the minimization objective underlying the RRM models, one can derive the regret that is associated with a *choice set* itself, in a conceptually easy way: simply take the minimum (across alternatives) of regrets. However, note that – as mentioned earlier – the analyst has limited knowledge concerning the regret of alternatives; this is reflected by the error terms present in (1), which represent all sorts of factors that are unobserved by the analyst yet are important for the decision maker when she chooses from the set. The presence of error terms implies that the analyst cannot know for sure which alternative is chosen and what would be the total regret (RR) of that alternative, also once – after calibrating the models and obtaining estimates for βs – the systematic regret, denoted R, is fully known. As a consequence, the regret that is associated with a choice set has to be written in terms of an *expected* minimum (RRM). It has been shown (Chorus, 2012) that for RRM, and given the abovementioned i.i.d. Extreme Value Type I error term distributions, this expected minimum boils down to a convenient closed form formulation (where J denotes the number alternatives in the choice set), which is called the LogSum:

$$LS_{RRM}^{J} = E\left[\min_{j=1..J}\{RR_j\}\right] = \int_{-\infty}^{+\infty}\left[\min_{j=1..J}\{RR_j\} \cdot f(v)\right]dv = -\ln\left[\sum_{j=1..J}\exp\left(-R_j\right)\right] \quad (2).$$

There is one feature of the RRM-LogSum which is of particular relevance to the analyses presented in the next section: *improving an alternative's attribute(s) does not necessarily cause a decrease in the expected regret of a choice set*. More specifically, the expected regret

of a choice set may *increase* when an alternative with an initially poor performance on many of its attributes (and hence an initially low choice probability) is improved in terms of one of its attributes. It is easily verified that this particular type of non-monotonicity of the RRM-LogSum follows directly from the behavioral premises underlying the RRM model that were described further above: improving an attribute of an alternative with an a priori low choice probability will of course lead to a decrease in its own regret (i.e., the regret function of any alternative is monotonous in attribute changes). However, in line with the notion that regret arises from the *comparison* of alternatives, the attribute improvement will lead to increases in the regrets of competing alternatives. To the extent that these competing alternatives have higher choice probabilities than the considered (i.e., the improved) alternative, these increases in regret receive more weight in the LogSum than does the decrease in regret of the improved alternative. Only when the attribute improvement is of such a magnitude that the improved alternative becomes a popular alternative itself (i.e., when its choice probability becomes high relative to the competition), does the expected regret of the choice set – as formalized through the RRM-LogSum – start to decrease.

Taking this reasoning one step further, the RRM model postulates that the level of expected regret of a choice set will be relatively high when the choice set is, put colloquially, 'difficult to choose from' in the sense that every alternative is associated with a relatively high level of regret. This is for example the case when every alternative in the choice set has a poor (relative) performance on at least one attribute. In this situation, each alternative from the set is associated with non-trivial levels of regret. In contrast, when a choice set contains a 'clear winner' in the form of an alternative that outperforms the competition on most attributes, and which does not have a very poor performance on any attribute (compared to the competition), the level of expected regret that is associated with the choice set is relatively low. As such, the RRM model predicts that a deterioration of an alternative's attribute may in fact result in a decrease in choice set regret when it helps identify a clear winner in that set. Likewise, the RRM model predicts that an improvement of an alternative's attribute may lead to an increase in choice set regret when it hampers the identification of a clear winner and as such makes the choice more difficult[ix].

For illustrative purposes, consider the following illustrative example (depicted in Figure 2): suppose a decision maker faces a choice between three houses with two attributes each: attribute x represents the size of the garden, attribute y represents some metric measuring neighborhood quality. Assume that the three houses have the following performance: A =

{2,1}, B = {x_B, 1.5} and C = {1,2}. That is, A performs well on garden size (x) but less well on neighborhood quality (y). The opposite is the case for alternative C, while B has an intermediate performance on neighborhood quality. I now vary the size of $B's$ garden (x_B), and – assuming for ease of exposition that both attributes have unit weight – I plot the regrets of each house, as well as the total regret associated with the choice set, as a function of x_B. Figure 2 shows that regret is relatively low for very low values of x_B and that it reaches its lowest point for very high values of the attribute. For intermediate values of x_B however, regret is relatively high. This implies that improving house B in terms of the attribute 'garden size' when it initially performs (very) poorly in terms of that attribute, only decreases the expected regret associated with the choice situation when the improvement is such that the attribute, after the improvement, attains a (very) high value.

The behavioral intuition behind this non-monotonicity of the RRM-Logsum can be put as follows: when alternative B has a very poor performance on attribute x, this makes that there is a very high level of regret associated with that alternative. However, this very high level of regret for the alternative does not translate into a high level of expected regret for the choice situation, because there are alternatives with much lower regrets available (implying that B has only a very small chance to be chosen). Furthermore, the fact that B performs poorly on x implies that alternatives A and C have relatively low regrets (since their comparisons with B barely generate regret at all). When x_B attains an intermediate value, B's regret decreases but the regrets associated with the other two alternatives increase since now, comparisons with B does generate some regret. The result is a situation where all regrets are of about similar magnitude, and expected regret associated with the choice situation as a whole *increases* – because the regret associated with the alternative(s) with lowest regrets (A, C) increases. Only when x_B becomes very high, does the expected regret associated with the choice situation start to decline: in that situation, the regret associated with A and C grows, but since B's regret is now (much) lower than these two regrets this increase in A's and C's regret becomes more and more irrelevant (as their choice probability now becomes very low). The fact that B's regret declines, now finally starts resulting in a lower level of expected regret associated with the choice situation as a whole. Only when x_B becomes very high, a lower level of expected regret is obtained than was associated with the situation when B performed very poorly on x.

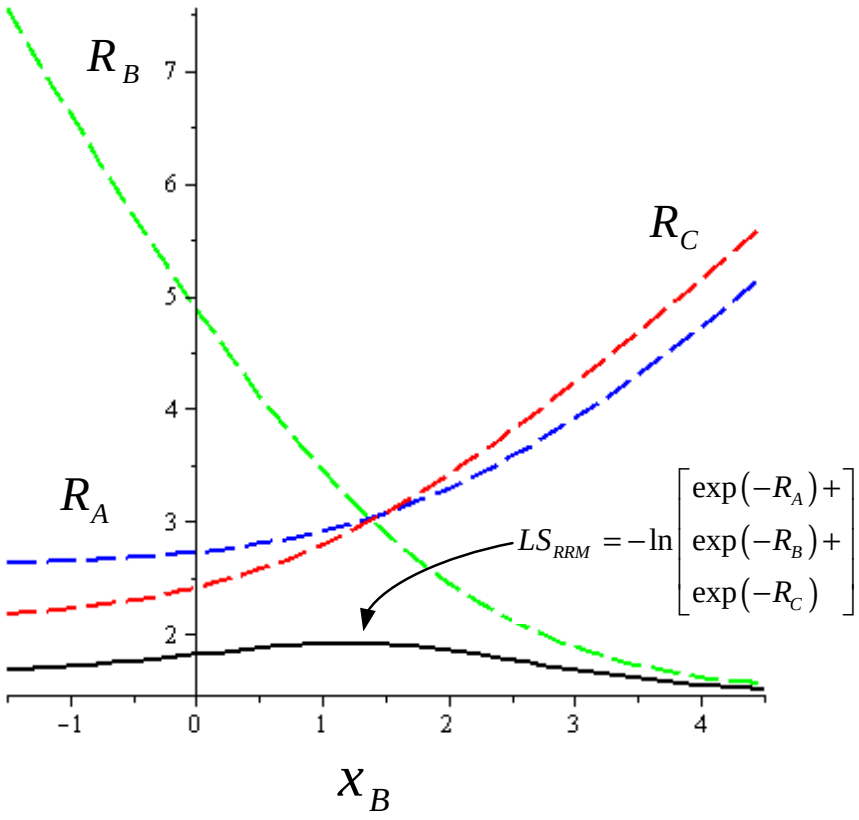

Figure 2:

The RRM-Logsum – solid line – as a function of attribute performance

(source: Chorus, 2012)

It should be clear then, that this non-monotonicity of the RRM-LogSum is not just a mathematical artifact: it is a direct result of the RRM model's underlying behavioral premises. Interestingly, this rather peculiar property of the RRM-Logsum is in line with recent empirical work in consumer psychology concerning decision-makers' preferences for choice sets as a function of their size and composition (e.g., Schwartz et al. 2002).

3.2. Morally Problematic Choice Architectures

Consider a choice architect with the authority to determine the values of every attribute, for every alternative in a choice set[x]. The architect is faced with an initial choice situation, where alternatives – given their attributes – have a particular probability of being chosen by the

decision maker; her goal is to change the attribute values of one or more alternatives in such a way that a particular change in choice probabilities is achieved. This architect may be – working for – a private sector party (e.g. a consumer products firm, in which case the decision maker is a consumer) or a government agency (e.g. a Ministry of Transport, in which case the decision maker is a citizen). For ease of exposition, I make a number of additional assumptions which do not affect the generic applicability of the argument being put forward further below:

- The initial choice set, faced by the decision maker, contains a fixed number of alternatives which are described in terms of a fixed number of attributes. These numbers cannot be altered by the choice architect. In the Private sector party example, alternatives may refer to different consumer goods, e.g. smartphones; attributes are then quality aspects, e.g. design features of a smartphone. In the Ministry of Transport example, alternatives may refer to different courses of action taken by a citizen/traveler, e.g. to work from home, carpool, or drive alone to work; in this case, attributes are policy-dimensions, e.g. tax incentives or rules to promote carpooling.
- The choice architect changes, at will, one or more attributes of one or more alternatives, with the aim of changing the probability that a randomly sampled decision maker chooses a particular alternative. That is, the choice architect aims to change the market shares of, or distribution of demand across, different alternatives.
- From the viewpoint of the decision maker, each attribute is formulated in such a way that increasing its value is beneficial to her. From the viewpoint of the choice architect, increasing an attribute's value is costly to her. For example, to increase the market share of a smartphone, a consumer firm may decide to increase its battery life or improve its camera. Doing so is costly for the firm. Or, to increase demand for carpooling, the Ministry of Transport may decide to introduce a tax-incentive or to build carpool-facilities; these are costly from the perspective of the Ministry. I refer to these costs as 'design costs'.

Given these assumptions, it is not straightforward what makes a choice architecture morally problematic. As seen in the previous subsection, different choice tasks may impose different regret levels, but this in itself does not imply that every choice architecture that has a relatively high level of choice set regret felt by the decision maker is morally problematic. More specifically, consider the situation where a choice architect is able to achieve her goal

of redistribution of market share across alternatives, at the cost of some increase in choice set regret. Would this have to be called a morally problematic choice architecture? Intuitively, one might be tempted to let the answer depend on the proportionality of the change (i.e., increase) in regret levels, compared to the achieved redistribution of market share: a substantial modal shift to the carpool alternative may justify a small increase in choice set regret among commuters, but a marginal increase in market share for a particular smartphone which comes at the cost of a large increase in choice set regret among consumers may be considered unjustifiable. However, comparing the size of regret increases faced by decision makers with the size of market share redistribution achieved by the choice architect is fraught with difficulty, in light of the fact that these are non-commensurable entities; see Radin (1993) and Harel & Porat (2011) for more about non-commensurability. Hence, it is very difficult, if possible at all, to establish a rigorous notion of what would constitute proportionality in this context. As such, I choose to formulate – inspired by the notion of Pareto-optimality – a more narrow definition of morally problematic choice architectures which circumvents explicitly comparing regret levels and market share redistribution:

A choice architecture is considered morally problematic, when there is another choice architecture which generates the same choice probabilities (market shares), at the same design costs, but resulting in lower choice set regret.

In the following, this definition of morally problematic choice architectures is illustrated using a very simple and stylized example: the initial choice set from which the decision maker has to choose, contains three alternatives, each described in terms of four attributes. All attributes are formulated in such a way that their associated taste parameter (attribute weight, or β) equals 1 (which implies that higher attribute values are preferred over lower ones by the decision maker), and that the associated design cost faced by the choice architect equals 1 unit per unit increase in an attribute's value. The initial choice set is depicted in Figure 3. Clearly, in this initial choice set, alternative B is superior in terms of every attribute; plugging the attribute values and the associated taste parameters in the RRM model (i.e., equation 1 with $\mu = 1$), results in a choice probability of 1 (market share of 100%) for alternative B, and a choice set regret of 0.5. The design cost of this choice set, which by definition equals the sum of all attribute values in the set, equals 24.

INITIAL CHOICE SET	Alternative A	Alternative B	Alternative C
Attribute 1	2.0	4.7	0.5
Attribute 2	1.5	4.2	2.1
Attribute 3	1.6	3.9	0.1
Attribute 4	0.5	2.8	0.1
Choice probability	0	1	0
Design cost of Choice set	24		
Choice set regret	$-\ln\left[\sum_{j=1..J}\exp\left(-R_j\right)\right] = 0.5$		

Figure 3: Initial choice set

The aim of the choice architect is to redistribute choice probabilities (market shares) such that half of the demand for alternative B is transferred to alternative C, which may be a more sustainable travel mode (Ministry of Transport example) or a smartphone with a higher profit margin (consumer firm example). The choice architect considers two interventions that may do the job. The first choice architecture is depicted in Figure 4, the second in Figure 5. Both choice sets achieve the aim of re-distributed market shares (again note that choice probabilities are computed by plugging attribute values and associated taste parameters into the RRM model discussed in section 2). Furthermore, both come at the same design cost, which is obtained by summing up all attribute values in the choice set; more specifically, the aimed for redistribution of demand comes at an increase of 50% in design costs. However,

whereas the first architecture imposes on decision makers a choice set regret of 3.3 units, the second architecture imposes a choice set regret of 8.3 units.

ARCHITECTURE (I)	Alternative A	Alternative B	Alternative C
Attribute 1	3.1	3.8	3.6
Attribute 2	0.4	3.5	3.2
Attribute 3	1.5	3.7	4.1
Attribute 4	3.0	3.1	3.1
Choice probability	0	0.5	0.5
Design cost of Choice set	36		
Choice set regret	$-\ln\left[\sum_{j=1..J}\exp\left(-R_j\right)\right] = 3.3$		

Figure 4:

A choice architecture

The reason why the second ‘architectured’ choice set (figure 5) generates so much more regret than the first one (Figure 4), is that in the first choice set the two popular alternatives are very similar in every attribute and as such, choosing one of them generates hardly any regret. In the second set however, there is much difference between the two popular alternatives in terms of three out of four attributes; i.e., alternative B performs poorly on attribute 1 and 4 (compared to C), and alternative C performs poorly on attribute 3. As a result, a choice for either one of the two popular alternatives (B and C) still generates considerable attribute-regret.

ARCHITECTURE (iI)	Alternative A	Alternative B	Alternative C
Attribute 1	0.8	1.9	4.4
Attribute 2	0.5	4.1	4.1
Attribute 3	4.0	4.0	0.5
Attribute 4	5.0	2.5	4.6
Choice probability	0	0.5	0.5
Design cost of Choice set	36		
Choice set regret	$-\ln\left[\sum_{j=1..J} \exp\left(-R_j\right)\right] = 8.3$		

Figure 5:

A morally problematic choice architecture

In other words, although the two architectures are exactly the same in terms of the resulting distribution of demand across alternatives, and in terms of design costs, the second architecture imposes much more regret on the decision maker and as such constitutes a morally problematic choice architecture. When considering an intervention in an existing choice set, a choice architect is recommended to explore different choice sets capable of achieving his design goals, and choose the one with minimal choice set regret.

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References

Avineri, E. (2012). On the use and potential of behavioural economics from the perspective of transport and climate change. *Journal of Transport Geography*, *24*, 512-521.

Bell, D. E. (1982). Regret in decision making under uncertainty. *Operations research*, *30*(5), 961-981.

Ben-Akiva, M. E., & Lerman, S. R. (1985). *Discrete choice analysis: theory and application to travel demand* (Vol. 9). MIT press.

Bleichrodt, H., & Wakker, P. P. (2015). Regret theory: A bold alternative to the alternatives. *The Economic Journal*, *125*(583), 493-532.

Chaugule, S., Hay, J. W., Young, G., Martin, O. A., & Drabo, E. F. (2015). Does differential framing of opt-out alternatives in discrete choice experiments (dces) matter? Comparison of random utility maximization (rum) and random regret minimization (rrm) models. *Value in Health*, *18*(3), A24-A25.

Chorus, C. G., Arentze, T. A., & Timmermans, H. J. (2008). A random regret-minimization model of travel choice. *Transportation Research Part B: Methodological*, *42*(1), 1-18.

Chorus, C. G. (2010). A new model of random regret minimization. *European Journal of Transport and Infrastructure Research*, 10(2), 181-196.

Chorus, C. G. (2012). Logsums for utility-maximizers and regret-minimizers, and their relation with desirability and satisfaction. *Transportation Research Part A: Policy and Practice*, *46*(7), 1003-1012.

Chorus, C. G. (2014a). A generalized random regret minimization model. *Transportation research part B: Methodological*, *68*, 224-238.

Chorus, C. G. (2014b). Acquisition of ex-post travel information: A matter of balancing regrets. *Transportation Science*, *48*(2), 243-255.

Chorus, C. G. (2014c). Benefit of adding an alternative to one′ s choice set: A regret minimization perspective. *Journal of choice modelling*, *13*, 49-59.

Chorus, C., van Cranenburgh, S., & Dekker, T. (2014). Random regret minimization for consumer choice modeling: Assessment of empirical evidence. *Journal of Business Research*, *67*(11), 2428-2436.

Chorus, C. G., & van Cranenburgh, S. (2018). Specification of regret-based models of choice behaviour: formal analyses and experimental design based evidence—commentary. *Transportation*, *45*(1), 247-256.

Coricelli, G., Critchley, H. D., Joffily, M., O'Doherty, J. P., Sirigu, A., & Dolan, R. J. (2005). Regret and its avoidance: a neuroimaging study of choice behavior. *Nature neuroscience*, *8*(9), 1255-1262.

Greene, W. H. (2012). *NLOGIT: Version 5: Reference Guide*. Econometric Software, Inc.

Harel, A., & Porat, A. (2011). Commensurability and Agency: Two Yet-to-Be-Met Challenges for Law and Economics. *Cornell Law Review*, *96*, 749.

Hensher, D. A., Rose, J. M., & Greene, W. H. (2015). *Applied choice analysis*. Cambridge Univ. Press.

Jang, S., Rasouli, S., & Timmermans, H. (2017). Incorporating psycho-physical mapping into random regret choice models: model specifications and empirical performance assessments. *Transportation*, *44*(5), 999-1019.

Johnson, E. J., Shu, S. B., Dellaert, B. G., Fox, C., Goldstein, D. G., Häubl, G., ... & Wansink, B. (2012). Beyond nudges: Tools of a choice architecture. *Marketing Letters*, *23*(2), 487-504.

Kaplan, S., & Prato, C. G. (2012). The application of the random regret minimization model to drivers' choice of crash avoidance maneuvers. *Transportation research part F: traffic psychology and behaviour*, *15*(6), 699-709.

Knight, F. H. (1921). Risk, uncertainty and profit. *New York: Hart, Schaffner and Marx*.

Leong, W., & Hensher, D. A. (2012). Embedding decision heuristics in discrete choice models: A review. *Transport Reviews*, *32*(3), 313-331.

Lim, J., & Hahn, M. (2016) Random regret minimization model versus random utility maximization model: When to use what in marketing. *INFORMS Marketing Science Conference*, Shanghai, China

Loomes, G., & Sugden, R. (1982). Regret theory: An alternative theory of rational choice under uncertainty. *The economic journal*, *92*(368), 805-824.

McFadden, D. (1973) Conditional logit analysis of qualitative choice behavior. Chapter 4 in Zarembka, P. (Ed.) *Frontiers in Econometrics*, Academic Press, New York, p. 105-142

McFadden, D. (2001). Economic choices. *The American Economic Review*, *91*(3), 351-378.

Radin, M. J. (1993). Compensation and commensurability. *Duke Law Journal*, *43*(1), 56-86.

Savage, L. J. (1951). The theory of statistical decision. *Journal of the American Statistical association*, *46*(253), 55-67.

Schwartz, B., Ward, A., Monterosso, J., Lyubomirsky, S., White, K., & Lehman, D. R. (2002). Maximizing versus satisficing: happiness is a matter of choice. *Journal of personality and social psychology*, *83*(5), 1178.

Selinger, E., & Whyte, K. (2011). Is there a right way to nudge? The practice and ethics of choice architecture. *Sociology Compass*, *5*(10), 923-935.

Sunstein, C. R. (2015). Nudging and choice architecture: Ethical considerations. *Yale Journal on Regulation, Forthcoming*.

Thaler, R. H., Sunstein, C. R., & Balz, J. P. (2014). Choice architecture. *The behavioral foundations of public policy*.

Thorndike, A. N., Sonnenberg, L., Riis, J., Barraclough, S., & Levy, D. E. (2012). A 2-phase labeling and choice architecture intervention to improve healthy food and beverage choices. *American Journal of Public Health*, *102*(3), 527-533.

Train, K. E. (2009). *Discrete choice methods with simulation*. Cambridge university press.

Tversky, A., & Kahneman, D. (1991). Loss aversion in riskless choice: A reference-dependent model. *The quarterly journal of economics*, 1039-1061.

van Cranenburgh, S., Guevara, C. A., & Chorus, C. G. (2015). New insights on random regret minimization models. *Transportation Research Part A: Policy and Practice*, *74*, 91-109.

Vermunt, J. K. & Magidson, J. (2014). *Upgrade manual for Latent GOLD Choice 5.0*. (Belmont, USA).

Zeelenberg, M., & Pieters, R. (2007). A theory of regret regulation 1.0. *Journal of Consumer psychology*, *17*(1), 3-18.

Zeelenberg, M., & Pieters, R. (2004). Consequences of regret aversion in real life: The case of the Dutch postcode lottery. *Organizational Behavior and Human Decision Processes*, *93*(2), 155-168.

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[ii] Strictly speaking, Savage's Minimax Regret framework refers to decision under uncertainty, as opposed to risk, in the sense that it does not presume that the decision making holds particular perceptions regarding probability distributions (Knight, 1921).

[iii] In fact, some lotteries are specifically designed to trigger regret aversion associated with *not* buying a lottery ticket (Zeelenberg & Pieters, 2004).

[iv] Note also that the RRM model can easily extended to cover risky decision making as well (Chorus et al., 2008; Chorus, 2014b); in this Chapter, I will focus on riskless choice contexts.

[v] A definition of the notion of Choice architecture presented on Wikipedia (Lemma 'Choice architecture', accessed 18 July 2016) reads as follows: "Choice architecture is the design of different ways in which choices can be presented to consumers, and the impact of that presentation on consumer decision-making. For example, the number of choices presented, the manner in which attributes are described, and the presence of a 'default' can all influence consumer choice.".

[vi] It could also include characteristics of the decision maker; for ease of exposition, I ignore this extension in the remainder of this Chapter.

[vii] This does not imply that I here present the RRM model as a 'better' or 'more realistic' choice model than linear in parameter RUM models. Rather, in our view choice behavior is a subtle and multi-facetted phenomenon (with great levels of heterogeneity across individuals and contexts); this makes it important that there are multiple models available to study choice behavior. The RRM model has been developed to form an addition to the choice modeler's toolbox, certainly not as a potential replacement of other models.

[viii] The first part of this section draws extensively from Chorus (2012) and Chorus (2014c).

[ix] It may be noted that, in addition to this property, the RRM-Logsum differs from the RUM-Logsum in another fundamental way: whereas the latter will always increase if one attribute is improved for all alternatives to a similar extent, this is not the case for the RRM-Logsum. Since regret is a function of *relative* performance, improving all alternatives along the same attribute and to the same extent (e.g. by making all alternatives five dollar cheaper) will leave the expected regret associated with the choice situation unchanged.

[x] The realism of this assumption can be debated, as in some instances a choice architect will only have the authority to determine some attributes of some alternatives in the set, e.g. in the situation where a consumer goods firm introduces a new product in a choice set partly shaped by competitor firms. However, for reasons of clarity of exposition I here choose to maintain this assumption.