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# Regret Theory as an Alternative Framework in Consumer Food Choice: an Application of the Random Regret Minimization Model

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# Abstract

*In consumer behaviour literature, discrete choices of food are usually assumed to be driven by maximization of utility, and modelled through the Random Utility Maximization (RUM) choice model. Nevertheless, other behavioural paradigms have been proposed in marketing literature, which account for loss aversion and regret minimization. Hence, this study investigates the usefulness and potential in the food domain of a discrete choice model that follows the regret minimization principle, the Random Regret Minimization (RRM) model, as an alternative and complement to existing RUM models. The study also investigates whether and to what extent a number of personality traits influence the use of a utility-maximizing, or regret-minimizing decision rule. To the best of our knowledge, this is the first attempt to explore whether and how anticipated regret affect consumers' choice of food products, while in general a direct and significant impact on future choices has been found.*

*The thesis begins with a conceptual model for the food choice process, which takes into account how values related to food and personal factors contribute to drive food choices. Then, consumer choice strategies developed in the literature are introduced and discussed in light of the existing empirical applications to food choice.*

*Based on data gathered from a discrete choice experiment, the RRM discrete choice model is applied and compared with the RUM classical model.*

*Results show that at the aggregate level the two models have similar goodness of fit to the data and prediction ability. Still, each of them shows better fit for particular subgroups of consumers, based on personality traits. Hence, the present study reveals a potential for the RRM model applications in the food domain. Nonetheless, the two models are subject to different interpretations and feature distinct behavioural properties. As such, the RRM can be seen as a valuable addition to existing methodologies in consumer choice modelling, specifically in the food domain.*

# Introduction

In marketing studies, an overarching aim is to understand why people buy what they buy, in order to develop products that address consumers' real needs, and to address these products to the right consumer. This holds for consumer goods in general, and in particular for food products, for which managers can use different leverages to attract consumers and differentiate products based on several attributes (e.g. brand, taste, nutritional composition, packaging design, claims, production process, etc.).

At the same time, food choices and dietary styles have an effect on people's health, therefore it is in the interest of policy makers to develop adequate long-term strategies to help people make healthier choices (Nestle and Jacobson, 2000; Waterlander et al., 2009).

Explaining food choices is important nearly as much as it is complicated. Many factors contribute to the consumer choice of food, including situational, physiological, cultural, social, and psychological aspects (Furst et al., 1996; Martins and Pliner, 2005; Mela, 1999; Asp, 1999; Frewer and Van Trijp, 2006). Moreover, food choices are often driven by habits, that is to say consumers simply choose what has been chosen in the past and might not engage in cognitive reasoning while choosing, depending on the specific product and situation (Adamowicz and Swait, 2013; Cohen and Farley, 2008).

The dominant approach in analyzing and predicting food choices typically assumes that consumers are (most) inclined to choose the option that they expect will result in the highest post-purchase and post-consumption satisfaction, formally expressed through the idea of expected utility maximization (Savage, 1954). Nevertheless, the maximization of utility represents only one of the possible goals that consumers may pursue in choosing foods. Other paradigms have been proposed in the literature, mainly taking into account the phenomenon of loss aversion.

Loss aversion refers to a phenomenon that can take place in the consumers' mind, when different subjective evaluations are attached to losses and gains of the same size, the loss being perceived as more undesirable than the gain is attractive. Prospect theory (Kahneman and Tversky, 1979) takes into account this issue, assuming that consumers' evaluations are based on perceived gains and losses with respect to a reference point. Reference points can be different for different individuals and situations, for instance[1] if an individual usually purchases a product for 5€, he/she would consider a similar product that costs 7€ as a loss, while someone with a reference price of 9€ sees it as a gain.
A different choice model has been recently proposed, which assumes that people anticipate the regret that would derive from choosing a sub-optimal alternative. In economic theories, regret is defined as: "the difference in value between the assets actually received and the highest level of assets produced by other alternatives" (Bell, 1982). Regret is a negative emotion and people tend to be regret averse. The Random Regret Minimization (RRM) model (Chorus, 2010) incorporates the idea that consumers anticipate possible future regret while choosing and aim to minimize it. The anticipated regret arises from making trade-offs between the attribute values of alternatives – in absence of a dominant alternative – and choosing the alternative that performs best overall, but might have an inferior performance on one or more attributes.
Anticipated regret has proven to be a significant predictor of future choices (Coricelli et al., 2005), and studies found that it influences decision making in several fields (e.g. marketing, economics, health behaviour etc.) (see Joong et al., 2013; Abraham and Sheeran, 2003; Simonson, 1992).

To date, the RRM model has been applied mainly in contexts of transport, policy, health, shopping destinations, leisure and dating choices (Chorus, 2010; Chorus, Annema, Mouter, and van Wee, 2011; Chorus and Rose, 2011; De Bekker-Grob and Chorus, 2013; Thiene, Boeri, and Chorus, 2012), but to our knowledge it has never been explored in relation to food choice.
In previous studies, regret is assumed to have a different weight on choice based on the context and choice setting, following the assumption that the more the decision

1 The reference point can be internal (based on memory or previous experience) or external (based on stimuli at the point of purchase). In this example, an internal reference price is considered (Neumann and Böckenholt, 2014, see).

is difficult, the more regret is taken into account (Zeelenberg and Pieters, 2007). Nevertheless, individuals might perceive differently the importance and difficulty of the choice, and they might differ in how they make choice in a similar situation; this heterogeneity in individual's choices needs to be taken into account.
Thus, in this thesis the RRM model is introduced into the food context through an empirical illustration and its potential is critically discussed in relation to individuals' heterogeneity.
The aim of the present study is to draw attention to a regret-based approach to decision-making and its impact on choice modelling. Modelling regret may provide important complementary insights in consumer food-choice processes beyond existing approaches.
In this study, the RRM choice model is tested on food choices, and individual heterogeneity in preferences are taken into account. The choice model is applied to discrete food choices taken at the supermarket, thus referring to the choice to buy a specific product having several alternatives available, likely to have different prices. The performance of the RRM model is compared with its utility maximization-based counterpart.

The thesis starts with a detailed description of the food choice process, following the conceptual framework proposed by Furst et al. (1996). Food related values considered in food choice are outlined, than the personal characteristics that contribute in shaping food choices are discussed.
Chapter 2 presents some of the most important theories regarding decision strategies in consumer choices, which attempt to explain how the available information is evaluated by consumers and results in the final decision, including utility- and regret-based choice theories. The chapter also provides examples of empirical applications in the food domain.
Chapter 3 provides a definition of Discrete Choice Models and displays the statistical models which are estimated on discrete choices, belonging to the Logit family. It also provides a presentation of Discrete Choice Experiments and how they are applied in the food literature.
Chapter 4 is a literature review of the empirical results obtained in RRM and RUM models comparisons.
Finally, Chapter 5 describes the empirical study's settings and results. In our experimental setting, the RRM model is applied to stated choices of cheese based on

price, quality, sustainability of the packaging and preservability (i.e. days left until the best by date). The Results section reports the main results obtained, focusing on comparisons in performance between estimated RUM and RRM models, and segmentation analysis. Lastly, results are discussed in light of existing literature, and strategic implications, limitations and directions for future research are outlined.

# Chapter 1

# The food choice process

The study of what governs the choice of consumers is pivotal in food marketing. By knowing the mechanism(s) that drives people choices, researchers can predict future choices; this allows companies to manipulate the marketing strategy in order to increase their profit and policy makers to develop effective interventions.
Nevertheless, explaining and defining the consumer food choice process is not an easy task. Sobal et al.'s article entitled "Food Choice Is Multifaceted, Contextual, Dynamic, Multilevel, Integrated, and Diverse" gives an idea of the multi-dimensionality of the process (Sobal et al., 2014). It is not only how the choice is made, but the fact that the time, place, reasons, and people involved all have an interrelated effect on how and what people choose.
The present chapter aims to give an overview of the main characteristics of the food choice process, based on a conceptual framework from Furst et al. (1996). The involved dimensions are discussed and personal factors which affect food choices are presented.

## 1.1 A conceptual model of food choice

Figure 1.1 shows a conceptual model for the food choice process proposed by Furst et al. (1996). This model has been built on information collected by the researchers (Furst, Connors, Bisogni, Sobal, and Falk) in qualitative interviews, and it summarizes how the choice of food is shaped.
The model represents how a single food choice happens, which factors are involved

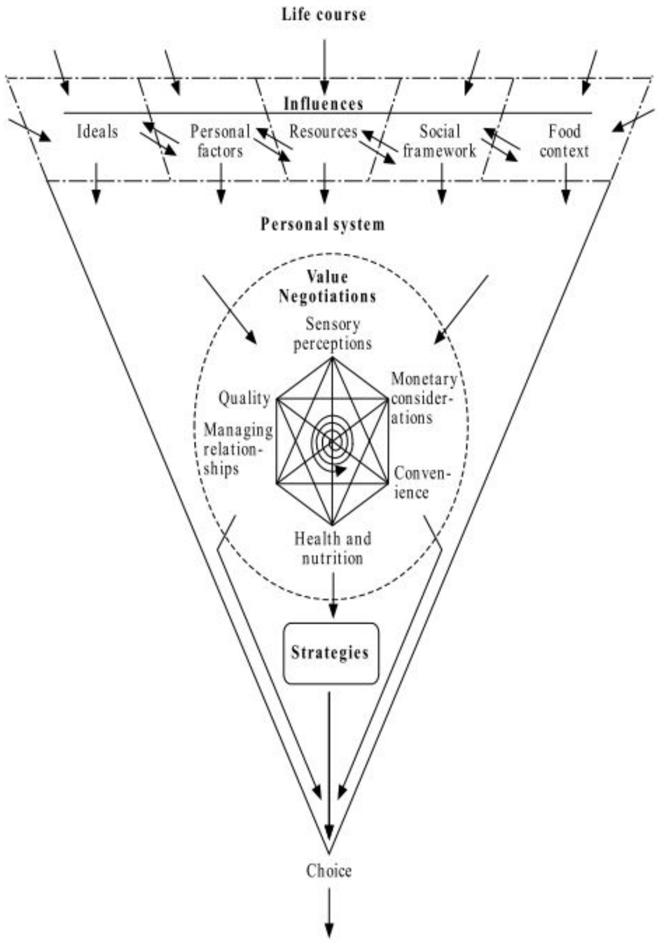



Figure 1.1. Conceptual model of food choice (Furst et al. (1996))

and how they affect the final choice. The main process represented is called *value negotiation*, a trade-off among personal values people make when choosing; this leads to the final choice by means of a decision strategy for the choice. Both operations can be performed with different degrees of conscious reflection, depending on the specific choice context. Value negotiation and strategy application together form the *personal system*. Personal systems for food choice are affected by several *influences*: ideals, personal factors, resources, social framework and food context; which in turn are generated by the *life course* of the individual. The latter includes the personal experiences and the environment to which a person has been and is exposed (Furst et al., 1996).

In the present thesis, the main focus is on the personal system, since it represents the process activated in making choices, and on personal factors that can explain observed heterogeneity in choice. The reader interested in the other influences can refer to Furst et al. (1996).

The personal system is discussed in detail in the following sections; Section 1.2 outlines the food related values and Section 1.3 gives an overview of the main personal factors that can have a role in food choice. Chapter 2 presents the choice strategies with reference to the consumer literature, and evidence in the food domain.

## 1.2 Food related values

In studying behaviours, values are the main independent variables (Rokeach, 1973). According to the definitions given in the literature, values are intended as concepts or beliefs: values drive behaviours and choices by acting as goals or desirable end states. Moreover, values are inherit in individuals, meaning that the same value can hold in different situations, and they can be traded-off in their relative importance (Schwartz and Bilsky, 1990). Therefore, values shape attitudes and preferences in consumer behaviour.

Values can be distinguished based on their motivational content, i.e. the goal they pursue (Bilsky and Schwartz, 1994).

In the conceptual framework by Furst et al. (1996), the value negotiation represents the phase in which an individual's values related to food are weighted and adapted to each particular choice situation. Individuals have different values, and each of them can have a different weight in their choice, depending on the choice context. For instance, when buying a food item that involves potential safety risk, such as fish, one could attach more importance to health and quality dimensions and less to monetary considerations; the opposite could happen for a standardized product like breakfast cereals or crackers, in buying these items price consideration might be stronger. Also, value considerations could be different when an individual is buying for him/herself with respect to the case in which he/she is buying a food to share with other members of the family or friends. Another factor affecting value negotiation might be the relative state of hunger during the shopping, which could lead to increased importance of sensory factors in comparison to health dimension. The links and the spiral at the centre of the value negotiation in Figure 1.1 highlight the interconnected nature of personal values and the recurrent type of process. Each

time, based on the peculiarities of the choice, values are compared and balanced; all values could be equally important, or one or more values could be deemed to be the deciding factor in a given situation.
The six values reported in the scheme were the most frequently mentioned by consumers in Furst et al.'s experiment; these values are related to dimensions of: sensory, price, convenience, health and nutrition, social relationships and quality. Other mentioned values were ethics, tradition and familiarity (Furst et al., 1996).
Food related dimensions such as pleasure, health, tradition, convenience, familiarity, prestige and price were described also in other previous works (Rappoport et al., 1992; Lau et al., 1984). Furthermore, Steptoe et al. (1995) developed and validated a multidimensional questionnaire – called Food Choice Questionnaire – to assess the importance of different factors in food choice; they found nine dimensions: health, mood, convenience, sensory appeal, natural content, price, weight control, familiarity and ethical concerns. In their study, sensory appeal, health, convenience and price were rated as the most important factors overall; nonetheless, they found sub-segments in the population that differed on the relative importance placed on the nine factors.

### 1.2.1 Sensory perceptions

Sensory properties are often the most important factor in food selection, such as in the study by Furst et al. (1996), where taste and flavour were the primary driving factors for most of the people.
The value of sensory perception refers to personal preferences regarding the organoleptic characteristics of a food item in terms of its taste, texture and odour[1]. These physical characteristics of a product are called its intrinsic attributes (e.g. colour, flavour, smell). On the other hand, all the features of a product which are not "physical" are called extrinsic attributes (e.g. brand, quality mark, price, country of origin, written information on the label, etc.) (Mancini et al., 2017).
Furst et al. (1996) found that sensory was sometimes in conflict with convenience and monetary values: people acknowledged the taste of a homemade dish (e.g. a pie) is not comparable with the one of a ready-to-eat similar dish, but often they had

1 Sensory science is a broad field, and it is not in the interest of this study to go into this issue. For the purposes of the present study, the other dimensions are presented in more detail.

no time to bake or cook and choose the ready solution; moreover, often branded products are more tasty than similar private label (cheaper) products.

### 1.2.2 Monetary considerations

Monetary considerations refer to the price of a food product, and to the perceived quality/price tradeoff. This value is likely to dominate the food choice in some circumstances; sometimes people just buy the cheapest product (Furst et al., 1996). The same price can be subject to different evaluations; a high price can be appreciated as a signal of quality for one consumer, but it may represent a barrier for another consumer. Thus, price is mostly in conflict with the values of quality and taste; it can be the most or less important value depending on the situation, e.g. one might buy a food only when it is on discount – switching category, for example with fruit (Furst et al., 1996) – or one can buy a food regardless of the cost – "choice of a treat" (Furst et al., 1996).

### 1.2.3 Quality

Consumers in Furst et al.'s study referred to quality as a "level of excellence", which was associated with good ingredients, freshness, branded and good looking products. Nevertheless, quality was also related to other dimensions, such as taste, health and price.

The value of food quality is a broad concept and includes several sub-dimensions. Steenkamp (1989) identified four approaches to product quality: the metaphysical approach, the production management approach, the economic approach, and the behavioural or perceived quality approach of marketing and consumer behaviour. The first approach concerns the being of quality, under a philosophical perspective; the production management approach to quality focuses on the production method and quality controls and standards; the economic approach adopts an economic perspective to quality-related aspects, such as quality competition; the perceived quality approach concerns the way consumers form judgments about the quality of a product, i.e. the subjective quality.

Accordingly, the quality that a consumer values often is not the objective quality, but the subjective quality (Grunert, 2005; Brunsø et al., 2002). Subjective or perceived quality is the quality as perceived and judged by consumers, which might rely on incomplete information and depends on personal and situational variables (Steenkamp, 1989).

Still, it is not clear to which characteristics subjective quality is linked. In this sense, there are two main approaches: in the first one – the holistic approach – (subjective) quality refers to all the desirable properties a product is perceived to have (Grunert, 2005); in other words, a product feature adds to its quality to the extent that consumers believe that feature to be a desirable property. In this sense, when people prefer cheaper prices, a cheaper price is signal of quality; also, a convenient product might be perceived as having more quality if convenience is seen as a desirable property. Nevertheless, the second approach – the excellence approach – acknowledges that products can have desirable properties that consumers may not view as part of quality (Grunert, 2005). For instance, convenience foods are generally perceived as having low quality, even though for consumers convenience represents a desirable property (Grunert, 2005).

Consumers perceive quality under four major dimensions: sensory, health, convenience, and process (Brunsø et al., 2002). In particular, the production process refers to how the food is produced, with reference to how it is cultivated or raised (organic, animal welfare, no GMO, local etc.). Consumers' interest in and value attached to production practices is growing, leading to an increasing demand of "natural" products and ingredients. The production process has become a unique dimension of quality, which not necessarily relates to the taste or healthiness of the product (Brunsø et al., 2002). The process-related quality is usually signalled with a mark – also called *extrinsic cue* – therefore the consumers' perceived quality depends on the knowledge of and trust in these quality marks.

Despite being a value itself, process related aspects such as naturalness are often associated with the health value.

### 1.2.4 Health and Nutrition

The value of health and nutrition was related to three dimensions: disease avoidance and control, weight control, and well-being (Furst et al., 1996). Consumers had distinct views of health and nutrition, the former being associated with avoidance of certain foods (e.g. high in salt or fat), while the latter with consumption of nutritious foods such as vegetables.

In general, the health dimension includes both safety and nutritional aspects. In the mind of consumers, health is often associated with weight control and low-fat diets (Lappalainen et al., 1998). The healthiness of a food product can be inferred based on personal knowledge, nutritional labels and health claims (Nocella and Kennedy, 2012; Kozup et al., 2003; Garretson and Burton, 2000). Moreover consumers could use the best-by date or expiration date as a proxy of healthiness or freshness (Ragaert et al., 2004).
Health orientation, or attitude, can sometimes be in contrasts with other food values, especially taste and convenience.

### 1.2.5 Convenience

In the experiment by Furst et al. (1996), convenience was mainly associated with saving time in preparation of a meal and saving time in shopping expeditions, i.e. the convenience of buying larger-sized products. Moreover, ease of preparation was considered part of convenience, together with the convenience of easily find products at the store, related to an adequate display of products on the shelves.
In general, the convenience construct refers to food products which allow consumers to save time, culinary skills, and energy inputs, with respect to raw foods (Traub and Odland, 1979).
Consumers seem to trade off between health and convenience (Ragaert et al., 2004). For instance, beliefs about physical health were found to have a negative effect on the purchase of convenience foods (de Boer et al., 2004). Moreover, fresh fruits are perceived to be healthier and less convenient than dried fruits (Sijtsema et al., 2012). However, healthiness is not significantly correlated to convenience orientation according to Candel (2001). Furthermore, Olsen et al. (2012) found health orientation to increase the likelihood of buying a (healthy) ready meal.

### 1.2.6 Sustainability and ethical consumption

A value which is not mentioned in the conceptual framework, but is gaining importance in the last years is sustainability. Sustainable food products contribute to sustainable goals in three dimensions: economic (i.e. fair prices for farmers and consumers), social (fair human working and trade conditions), and environmental (animal welfare and natural preservation) (Vermeir and Verbeke, 2006).

The sustainability of a food product refers to its attributes: the ingredients, the production process, and the packaging; and it can have both an environmental or ethical meaning in the mind of consumers (Vermeir and Verbeke, 2006; Mancini et al., 2017; Steenis et al., 2017).
A *conscious consumer* is an individual that, through his/her choices, express a sustainable behaviour. The sustainable behaviour can be expressed through individuals' own health protection, the search for information and certifications, the care about environmental biodiversity and climate change, the attention to resources waste, the support of local communities and small businesses (Mancini et al., 2017; Grunert, 2011).
Given the recent introduction of sustainability labels and the recently augmented consumer awareness, it is quite unlikely that sustainability enters the value negotiation phase directly. Most likely, sustainable aspects are not going to be valued against more familiar aspects like taste and convenience, but rather perceived as added features, in relation to price (Grunert, 2011). Moreover, Mancini et al. (2017) found a correlation between food sustainability and quality, meaning that sustainability attributes might be regarded as another sub-dimension of product quality.

### 1.2.7 Managing relationships

The last value included in the food value negotiation process is managing relationships. This means taking into account other people's preferences when making food choices, and thus accommodating others' tastes. But this is not the only way in which others' opinion can be taken into account when making food choices.
Social norm – an implicit set of behaviours that is considered acceptable in a group – has proven to affect what and how much people eat. According to Higgs (2015), the eating behaviour of relevant others is considered as a guide for individual's own behaviour in a given context. For instance, people tend to consume similar amounts to dining partners, or they tend to eat more when told other people have eaten more (Pliner and Mann, 2004; Higgs and Thomas, 2016). Also, dietary choices tend to converge with a normative dietary style, as perceived by the individual as a socially or culturally acceptable behaviour (Higgs, 2015).

The next section discusses the personal factors which affect food choices. Then, Chapter 2 deals with the possible strategies for making food choices.

## 1.3 Personal factors

Food choice decisions are diverse, each individual negotiates food choice values differently depending on personal characteristics, social framework and the food context (Sobal et al., 2014; Connors et al., 2001). In particular, how each individual manages values in food choices is of great interest for food consumption researchers (Connors et al., 2001). Knowing personal characteristics that affect food choice and habits allows managers and policy makers to segment the market, in order to reach the desired sub-group of consumers.
The following sections outline the main findings in the literature regarding heterogeneity in food choices. More specifically, the main personal features that can cause different choice patterns are presented. Demographic variables, lifestyles and psychological variables that affect food choice are displayed.

### 1.3.1 Demographic characters

Demographic characters are individual characteristics such as gender, age, income, education level, household composition, country and type of area in which a person lives (Albisu et al., 2012). Broad evidence suggests that demographic traits affect food consumption, although more recent segmentation research focuses more on the so-called *psychographic* – psychological and lifestyle variables – which are assumed to be the traits responsible of heterogeneous behaviours (Asp, 1999).
Behind gender differences in food choice lie socio-cultural variables, genetics and evolution, different importance attributed to health and looks, and differences in average income level and price sensitivity (Heiman and Lowengart, 2014).

The main findings on demographics affecting food choice values are outlined below:

- gender of the consumer has an influence on the demand for convenience food: in a study about consumption of ready meals in Sweden, female respondents were found to be in general more demanding than males, and their priorities were different. The most important aspects for women were related to health and nutrition; whereas men were more interested in aspects related to the ease of use and preparation (Ahlgren et al., 2006);

- gender, age and educational effects were found on health interest in food: women, older respondents, and respondents with high educational level were more interested in eating healthily. Females were also more interested in eating light products, whereas males rated taste as the most important factor affecting their food choice (Roininen et al., 1999);

- gender differences were found on food choice values in general: women had higher values on all food choice motives except Sensory Appeal and Familiarity, meaning women are in general more preoccupied with food (Steptoe et al., 1995);
- age was found to affect the adoption of a heathy diet: older respondents were more interested than younger respondents in healthy dietary practices and in using natural products (Steptoe et al., 1995);
- dietary factors were related to the demographic variables of gender and age: older (but not necessarily elderly) participants reported eating more fiber-rich foods in their diets than did younger ones, and women reported more avoidance of fats from meats than did men (Goldberg and Strycker, 2002);
- significant differences in motivation for food choice emerged between people with low and high BMI: the former eat more often because of physiological hunger while those with a higher BMI rely more on social norms and emotional cues (Renner et al., 2012);
- higher income has been found to encourage the consumption of convenience food; also, those who work more than 30 hours per week are the most convenience oriented consumers (Bonke, 1996).

These are only some examples of the differences in values found based on demographics. The number of experiments that have taken into account demographic differences on food related values and eating patterns is extensive. For further information, see also Frewer and Van Trijp (2006), Part III.

### 1.3.2 Psychographics

Lifestyles and personalities have been demonstrated to have an impact on food choice behaviour, over and above demographic characters. For instance, consider a woman that practices sport every day, has an health oriented dietary style and

lives alone; now think to a woman that has two children and a full time stressful job. It is likely that the different lifestyles they have result in different preferences and choices, even if they are both women and the same age.
The term lifestyle refers to the main interests, opinions and activities of each individual, whereas personality refers to the psychological traits peculiar of each person. Segmentation based on lifestyle and personality is called *Psychographic segmentation* – as opposite to the traditional segmentation based on demographic characteristics. The next sections describe in detail the two types of variables, and the main studies concerning food preferences.

## Lifestyles

The lifestyle (or life style) represents the way of living of individuals; it is expressed through behavioural patterns and refers to the set of activities, attitudes, interests and opinions of a person.
Scholderer et al. (2004) provided a definition of lifestyle: "Lifestyle is defined as an intervening system of cognitive structures that link situation-specific product perceptions (…) to personal values". Thus, lifestyles are situation-specific and can be specific to a product class.
The choices people make can be greatly influenced by their lifestyle. Lifestyle drives needs and wants, and can be influenced by factors such as culture, family and peers, and social class.
In a famous study, Brunsø and Grunert (1995) developed an instrument for measuring Food-Related Lifestyle (FRL). The FRL assumes the existence of five dimensions (or cognitive structures) that act as mediators between values and perceptions and behaviours: purchase motives, ways of shopping, quality aspects, cooking methods, and consumption situations (displayed in Figure 1.2).
The FRL instrument has been cross-culturally and nomologically validated (Scholderer et al., 2004; O'Sullivan et al., 2005; Brunsø et al., 2004) and applied in several studies in the food literature (e.g. Hoek et al., 2004; Nie and Zepeda, 2011; Pérez-Cueto et al., 2010). These studies explored a number of issues: Hoek et al. (2004) found differences between vegetarians and meat eaters in the five aspects of food-related lifestyle; Nie and Zepeda (2011) used FRL to segment food consumers and found four segments: rational, adventurous, careless and conservative uninvolved consumers, which differed in frequency of shopping at farmers' market and for organic food;

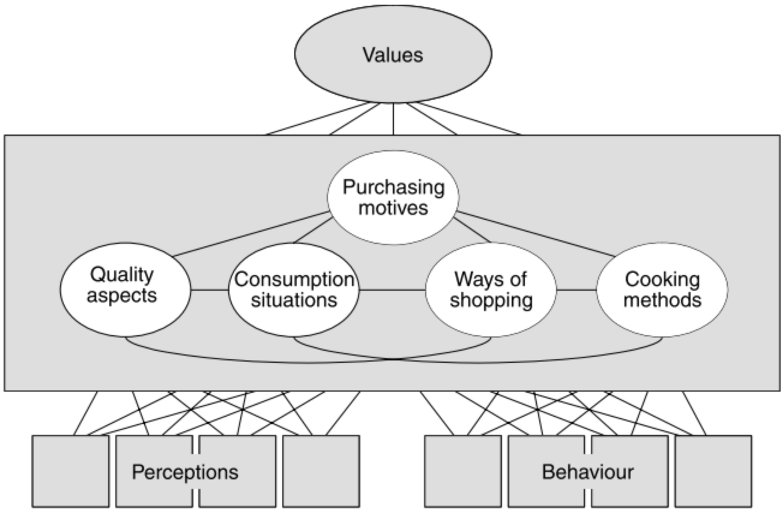



Figure 1.2. The Food-Related Life style model (from Grunert (2006))

Pérez-Cueto et al. (2010) studied the associations between obesity and FRL, finding that sub-dimensions of the quality aspect (health, organic production and freshness) are associated with not being obese.

Other studies in the food domain took into account lifestyles, but deviating from the FRL conceptualization. Goetzke and Spiller (2014) analyzed health-improving lifestyles according to five dimensions: physical activity, stress management, responsibility, spiritual wellness and beauty, and linked them to the purchase of organic and functional food. They found a link between the choice of organic food and active and spiritual lifestyle, and between choosing functional food and having a passive lifestyle (focused on beauty and passive relaxation). Moreover, Myrland et al. (2000) found a positive relationship between the level of physical activity and the consumption of seafood. Furthermore, de Jong et al. (2003) explored how lifestyles such as smoking, alcohol consumption, vegetable, fibre and fat intake and physical activity affect the consumption of seven types of functional foods, finding product specific and non-generalizable results.

## Psychological and personality traits

In a study in the field of psychology from Bouchard Jr. (2004), psychological traits were divided into: personality traits, psychiatric illnesses, social attitudes, intelligence and interests. Personality refers to the "unique pattern of traits" of individuals,

with traits being defined as "any distinguishable, relatively enduring way in which one individual differs from others" (Bilsky and Schwartz, 1994; Guilford, 1959).
In general, there is consensus in the psychological literature on the overall characterization of personality traits into five categories, the so-called Big Five or Five Factors: Openness, Conscientiousness, Extraversion, Agreeableness and Neuroticism, also identified with the acronym OCEAN (Costa Jr and McCrae, 1992; Perugini and Gallucci, 1997; John and Srivastava, 1999). Openness to experience measures the willingness to explore new and unfamiliar experiences; conscientiousness refers to self-discipline such as being organized, active, and hardworking; extraversion refers to the inclination to be sociable; agreeableness is related to sympathy, cooperation and friendliness; lastly, neuroticism refers to emotional instability such as anxiety and inability to react to stressful situations (Bazzani et al., 2017; Perugini and Gallucci, 1997)
Whether and how these personality traits affect food choices and eating patterns has been explored in the literature. For instance, Conner et al. (2017) studied how the big five personality traits are associated with fruit and vegetable consumption, they found that openness, extraversion and conscientiousness were associated with higher consumption of fruits and vegetables; the other two personality traits did not show an effect. Also, Carrillo et al. (2012) tested how conscientiousness, neuroticism and agreeableness relate to health and weight control as moderators in the consumption of low fat, low sugar and high calories food products. They found no effect for the agreeableness construct, while the neuroticism and conscientiousness presented a positive effect on health and weight control. Nonetheless, opposite results were obtained by Booth-Kewley and Vickers Jr (1994) and Goldberg and Strycker (2002), who found an association between neurotic personality and unhealthy behaviour. In particular, Goldberg and Strycker (2002) results confirm the effect of openness to experience and conscientiousness in predicting healthy dietary practices, on the other hand extraversion and neuroticism were associated to less healthy diets in terms of fats.
Impulsiveness as a personality trait has been also tested in the food literature, in relation to sensory perceptions. Impulsiveness measures the tendency to act on the spur of the moment, without taking into account potential risks. Saliba et al. (2009) found impulsiveness to be positively associated with a preference for sweet taste in wine, while openness was negatively related.

Broadly acknowledged food-related psychological traits are food neophobia, food involvement and variety seeking. Food neophobia is a measure of the reluctance to try novel or unfamiliar foods. Food involvement is a measure of importance of food in consumers own life, e.g. enjoyment in talking about food, thoughts about food during a typical day, and engagement in food-related activities such as food shopping, meal preparation, eating and disposal (Eertmans et al., 2005). Variety seeking is a variation in the response to an item of an individual with reference to the previous response in the same category, due to variation per se (Van Trijp et al., 1996). Variety seeking trait correlates positively with food involvement and negatively with food neophobia (Van Trijp et al., 1996).

In the study by Eertmans et al. (2005), food choice motives (i.e. values) were considered as mediators between food-related personality traits and food choice (intake). In their view, values in the personal system for food choice represent the "generative mechanism" through which traits are able to influence food intake (Eertmans et al., 2005). They found that food involvement was associated with price and ethical concern values, whereas convenience, weight control, and familiarity were associated with food neophobia. Furthermore, Marshall and Bell (2004) found that sensory and health values were interacting with food involvement, acting as mediators for food-involved individuals towards a more healthy and tasteful diet. Food involvement also affect habits such as the number of away-from-home consumed meals (Marshall and Bell, 2004).

Kim et al. (2010) analyzed the association between food neophobia and food involvement with satisfaction and loyalty in hospitality and tourism, and found an opposite effect of the two food-related personality traits: neophobia affected negatively satisfaction and loyalty, while food involvement had a positive effect. Moreover, food neophobia and involvement affect consumers attitude towards and intention to buy organic food in Taiwan (Chen, 2007).

Byrnes and Hayes (2013) studied how personality traits moderate sensory perceptions and liking. They analyzed the relationship between capsaicin burn and liking of spicy food, taking into account sensitivity to reward, sensitivity to punishment and sensation seeking personality traits. They found sensitivity to reward and sensation seeking to be positively related to liking of a spicy meal, whereas sensitivity to punishment was negatively correlated with the liking of spicy foods (Byrnes and Hayes, 2013). A similar study by Spinelli et al. (2018) took into account sensitivity to reward and to punishment as well, and also sensitivity to disgust, private body consciousness (i.e. awareness of internal bodily sensations), alexithymia (i.e. the difficulty in the identification and verbal description of subjective and others emotional feelings), and food neophobia. People more sensitive to reward liked more the spicy food, more neophobic and more sensitive to disgust individuals had lower liking scores for the spicy food. Low sensitivity to punishment was significantly affecting liking for males; no effect of private body consciousness and alexithymia was found. In a different study, Cliceri et al. (2018) measured how food neophobia, sensitivity to disgust and empathic responsiveness – defined as the ability to understand or feel the emotions other people are feeling – affect attitudes towards plant-based and animal based-dishes. More empathic individuals had positive attitudes towards plant-based dishes and negative attitudes towards animal-based dishes, no effect was found for the other personality traits.

It is evident how psychological and personality traits contribute in shaping values and attitudes of consumers, and therefore affect individuals' eating patterns.
The present chapter has discussed the food choice in terms of driving factors (i.e. values) and individual traits that can affect values, preferences and attitudes. Chapter 2 outlines and describe how consumer choice is made, and thus the different strategies consumers adopt to evaluate food products when choosing.

# Chapter 2

# Decision strategies in consumer choice

Explaining consumer choices, as well as predicting future choices, can be rather complex. Indeed, people often experience uncertainty when faced with a choice among several alternatives and sometimes will not make the same choice if presented with a similar choice-situation in the future. In fact, several factors can intervene, such as changes in the environment and/or in personal values and the social context (see Chapter 1 for an overview of determinants of consumer food choice). This does not mean that choices are totally random, but that choice behaviour can be represented as a probabilistic process, which includes a random part (Luce, 1959).

The decision-making process can be seen as consisting of sub-stages of information acquisition, evaluation of information, and the expression of a decision (Payne et al., 1993). Probabilistic theories of choice differ based on the mechanism that underlies and thus governs choice, called decision strategy, which is an expression of how the available information is evaluated in order to make a decision.

Some of the most important theories developed in the marketing field are described throughout this chapter, that concludes by providing examples of empirical applications in the food domain.

## 2.1 Utility theory

The Utility theory is broadly applied in consumer behaviour studies.
An antecedent of the modern concept of utility emerged in the psychological literature on decision making more than ninety years ago, when Thurstone (1927) introduced a law for the comparison of perceived psychological stimuli. In his *law of comparative judgment*, Thurstone assumed a psychological construct as a continuum on which two perceived stimuli can be located, therefore the distance between the two is a measure of what he called the *discriminal difference*.
Several years later, Marschak (1960) interpreted the same concept in terms of economic choice, conceiving the perceived stimuli as satisfaction or utility levels. Since then, several researchers have dealt with this concept adding their contribution to shape the Utility theory in economics.
A pivotal contribution to the Utility theory has been provided by Luce (1959), which imposed an important assumption about the characteristics of choice probabilities, i.e. the Independence from Irrelevant Alternatives (IIA)[1], which simplified the subsequent formulation of the choice model by Marschak (1960). Marschak not only applied the theory in the economic field, but also provided a derivation of a choice model from the utility maximization decision rule, called Random Utility Maximization (RUM) model. This has been further elaborated by McFadden (1973, 1981), Nobel Prize winner for his work on RUM choice modelling (see the Prize lecture: McFadden (2000))[2].

In the economic field the term *utility* simply means the *value* attached to a good. Straightforwardly, the Utility theory assumes the maximization of utility as the decision process that drives choices; in other words, people are assumed to maximize the utility derived from a good when choosing.
In the review of economic theories of decision making by Edwards (1954) it is written: "Every object or action may be considered from the point of view of pleasure- or pain-giving properties. These properties are called the utility of the object, and pleasure is given by positive utility and pain by negative utility. The goal of action,

1 According to the IIA property, the choice probabilities ratio of any two alternatives in a choice set is assumed to be independent from the presence or absence of other alternatives in the choice set. In other words, the inclusion of an additional good decreases the choice probabilities of all other goods by an equal proportion.

2 The RUM model is presented in detail in Chapter 3. In this section, the theoretical implication are considered.

then, is to seek the maximum utility. (...) People choose the alternative, from among those open to them, that leads to the greatest excess of positive over negative utility. This notion of utility maximization is the essence of the Utility theory of choice".

This extract describes the idea behind the utility maximizing process, which remains valid today. The Utility theory is based on the rational evaluation of the features of a good, whose values are added up – with each feature scaled differently according to its importance – to obtain a final value of utility for each alternative available, i.e. imposing a weighted additive rule (WADD) (Payne et al., 1993). Therefore, the utility derived from a good is based on the characteristics or attributes that it possesses (Lancaster, 1966) and is typically evaluated by a linear combination, through a compensatory process.

In a compensatory framework, a negative utility, called dis-utility, provided by one of the attributes of the product can be compansated by a positive utility provided by a different attribute. In other words, a high value on one attribute compensates for a low value on another attribute for the same alternative.

Giving the broad consistency of this framework and its simplicity, utility maximization is most of the times accepted as the decision rule in consumer choice. However, a number of issues challenges its absolute validity.

First of all, traditional economic theories such as the Utility theory postulate that the economic – and thus completely rational – man has a full knowledge of the relevant aspects connected to the choice and of the alternatives available. The economic man is assumed also to have, and to always use, computational skills that enables him to correctly assess which of the available alternatives will reach the maximum utility, i.e. the highest attainable point on his preference scale, which is stable over time (Ford et al., 1989).

Already in 1955, Simon raised some doubts on the validity of this assumption, suggesting rather adopting a kind of rational behaviour that is "compatible with the access to information and the computational capacities that are actually possessed by organisms". Also, Kahneman and Tversky (1979) provided evidence for the violation of some of the axioms of Utility theory and proposed an alternative choice model (presented in Section 2.3).

Choice theories that deviate from Utility theory assume that, for instance, consumers act as satisficers rather than maximizers, thus not engaging in seeking the best possible outcome, but choosing the first option that meets some minimum requirements. Decision makers are assumed to not engage in full informed evaluations and trade-offs, since they often choose under constraints (e.g., time, effort, ability, budget), which limit the real choice set within they can maximize their utility. Furthermore, information asymmetry causes bias in the evaluation of the best option. These are only some examples of psychological and behavioural issues that can challenge the utility maximization decision rule. Theories that try to overcome these limitations are presented in the following sections.

Objections raised aganst the Utility theory concern also the information processing strategy, questioning the compensatory mechanism implied by the standard utility model. Alternative rules for the information processing strategy have been proposed, which accommodate for non-compensatory rules (Stüttgen et al., 2012; Gilbride and Allenby, 2004). In the next section, a detailed description of non-compensatory rules is provided.

## 2.2 Heuristics and Satisficing theory

In consumer research, studies based on the idea of utility maximization are predominant to date; at the same time, decision rules that apply simplified shortcuts called *heuristics* are sometimes taken as psychologically valid description of human decision making (Dieckmann and Dippold, 2009).

Decision strategies based on heuristics deviate from the assumption of rational economic man who carefully considers and weights all pieces of information available. In fact, consumers may not always invest significant effort into a complete and careful evaluation of alternatives. Sometimes, it can be more realistic to assume that consumers rely on simplified choice rules and/or reduced consideration sets, which are expression of a bounded rationality (Kahneman, 2003).

In consumer behaviour literature, the most known simplified rules for decision making are the lexicographic, the conjunctive and disjunctive rules, and the elimination-by-aspects.

The lexicographic decision rule (Bettman, 1979) assumes consumers to choose solely based on the attribute they consider the most important, i.e. they choose the alternative that performs best on that particular attribute, regardless of any other feature. If two or more alternatives carry the same level for the most important attribute, then the choice is based on the second attribute in the personal hierarchy. The process

continues until the best alternative is found, or all the attributes have been screened. The term lexicographic refers to the dictionaries, whose alphabetical order recalls the above-descripted mechanism, i.e. in searching for a word one proceeds letter by letter – the first one being the most important – if two words are tie in the first letter, the second letter is considered, etc.
Differently from the lexicographic rule, both the conjunctive and disjunctive strategies (Dawes, 1964) involve processes based on individual threshold values for the attributes, which are intended as the minimum requirement for the choice. Under a conjunctive process, products that pass all of the thresholds are acceptable, thus all the attributes are considered. On the other hand, the disjunctive rule considers all products that pass at least one threshold as acceptable.
Lastly, the elimination by aspects decision rule (Tversky, 1972) is based on a sequential elimination process of alternatives. In multiple stages – each of which is based on a desired level for one attribute – the alternatives that do not match that desired level are excluded from the consideration set. This strategy can be viewed as a combination of the lexicographic and the conjunctive rules: the evaluation process matches the one inherit in the lexicographic rule, however under the elimination by aspects rule not only the alternative that has the best value is retained, but all the alternatives that are above the threshold for the specific attribute are retained (that is to say the alternatives that are under the threshold are excluded). It can be seen as a lexicographic multi-stage process, each involving a single attribute conjunctive rule.

Having these definitions in mind, it appears that conjunctive and disjunctive rules – being based on thresholds for acceptable levels of the attributes of alternatives – could result in a sub-set of acceptable products, from which each alternative can be chosen indiscriminately. But how can researchers predict a unique choice under this decision rule, if there are more than one different but equivalent alternatives? These specific decision rules for the choice process involve what is called a *stopping rule* (Stüttgen et al., 2012). The stopping rule predicts that a consumer stops evaluating alternatives when he/her finds a *satisficing* alternative, according to the threshold(s) he/she has in mind. Accordingly, consumers do not evaluate all available alternatives on all the attributes simultaneously, but rather act sequentially and simply stop when they find an acceptable alternative.
This is in line with what is called a satisficing choice behaviour, which has been first

theorized by Simon in 1955. Following his conceptualization, the ultimate choice is search path-dependent and varies with the order in which alternatives are presented to the decision-maker. Still, the researchers may, or may not, be aware of the mechanism that determines the order of procedure (Simon, 1955).
The satisficing theory has recently received the attention of Stüttgen et al. (2012), which developed a satisficing choice model. In their model, the first alternative that is good enough – after a verification stage – is chosen. Their model is made up by two interrelated parts, search and evaluation, implying a process in which the consumer continuously acquires information, updating the evaluations of the alternatives.
Before Stüttgen et al., Gilbride and Allenby (2004) also proposed a choice model which included simple heuristics, allowing for conjunctive and disjunctive rules in a two-stage choice process. Here, the heuristic is intended as a screening rule used to restrict the consideration set, but the actual choice is still based on a utility-maximizing behaviour.

All of the heuristics discussed so far are non-compensatory; i.e. a good value for one attribute cannot compensate for a bad value on another attribute. Indeed, only one undesired characteristic may be enough to exclude the option from the consideration set. This represent an extreme simplification of the decision process, in which the decision maker does not engage in any trade-off between attributes (Stüttgen et al., 2012).
Simple heuristics have proven to be an accurate representation of the real decision strategy when the choice task is complex, and thus when the need for simplifying is stronger. More specifically, a relatively large number of options and/or of attributes can induce a shift from compensatory to noncompensatory information processing (see Dieckmann and Dippold (2009) for an overview of the studies on this issue).
Nevertheless, besides choice models including simplified choice rules have shown promising results, they can be more or less valid depending on the choice framework. Situational factors and the characteristics of the decision task may lead people to use different strategies (Payne et al., 1993); therefore, researchers must be careful in their decision regarding which choice strategy to use to reproduce and explain a particular consumer choice.
Theories have been proposed that allow for trading off attributes, but under a different perspective from the utility-based paradigm. These theories adopt a loss

aversion perspective and are outlined in the following sections.

## 2.3 Loss aversion and Prospect theory

According to Kahneman (2003): "A theory of choice that completely ignores feelings such as the pain of losses and the regret of mistakes is not only descriptively unrealistic, it also leads to prescriptions that do not maximize the utility of outcomes as they are actually experienced".

The "pain of losses" is triggered by what is called *loss aversion*, which seems to be inherent in human beings. The concept of loss aversion refers to the idea that loss and gain of the same size are given different subjective evaluations, loss being more undesirable than the gain is attractive. Loss aversion explains why people do not bet on a stake equal to the bet amount, having fifty percent chance of winning: the attractiveness of the possible gain is not sufficient to compensate for the aversiveness of the possible loss. With reference to consumer choice, this also implies that the amount of utility provided by the desired attributes of a product do not compensate for the same amount of dis-utility given by the undesired ones.

A further way to explain the loss aversion phenomenon relates to the loss being interpreted as giving up an object one already possesses. The motivation to avoid the loss is so great that the loss will be accepted only for a greater amount of money than the amount originally spent by the owner. This phenomenon is called *endowment effect* (Thaler, 1980). It describes the reluctance of people to give up assets that are already in their possession.

Several experiments have been carried out to test the endowment effect, and all give similar results, confirming the existence of the phenomenon (Knetsch and Sinden, 1984; Kahneman et al., 1990). In one of the most famous experiments, half of the participating students of the Cornell University were randomly assigned a coffee mug decorated with the University logo. Then some games were performed in which owners had to trade their mug to other students, that acted as buyers, in exchange for money; all the students knew that the mug was sold at the University store for $6.00. Despite the fictitious nature of the study and the fact that students did not own the mug prior to the experiment, the average selling price for the owners was indeed greater than the average buying price for the buyers (Kahneman et al., 1990).

The loss aversion also gives rise to the so-called *status quo bias* phenomenon, which refers to the tendency of people to remain in their current status, since the disadvantages of leaving it have greater impact than the advantages (Kahneman et al., 1991).

All these psychological mechanisms challenge the pure compensatory behaviour in the evaluation of alternatives assumed by the Utility theory. More importantly, taking into account the different value of gains and losses necessarily imply the existence of a reference point. Starting from these considerations, Kahneman and Tversky (1979) developed the Prospect theory, which represents a completely new economic paradigm with reference to the classical utility theory.

The Prospect theory is a behavioural economic theory that involves psychological effects into the choice evaluation; it has initially been developed in the field of risky choices and then extended to riskless choices (Tversky and Kahneman, 1991). According to Prospect theory, values are viewed as a function of the reference point or *status quo* and the magnitude of the deviation from that reference point. In case of probabilistic alternatives, it specifies how value and probability are evaluated by decision makers. The objective value (e.g. money) and objective probability are processed by human beings to become subjective value and decision weight. What typically happens is that the objective magnitude is not coherent with the internal evaluation. For instance, two ice creams are not twice as attractive as one; and the difference in subjective value between 200€ and 100€ appears larger than the difference between 1, 200€ and 1, 100€ . Therefore, as the objective value increases, the marginal value (or utility) – the additional utility gained from consuming one more unit of a good – experienced by the decision maker decreases. This concept is expressed through a concavity in the utility function with respect to the size of gains and a convexity with respect to the size of losses. When the value functions are pieced together, an S-shaped function is obtained (see Figure 2.1).

Moreover, in Figure 2.1 the curve relating subjective value to objective value for loss outcomes (the left side of the graph) is steeper than the curve relating subjective value to objective value for gain outcomes (the right part of the graph), exhibiting a loss aversion behaviour. For moderate gains and losses, the ratio of the slopes of the value function in the two domains is about 2:1 (Tversky and Kahneman, 1991). Thus, prospect theory assumes that values are attached to changes rather than to final states, going against the classical utility theory (Kahneman and Tversky, 1979).

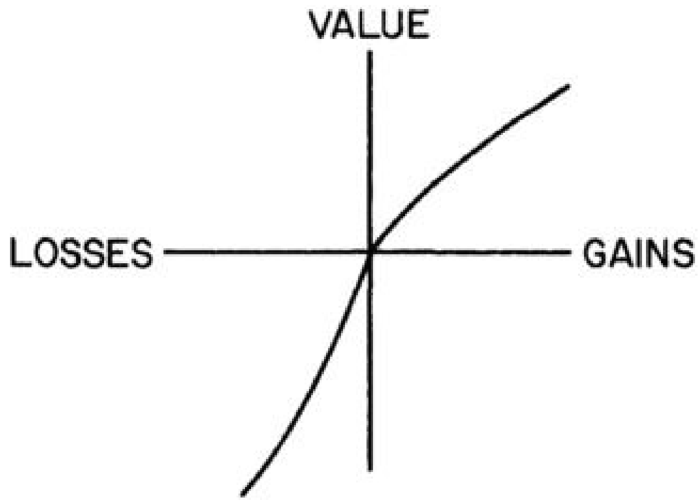



Figure 2.1. Value function (from Kahneman and Tversky (1984))

Throughout the years, many researchers followed the axioms of Prospect theory in their studies on consumer behaviour. The theorized reference-dependence under a loss-aversion perspective explains the impact of reference prices on consumer choice preferences that is found in the literature. Evidence of the existence of reference price is therefore a validation for Prospect theory (Mazumdar et al., 2005; Kalyanaram and Winer, 1995; Wang, 2018; Caputo et al., 2018a).
Although the reference-dependence assumed by Prospect theory seems perfectly logic, it is not always observed. List (2004) compared Utility and Prospect theory and found that different behavioural processes are used depending on the prior experience of consumers in the marketplace: prospect theory has a stronger predictive power for inexperienced consumers, whereas consumers with market experience exhibit behaviour consistent with neoclassical utility theory. This result reflects the idea of the endowment effect being a sort of mistake, whose effect could be reduced or avoided through exercise in market transactions. List concludes his study highlighting both successes and failures of, as well as challenges for, the two theories (List, 2004).
In the next section, a theory akin to loss-aversion is presented. This theory goes beyond the assumption of loss aversion in consumer behaviour, assuming the emergence of regret due to a loss, and a regret-averse decision process.

## 2.4 Regret theory

Regret theory, just as Prospect theory, has been developed in the attempt to overcome the psychological limitations of the classical Utility theory.
Loomes and Sugden (1982) are the fathers of Regret theory and believed that their theory was simpler and more intuitive than Prospect theory.
Regret theory is based on actions and consequences, under the assumption that the "psychological experience of pleasure" (i.e. the utility) connected to the action – in our case the choice of a single alternative – depends not only on the consequences of that specific action, but also on the potential consequences of other actions that have not been taken. Loomes and Sugden theorized the existence of *regret* and *rejoice*: regret is experienced when the consequences of a not chosen option would have been better than the one the decision maker has chosen, leading him/her to think to the missed opportunities, and lowering the pleasure derived from the actual choice. On the other hand, rejoice represents an extra pleasure derived from knowing that the best choice possible has been made. In Regret theory, not only consumers are assumed to feel regret and rejoice, but also to anticipate these feelings when making decisions.
Loomes and Sugden incorporate regret and rejoice into a modified utility function that consumers are assumed to maximize. They consider an individual in a situation where multiple states of the world can occur, each of which with probability $p_j$ with $j = 1, \ldots, n$. The individual is assumed to choose between two alternatives; each alternative is represented by a $n$-tuple of consequences, one consequence for each state of the world.
The modified utility $m_{ij}^k$ of choosing $i$ over $k$ is a function of the consequences $c_{ij}$ and $c_{kj}$ of the possible choices in the state of the world $j$:

$$m_{ij}^k = M(c_{ij}, c_{kj})$$

The function $M(.)$ assigns a real-valued index to every ordered pair of consequences. $m_{ij}^k$ is smaller or larger than $c_{ij}$ depending on the decremental or additional utility provided by experiencing rejoice or regret from choosing $i$ over $k$, caused by knowing $c_{kj}$.
Accordingly, the individual chooses $i$ over $k$ by maximizing the expected modified

utility $E_i^k$, calculated over all the possible states of the world:

$$E_i^k = \sum_{j=1}^{n} p_j m_{ij}^k$$

Loomes and Sugden's modified utility function is just one of the possible formulations for including regret in the choice modelling. Nevertheless, other regret-based behavioural theories and choice models have been proposed in the literature.

One of the most known choice models involving regret is the Random Regret Minimization (RRM) model developed by Chorus (2010). The RRM model incorporates the idea that consumers anticipate possible future regret while choosing and aim to minimize it.

In the context of riskless choices, the anticipated regret connected to the choice arises from making trade-offs between the attribute values of alternatives. In order to reach the alternative that has the best performance overall, sometimes the decision-maker has to accept a sub-optimal performance on one or more of the attributes of the alternative chosen, which may cause regret (Hensher et al., 2015). More specifically, the RRM model calculates the choice probability for an option by means of an attribute-by-attribute comparison with the other available options. Morevover, the regret minimization-based choice framework postulates that losses loom larger than gains, under a loss-aversion (and therefore regret aversion) perspective. This means that the same difference in an attribute level between two alternatives produces different impacts on choice probabilities depending on the fact that the considered alternative has a better or worse performance (see section 3.1 and Figure 3.1 for a detailed description of the behavioural process assumed by the RRM model). In other words, if a decision-maker is comparing product A with product B, and A costs 1€ more, the regret he/she anticipates is higher than the rejoice he/she would have felt if product A was 1€ cheaper than B.

This regret-based framework implies what is defined as *semi-compensatory* choice behaviour (Chorus et al., 2008; Chorus, 2010). Referring to the compensatory and non-compensatory behaviours outlined in the utility theory (Section 2.1) and heuristics (Section 2.2), respectively, a semi-compensatory behaviour is something in between. It is based on the evaluation of all the attributes of a product, like what occurs in the compensatory choice strategy, but the attributes losses and gains may

not compensate each other, since the same difference in attribute levels between two alternatives gives regret and rejoice of different sizes.
Another feature of the RRM model is that it allows for capturing choice set composition effects such as the compromise effect. The compromise effect is a well-known phenomenon in marketing and refers to consumers' tendency to choose products that overall have an intermediate performance on all attributes, rather than a high performance on some and a low performance on others (Simonson, 1989).

### Theory of Regret Regulation

The RRM model is based on the Theory of Regret Regulation by Zeelenberg and Pieters (2007). This theory provides a clear definition of regret – distinguishing it from akin emotions – specifies the conditions under which regret is felt, outlines the aspects of the choice that can be regretted, and displays the behavioural implications.
Regret is a "negative, cognitively based emotion that we experience when realizing or imagining that our present situation would have been better, had we decided differently" (Zeelenberg, 1999).
Evidence from neuroscience and psychology suggests that *anticipated regret* has a direct and significant impact on future choices (Coricelli et al., 2005; Joong et al., 2013; Simonson, 1992). Thus, regret is not only a reaction to unexpected bad outcomes, but also a driver of people's choices, and it has been found to influence decision making in several fields (e.g. marketing, economics, health behaviour etc.).
From a psychological perspective, researchers have found that regret is the most frequent and intense negative emotion in people's life (Saffrey and Roese, 2006; Shimanoff, 1984). However, regret is not a basic emotion since it implies a complex reasoning around what could have been, and therefore it heavily relies on comparison processes (Zeelenberg and Pieters, 2007).
Zeelenberg and Pieters (2007) state ten propositions which are the foundation of the Theory of Regret Regulation. Table 2.1 displays the propositions.
The authors found that anticipated regret plays a bigger role especially when a decision is complex and/or important.

The next section discusses the empirical applications in the food domain of the theories presented so far.

Table 2.1. Theory of Regret Regulation's propositions (Zeelenberg and Pieters, 2007)

| N | Propositions |
|---|---|
| 1. | Regret is an aversive, cognitive emotion that people are motivated to regulate in order to maximize outcomes in the short term and learn maximizing them in the long run. |
| 2. | Regret is a comparison-based emotion of self-blame, experienced when people realize or imagine that their present situation would have been better had they decided differently in the past. |
| 3. | Regret is distinct from related other specific emotions such as anger, disappointment, envy, guilt, sadness, and shame and from general negative affect on the basis of its appraisals, experiential content, and behavioural consequences. |
| 4. | Individual differences in the tendency to experience regret are reliably related to the tendency to maximize and compare one's outcomes. |
| 5. | Regret can be experienced about past ("retrospective regret") and future ("anticipated or prospective regret") decisions. |
| 6. | Anticipated regret is experienced when decisions are difficult and important and when the decision maker expects to learn the outcomes of both the chosen and rejected options quickly. |
| 7. | Regret can stem from decisions to act and from decisions not to act: the more justifiable the decision, the less regret. |
| 8. | Regret can be experienced about decision process ("process regret") and decision outcomes ("outcome regret"). |
| 9. | Regret aversion is distinct from risk aversion, and they jointly and independently influence behavioural decisions. |
| 10. | Regret regulation strategies are decision-, alternative-, or feeling-focused and implemented based on their accessibility and their instrumentality to the current overarching goal. |

## 2.5 Theory into practice: applications in the food domain

People can use several strategies to make a choice. How people make choices has been discussed in previous sections.
Decision making strategies for choice prediction in the food literature has been traditionally seen as a process of weighting and adding aspects of a product, in a utilitarian perspective (Scheibehenne et al., 2007; Stafleu et al., 1991). Utility represents the subjective value attached to alternatives in choice models, which are traditionally based on random utility maximization. Thus, there are hundreds of applications of choice models in the food literature based on the RUM theory.
In the present section, studies that take into account the limitations of RUM theory in food choices are discussed.

### Heuristics

Eating behaviour is often automatic and consumers might rely on low-effort processes when making everyday food choices (Cohen and Farley, 2008). Indeed, human beings have limited cognitive ability and usually rely on low-effort, fast and intuitive thoughts. In the literature, a dual-process model of thinking has been proposed, which distinguish between System 1's fast and intuitive thinking and System 2 thinking, which involves reasoned, slow and effortful decisions (Kahneman, 2003). Nonetheless, intuitive does not mean unconscious; the so-called heuristic judgement does not appear in the minds of people outside of awareness, but it still require basic consciousness and calculation (Dhar and Gorlin, 2013).
With regard to food decisions in particular, consumers might employ heuristics to reduce the effort put in the choice. This becomes especially true as the variety of food available in stores increases, augmenting the difficulty of trading-off between attributes and alternatives (Scheibehenne et al., 2007).
Heuristics that can be applied in food choices are mainly related to the lexicographic rule and attribute non-attendance. This means people base their choice on a small quantity of the whole information available and some attributes of the product are neglected in decision making. For instance, individuals following a strict weight-reduction diet might base the choice of food products mainly on the caloric content

of the food, ignoring other aspects (Roering et al., 1986). Attribute non-attendance can essentially be driven by two reason: a satisficing behaviour in which consumers ignore an attribute because it does not affect their utility, and a need for a simplified heuristic (Alemu et al., 2013).

Evidence of the use of a lexicographic decision strategy in food choice emerges from recent papers: Meenakshi et al. (2012) and Banerji et al. (2018) performed studies on maize and found that, for a subset of consumers, the price attribute was not taken into account in the choice, and the choice was uniquely based on the color or variety of maize. Moreover, they found interesting results in terms of demographic variables that affect the use of a lexicographic choice strategy: in the first study men were more prone to use a lexicographic rule as compared to women, in the second experiment participants who displayed lexicographic choices tended to be younger[3]. Berg and Preston (2017) in their study on local food had similar results: they found two distinct subgroups of consumers, one of which was made by individuals not interested in purchasing non-local food even at a zero price. In other words, their only requirement for food was to be local, and price was not considered in the choice. Therefore, the price seems to be irrelevant in some food choices. However, the irrelevance of the price attribute in food choices resulting from the above-mentioned studies might also derive from experimental settings, i.e. the differences in alternatives' price might be too small, leading to the perceived irrelevance for consumers. Also, respondents in Berg and Preston (2017) study may not have taken the price very seriously because this experiment was not incentive-aligned.

From the studies cited in the discussion above, it appears that simplified non-compensatory decision rules are sometimes adopted in making food choices. Still, decision-makers could rely on different choice strategies depending on the decision task (Payne et al., 1993). Lexicographic heuristics are usually adopted when the retrieval of information on the available options is costly, or when there are time constraints (see Dieckmann and Dippold (2009) for details on empirical studies). In the opposite situation, when time and cost constraints do not subsist, a compensatory choice model gives more adequate choice predictions. Accordingly, the compensatory utility maximization is the most widely assumed strategy in food

3 These results confirm the fact that demographic variables may affect food choices, which is discussed in Section 1.3.

choice studies, but researchers must be careful and adapt the assumed strategy case-by-case.

## Loss aversion

Another practical challenge to the Utility theory is represented by the proven existence of reference prices and loss aversion behaviour in food choices. In 1991, Tversky and Kahneman developed a reference-dependent theory of consumer choice, based on prospect theory and loss aversion[4]. This reference-dependent theory immediately found some support, given by the empirical finding of a reference price, based on sales data of eggs (Putler, 1992). Just one year later, Hardie et al. (1993) formulated a reference-dependent choice model and applied it to orange juice's brand choice. They found evidence for the consumers evaluation of product attributes relative to a reference level, and for the asymmetric consumer response to deviations of actual prices from reference prices, coherently with prospect theory. In their experiment, they assume that brands can be evaluated in comparison to other brands, that act as reference points, taking the most recently purchased brand as the reference, i.e. the currently held alternative represents the status quo.

The status quo reference has a strong impact on consumer preferences, especially on food products. Considering standardized packaged food products, a typical process described in the consumer behaviour literature suggests that individuals try different products until a satisficing good is found, and then repeatedly purchase this alternative over time until an external shock occurs, e.g. the option is out of stock, the consumer sees an appealing advertising for a competitor product, a different product is on discount, etc. Then the process starts again (Adamowicz and Swait, 2013). Consumers buy repeatedly the same brand or product because they do not want to engage in cognitively difficult trade-off operations (Adamowicz and Swait, 2013), leading to the development of food habits. Furthermore, consumer food habits can be explained by loss aversion and the endowment effect. Taking into account the relatively strong value attached to products in one's possession compared to products not in his/her possession, it's clear that consumers may develop a strong preference for the product already in their endowment, being less prone to exchange it for a different option (Cramer and Antonides, 2011).

4 See Section 2.3

Despite the proven existence of a loss-aversion behaviour in food choices, the results across studies are quite mixed with respect to the significance and magnitude of this phenomenon (see Neumann and Böckenholt (2014) for a meta-analysis of loss aversion in product choice). The mixed evidences on loss aversion can be a result of not adequately accounting for consumer heterogeneity across people, measures, and choice situations (Bell and Lattin, 2000; Klapper et al., 2005). In their study, Klapper et al. (2005) found that on average loss aversion is rather small regarding beverage and chocolate. However, by accounting for heterogeneity among people they indeed found a subgroup of loss averse consumers; and those consumers were similar on a psychographic variable, namely *quality consciousness*, which strongly affects loss aversion. Moreover, Antonides and Cramer (2013) in their study show that some types of food choices are more susceptible to loss aversion than other types. They found a difference in the endowment effect for hedonic (affective) and utilitarian (instrumental) types of foods, which was stronger for the first category.

A further implication of a reference-dependent behaviour is the compromise effect. Carroll and Vallen (2014) documented the existence of the compromise effect (or: extremeness aversion) with reference to calories intake. In their experiment respondents tended to avoid the largest and smallest caloric items available, regardless of the absolute calorie counts. Moreover, Sharpe et al. (2008) found that, when extreme alternatives were added to the choice set, consumers shifted their preferences to smaller and larger options that had become compromise options. Preference for intermediate options has been found also for meat in between mainstream and organic production (de Jonge et al., 2015; Van Herpen et al., 2015).

## Regret minimization

To the best of our knowledge, a choice model that assumes the minimization of anticipated regret as the decision rule for food choices has not been applied so far in the literature. Nevertheless, regret is often taken into account in decision-making, and empirical evidence supports the impact of anticipated regret on choice. For instance, anticipated regret is a significant predictor in the context of sexual and contraceptive behaviour (Richard et al., 1998) and has a direct influence on deciding to engage in physical exercise (Abraham and Sheeran, 2003). More akin to the food context, Joong et al. (2013) provided evidence that anticipated regret increases intentions to select an eco-friendly restaurant.

Moreover, some studies document the emergence of regret in connection to food choices. In a recent study by Skelton and Allwood (2017), different kinds of food purchases were listed as choices that were frequently regretted. In particular, regret arouse from the impulsive choices of unhealthy foods such as takeaways and confectionery, which are rewarding in the short time, but produce undesirable effects in the long run. The main cause of regret related to groceries was that they spoil and had to be thrown away, while other reasons involved health concerns, e.g. consumers wished they had made a healthier choice, or a less fat/caloric choice for weight reduction.

Consistently with Zeelenberg and Pieters's Regret Regulation Theory (2007), and in particular with the claim that anticipated regret plays a bigger role when a decision is complex and/or important, in some circumstances food choices could indeed be based on the anticipation of regret. Several reasons may enhance the perceived relevance of a choice. In particular, the relevance of food choices can be connected to the implications for health (including body weight and food safety), to financial consequences, and to social norms (e.g., peer pressure, fashion, animal welfare, environmental effects, etc.).

# Chapter 3

# Discrete Choice Models

In consumer behaviour research, Discrete Choice Models (DCMs) describe consumers' choices among a set of products (Train, 2009). DCMs are mathematical models that link the choice to the alternatives the individual faces when making the choice, i.e. the choice set. In a discrete choice framework, the choice set exhibits three characteristics: it is finite, exclusive and exhaustive (Train, 2009). This means that the choice set contains a finite and small number of alternatives, but at the same time it includes all possible alternatives under investigation, and these alternatives are different from one another.

Discrete Choice Experiments (DCEs) are methodologies for data collection in a discrete choice framework, the collected data are analyzed by means of DCMs. In the stated form, DCEs are made of multiple choice tasks that are presented to a respondent, which is asked to express his/her preferred alternative in the choice set. Alternatives are built as a combination of different attribute-levels. Since researchers are usually interested in analyzing several attributes and levels in a single choice experiment, the number of possible combinations to analyze sometimes gives rise to huge amounts of alternatives. To reduce the amount of possible choice sets, they are formed based on experimental designs. The experimental design allows the researcher to obtain valid and strong results by means of specific combinations of attribute levels for the alternatives in the choice set, ensuring the minimum estimation error.

The next sections display the mathematical formulations of utility-maximizing and regret-minimizing behaviours in choice models, and present estimation methods of logit models. The last section provides an overview of DCEs in the food literature.

## 3.1 Behavioural process specification: RUM and RRM

Consumers' choice is driven by factors related to the product, the self, and the environment, as discussed in Chapter 1. Some factors are observed and some are not known by the researcher. Thus, the chosen option among a finite number of alternatives can be explained by observed and unobserved factors through a certain function, which reflects the *behavioural process*.
Discrete choice models are usually derived under the assumption of utility maximizing behavioural process by the decision maker (Train, 2009).
The utility $U_i$ derived from the alternative $i$ is usually specified to be linear in parameters, and can be written as a weighted sum of the alternative's attributes $m$:

$$U_i = \sum_{m=1}^{M} \beta_m x_{mi} \tag{3.1}$$

Equation 3.1 displays the linear specification of utility, where $x_{mi}$ is the value or level of the attribute $m$ in the alternative $i$ and $\beta_m$ is the coefficient of the attribute $m$ (called *taste parameter*), representing the importance of the attribute in contributing to total utility. This specification of linear preferences is also called *vector model*[1] (Green and Srinivasan, 1978).
Equation 3.1 models the *deterministic utility*, i.e. the systematic utility, and enters the function of the so-called Random Utility, together with a random factor.
In Random Utility Maximization (RUM) models, the random utility associated to the alternative $i$ is a sum of a deterministic part and a random part and can be written as:

$$RU_i = U_i + \varepsilon_i \tag{3.2}$$

where $U_i$ is the deterministic part of the equation displayed (3.1), and $\varepsilon_i$ represent the random part. The random vector $\varepsilon_i \; \forall i = 1, \ldots I$ is assumed to be Independent and Identically Distributed (IID) extreme-value.

1 Other specifications of preferences have been proposed in the literature, e.g. the ideal-point model, which posits that the preference is related to the distance of the stimulus from an individual's ideal point (Green and Srinivasan, 1978).

Thus, the linear-in-parameter[2] RUM model is:

$$RU_i = U_i + \varepsilon_i = \sum_{m=1}^{M} \beta_m x_{mi} + \varepsilon_i \tag{3.3}$$

Under the assumption of utility maximization, the decision maker chooses the alternative $i$ if $RU_i > RU_j\ \forall j \neq i$. In other words, the alternative $i$ is chosen only if its associated utility is the greatest among all the utilities associated with alternatives in the choice set.

Although utility maximization is the most widely accepted framework in discrete choice modelling, alternative paradigms for decision making have been proposed, which allow for different decision rules (Hess, 2012). This study focuses on one alternative specification for the behavioural process, namely regret minimization. In 2008, Chorus first developed a regret-based model for travel choice. This model allows for the possibility that choices between travel alternatives are driven by the avoidance of negative emotions, rather than the maximization of payoffs (Chorus et al., 2008). This specification postulates that consumer choices are driven by pairwise comparisons on an attribute-by-attribute basis; the regret associated with a specific alternative derives from the comparison of that alternative with the best of the available alternatives. The attribute-level regret is calculated as:

$$R^m_{i\leftrightarrow j} = max\{0, [\beta_m(x_{jm} - x_{im})]\} \tag{3.4}$$

That is, at the attribute level $m$ the regret is 0 when the considered alternative $i$ outperforms alternative $j$. On the other hand, when the alternative $i$ is outperformed by $j$, regret equals the product of the importance of the attribute, $\beta_m$, and the difference in attribute-values, $x_{jm} - x_{im}$.

Although being highly intuitive, this formulation is discontinuous around zero, therefore the partial derivatives of the function with respect to $x$s and $\beta$s cannot be computed in that area. This causes non-trivial theoretical and practical difficulties in the estimation of the model (Chorus, 2012a). These problems have been solved

2 This is only one of the possible specifications for the taste parameters. In some contexts, it could be useful to allow parameters to enter the utility function as exponential factors or in the logarithmic form, based on specific restrictions imposed by the choice setting (e.g. parameters are interpretable only if they are at the exponential). See examples provided by Train in his book, page 62-63 (Train, 2009).

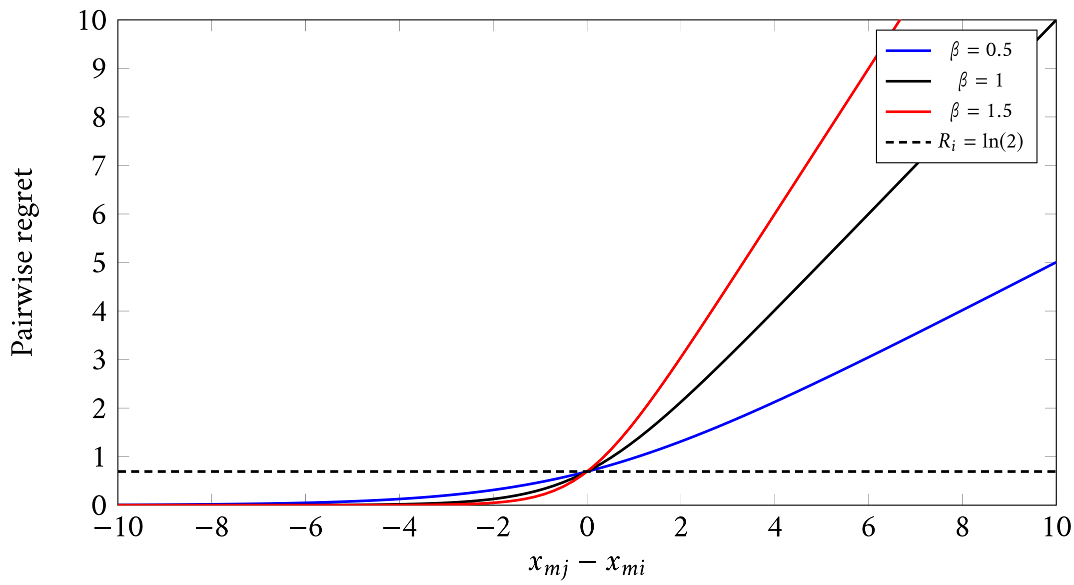
by means of the adoption of a smooth function, which was introduced by Chorus (2010) in his Random Regret Minimization (RRM) model, which is considered in the present study.

The new RRM model takes into account the regret for a specific alternative as an aggregation of the regret emerging from the comparisons with all available alternatives, rather than only with the best. Consumer choices are driven by pairwise comparisons between all available alternatives, on an attribute-by-attribute basis. If one or more of the competing alternatives performs better (on one or more attributes) than the considered alternative, a certain level of regret is anticipated when choosing that alternative. Moreover, Chorus (2010) specification postulates that any anticipated regret – that is due to a loss, i.e. a lower performance on one attribute of the considered alternative with respect to the competing alternatives – has a bigger influence on choice probabilities than the anticipated rejoice – that would come from an equal gain, i.e. the same difference in performance in the opposite direction (the considered option being the one that performs better). In other words, there is an asymmetry in the sense that losses loom larger than gains. At the attribute level *m*, the anticipated regret or rejoice that emerges by comparing the alternative *i* with the alternative *j*, called pairwise regret, is formulated as follows:

$$R_{i\leftrightarrow j}^{m} = ln(1 + \exp[\beta_m(x_{jm} - x_{im})]) \tag{3.5}$$

The size of the taste parameter $\beta_m$ represents the maximum increase (or decrease) in regret resulting from a unitary increase in the attribute (Chorus, 2012a), and measures the relative importance of an attribute.
However, differently from what occurs in the RUM model, in the RRM model the value of $\beta_m$ also reflects the relative importance of regret respectively to rejoice for the attribute *m*, since it can modify the shape of the attribute level regret function. In other words, $\beta_m$ is a measure of the *profundity of regret* for the attribute *m* (van Cranenburgh et al., 2015).
More specifically, the non-linear specification of the attribute level regret in (3.5) accommodates for different degrees of asymmetry between regret and rejoice, depending on $\beta_m$. The larger the taste parameter, the stronger the difference between the regret generated by a loss and the rejoice generated by an equivalent gain.

Figure 3.1. Attribute level regret function




Whereas, a relatively small taste parameter implies that regret and rejoice generated respectively by a loss and an equivalent gain are about the same size. Therefore, the extent to which the RRM model imposes a regret minimizing behaviour is likely to vary across attributes, depending on the estimated $\beta$.

Figure 3.1 displays an example of the attribute level regret function with different values of positive $\beta$[3]. The graph shows that as $\beta$ increases the difference between the impacts of loss and gain widens. In other words, more important attributes lead to higher anticipated regret, the difference in performance of the attributes held constant. The dashed line represents the situation of null regret, and thus the case in which $x_{jm} = x_{im}$, which occurs at $y = \ln(2)$.

Starting from the formulation of the attribute-level regret function displayed in Equation 3.5, Chorus developed the RRM choice model (Chorus, 2010):

$$RR_i = R_i + \varepsilon_i = \sum_{j \neq i} \sum_m ln(1 + \exp[\beta_m(x_{jm} - x_{im})]) + \varepsilon_i \tag{3.6}$$

Here, like in the utility-based approach, $RR_i$ is composed of a deterministic, systematic part and a random part (hence it is called random regret). In any particular choice situation, consumers are supposed to select the alternative associated with

3 In case of negative values for $\beta$, a specular graph with respect to $x = 0$ is obtained.

the lowest total anticipated random regret; i.e. the decision maker chooses the alternative $i$ if $RR_i < RR_j \; \forall j \neq i$.
Equation 3.6 models the deterministic regret (rejoice) for an alternative $i$ as a summation of different amounts of regret (rejoice) invoked by comparisons to other available alternatives $j \neq i$ in terms of their values on each attribute $m$. Assuming that lower values on attribute $m$ are less attractive (i.e. $\beta_m > 0$), a lower value of alternative $i$ relative to another available alternative $j$ on attribute $m$ generates anticipated regret, and a higher level generates anticipated rejoice.
The asymmetry in the impact of losses and gains differentiates the RRM model from the linear-in-parameter RUM model in (3.3), which assumes that contributions of losses and gains to utility are symmetric. Furthermore, the random utility in Equation 3.3 does not depend on the other available alternatives.

## 3.2 Estimation methods

### 3.2.1 Multinomial Logit model

In discrete choice modelling, the most widely used type of model to transform random utility (and random regret) into choice probabilities is logit (Train, 2009). The original logit formulation has been derived by Luce (1959), who first hypothesized the property of Independence from Irrelevant Alternatives (IIA), of critical importance for the derivation of the model.
According to the IIA property, the choice probabilities ratio of any two alternatives in a choice set is assumed to be independent from the presence or absence of other alternatives in the choice set. This means that the inclusion of an additional alternative decreases the choice probabilities of all other alternatives by an equal proportion. By assuming this property and extreme value distribution for the errors, McFadden (1973) obtained the logit formulation for choice probabilities[4]:

$$P_i = \frac{e^{U_i}}{\sum_j e^{U_j}} \tag{3.7}$$

4 see Train, pag 41 (2009) and the Prize lecture of McFadden (2000) for more details about the derivation of logit model in the RUM context

If the choice set comprises only two alternatives ($J = 2$), the model is called Logit model. On the other hand, if there are more than two alternatives in the choice set ($J > 2$), then the denominator becomes the sum of more than two terms and the model is called Multinomial Logit (MNL) model[5].
A summary of the steps followed in obtaining the logit formula is displayed below.

As explained in the Section 3.1, both the random utility and the random regret formulations are composed of a deterministic and a random part. The latter accounts for all the unobserved factors that contribute to the choice. The random term distribution is specified based on the researcher assumptions regarding the specific choice situation.
Assuming that the random vector $\varepsilon_i$ $\forall i = 1, \ldots, I$ is Independent and Identically Distributed (IID) extreme-value, the density for each unobserved component is:

$$f(\varepsilon_i) = e^{-\varepsilon_i} e^{-e^{-\varepsilon_i}}$$

and the cumulative distribution is:

$$F(\varepsilon_i) = e^{-e^{-\varepsilon_i}}$$

The difference between two IID extreme-value variables follows a logistic distribution. Therefore, taking $\varepsilon^*_{ij} = \varepsilon_i - \varepsilon_j$ it holds:

$$F(\varepsilon^*_{ij}) = \frac{e^{-\varepsilon^*_{ij}}}{1 + e^{-\varepsilon^*_{ij}}}$$

The choice probability $P_i$ for the alternative $i$, in an utility maximization context, $\forall j \neq i$ is:

$$P_i = Prob(RU_i > RU_j)$$

And can be written as:

$$P_i = Prob(U_i + \varepsilon_i > U_j + \varepsilon_j)$$

$$P_i = Prob(\varepsilon_j < U_i + \varepsilon_i - U_j)$$

5 Sometimes also called Conditional Logit model, since it is conditioned to the available set of alternatives (McFadden, 2000).

$\varepsilon_i$ has cumulative distribution:

$$F(\varepsilon_i) = e^{-e^{-\varepsilon_i + U_i - U_j}}$$

Since $\varepsilon_i$s are independent of each others, the cumulative distribution over all $j \neq i$ is the product of all the individual cumulative distributions, given $\varepsilon_i$:

$$P_i | \varepsilon_i = \prod_{j \neq i} e^{-e^{-\varepsilon_i + U_i - U_j}}$$

But $\varepsilon_i$ is not given, therefore the choice probability is calculated through the integral over all possible value of $\varepsilon_i$, weighted by its density.
After algebraic treatments, the logit choice probability is obtained:

$$P_i = \frac{e^{U_i}}{\sum_j e^{U_j}} \tag{3.8}$$

The same logit formulation of choice probability can be applied in a regret minimizing framework:

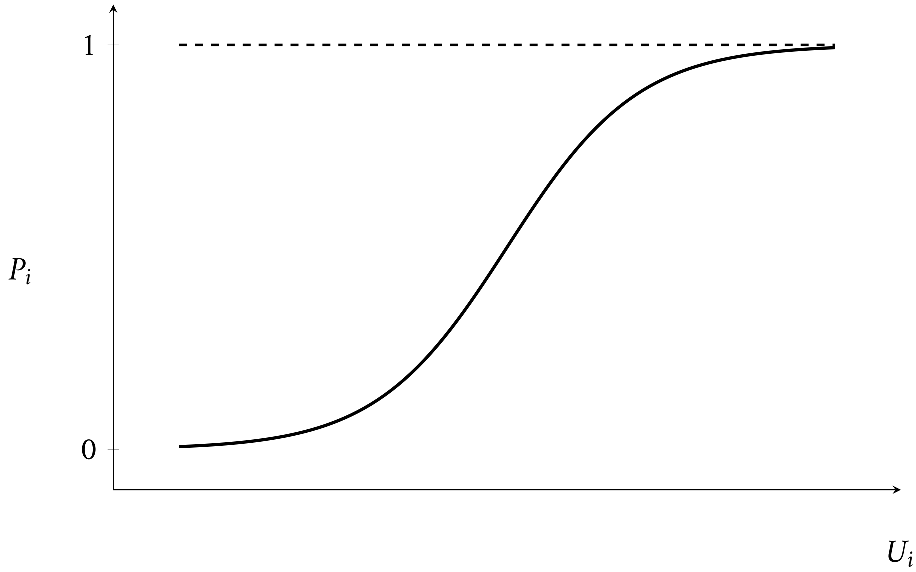
$$P_i = \frac{e^{(-R_i)}}{\sum_j e^{(-R_j)}} \tag{3.9}$$

The logit specification of choice probabilities has several favourable properties:

- $0 < P_i < 1$
- $\sum_{i=1}^{J} P_i = 1$
- The relation between utility and logit probability is S-shaped.

The properties that are required for a probability are respected: the range of $P_i$ is between zero and one, and the choice probabilities for the available alternatives sum to one. Moreover, when the utility increase, $P_i$ approaches one with an S-shaped probability function (Figure 3.2): this means that the change in choice probability is not linear and depends on the level of utility. In other words, if the deterministic utility of an alternative is quite high (low), a small change in utility will not affect the probability of being chosen, which approaches one (zero). On the contrary, when the choice probability is around 0.5 the same change in utility will change the probability to a higher extent, since the curve is steeper around this level.

Figure 3.2. Logit curve




The logit probability in (3.7) can be written explicitly, assuming a linear specification for the parameters entering the utility function, as in (3.3):

$$P_i = \frac{e^{\beta x_i}}{\sum_j e^{\beta x_j}} \tag{3.10}$$

with $\beta$ being the vector of parameters, and $x_i$ and $x_j$ the vectors of observed attribute levels for the alternatives. Likewise, the logit model for the regret function can be written explicitly as:

$$P_i = \frac{\exp(-\sum_{k \neq i} \sum_m ln(1 + \exp[\beta_m(x_{km} - x_{im})]))}{\sum_j \exp(-\sum_{k \neq j} \sum_m ln(1 + \exp[\beta_m(x_{km} - x_{jm})]))} \tag{3.11}$$

with $\beta_m$ being the parameters for the $m$ attributes, and $x_i$, $x_k$ and $x_j$ the vectors of observed attribute levels for the alternatives.

Concerning the estimation procedure, both RUM-based[6] and RRM-based MNL models can be estimated by means of Maximum Likelihood procedure. This is an iterative optimization process that estimates the parameters that maximize the likelihood of the data given the choice model.

After estimating a model, the fit of such model to the data can be evaluated using

6 From here on for simplicity the linear-in-parameter specification of the RUM is called RUM.

different measures. In particular, the (log)likelihood value is generally used as a measure of the goodness of fit of the model through the so-called *likelihood ratio index*. This index compares the performance of the estimated parameters with a model in which all the parameters are fixed at zero (which represents the worst case, i.e. having no model at all) (Train, 2009). The likelihood ratio index is defined as:

$$\rho^2 = 1 - \frac{\ln \mathcal{L}(\hat{\beta})}{\ln \mathcal{L}(\beta_0)}$$

where $\ln \mathcal{L}(\hat{\beta})$ is the value of the log likelihood function at the estimated parameters and $\ln \mathcal{L}(\beta_0)$ is the log likelihood function of a model with all the parameters set equal to zero. The index $\rho^2$ varies between 0 and 1: in the worst case $\rho^2$ equals zero and it means that the estimated parameters have the same fit of zero parameters (i.e. the estimated model is no better than no model); in the best case, the estimated parameters fit perfectly to the data and thus the likelihood function is one, and the log likelihood function is zero, which means $\rho^2$ equals one.

The likelihood ratio index has no interpretable meaning (Train, 2009, pag. 79). In comparing two models estimated on the same data one can only say it is preferable to have higher values for $\rho^2$, since it means that the parameters fits the data better. Nested models can be tested against one another using the *likelihood ratio test*. The likelihood ratio test compares the performance of two models according to a null hypothesis on the estimated parameters; the typical null hypothesis assumes some parameters to be equal to zero, i.e. one model can be seen as a reduced form of the other. The Likelihood Ratio is defined as $LR = \mathcal{L}(\hat{\beta_H})/\mathcal{L}(\hat{\beta})$ where $\mathcal{L}(\hat{\beta_H})$ is the maximum value of the likelihood function under the null hypothesis and $\mathcal{L}(\hat{\beta})$ is the unconstrained maximum of the likelihood function.

The likelihood ratio test statistic is defined as $-2ln(LR)$ or $-2[\ln \mathcal{L}(\hat{\beta_H}) - \ln \mathcal{L}(\hat{\beta})]$. The statistic is distributed chi-squared with degrees of freedom equal to the number of restrictions implied by the null hypothesis.

However, two models estimated using different specifications – and thus non-nested – cannot be compared via likelihood ratio test. For the comparison in fit of non-nested logit models, a different test can be used, namely the Ben-Akiva and Swait (BAS) test (Ben-Akiva and Swait, 1986). The BAS test considers the null hypothesis that the model with the lower likelihood is the "true" one. A significant difference in fit between the model with the higher likelihood and the model with the lower likelihood leads to the rejection of this null hypothesis. In other words, the test generates an upper limit for the probability that the model with the lower (log-)likelihood actually provides the best representation of the data-generating process. This upper bound can therefore be considered as a "conservative proxy" for the significance (i.e. p-value) of a difference in model fit between two non-nested models.

The BAS test is based on the likelihood ratio index, corrected for the number of parameters, $K$:

$$\overline{\rho}^2 = 1 - \frac{\ln \mathcal{L}(\hat{\beta}) - K}{\ln \mathcal{L}(\beta_0)}$$

The BAS test specifies an upper limit for the probability. Consider $f$ and $g$ as two non-nested models, with $K_f$ and $K_g$ parameters, respectively. Then, it holds:

$$Pr[\overline{\rho}_A^2(g) - \overline{\rho}_A^2(f) \geq z] \leq \phi[-(-2z \ln \mathcal{L}(\beta_0) + (K_g - K_f))^{\frac{1}{2}}] \tag{3.12}$$

If $z$ is taken equal to the difference between the two likelihood ratio indexes, then the value on the right hand side represents the asymptotic upper bound for the probability of rejecting the null hypothesis, i.e. the p-value for the null hypotesis that the model with the lower fitness measure is the true one. If the null hypothesis is rejected, the model with the higher fitness measure is the true one at a certain level of confidence.

For testing hypotheses about single parameters in discrete choice models, standard t-statistics can be used. For hypotheses involving more than one parameter simultaneously, a likelihood ratio test can be used. The likelihood function value is also used for the calculation of the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). These indexes provide a measure of the relative quality of models estimated on the same data: they estimate the amount of information lost by a given model, introducing a penalty term to correct for the number of parameters in the model; the penalty term is larger in BIC than in AIC. The indexes are calculated as follows:

$$AIC = 2K - 2 \ln \mathcal{L}(\hat{\beta})$$

$$BIC = \ln(n)K - 2 \ln \mathcal{L}(\hat{\beta})$$

where $K$ is the number of parameters, $n$ is the number of observations and $\ln \mathcal{L}(\hat{\beta})$ is the log likelihood of the estimated model.

## Including systematic taste variation

People have different tastes. In choice processes, the value that people place on different aspects or attributes (captured by the $\beta$s) of the alternatives may differ. Different tastes can be related to socio-demographic factors like gender, age and income, and to psychological variables and lifestyles. Variations that are related to, and can be explained by these factors are called *systematic taste variations*.
The MNL model can be extended in order to account for systematic taste variations, both in the RUM and in the RRM specifications. These variations are included in the formula as interaction terms (Train, 2009). For example, consider the case in which researchers want to see if males and females place different importance to the price for a given product. The coefficient for price can be expressed as a combination of a generic coefficient plus an interaction term, such as:

$$\beta_{price*} = \beta_{price} + \beta_{int}\, D_{female} \tag{3.13}$$

where $D_{female}$ is a dummy variable equal to one when the respondent is female and zero otherwise. If $\beta_{int}$ is significant, it means that males and females attach different value to the price. In particular, the average utility of price for males equals $\beta_{price} * price$ and for females is $(\beta_{price} + \beta_{int}) * price$.
The same result can be reached segmenting the population and estimating models on subsamples, e.g. estimating the model on females and on males separately and testing whether the estimated $\beta$s are significantly different.
Other types of systematic taste variation can be included in the same way – via the addition of interaction terms in the model specification – for continuous variables (such as age, income, etc.). In this case, the dummy variable in (3.13) is replaced by the specific value (e.g. the age), and the $\beta_{int}$ represents the additional utility attached to the price provided by being one year older. At the same time, cutoff values may be used to group similar people, e.g. age classes, and the associated dummy included in the model.
However, it is unlikely to be able to describe the heterogeneity in population entirely via interaction terms, and more sophisticated models exist to model taste variations

that cannot directly be ascribed to observed characteristics.

### 3.2.2 Mixed Logit model

People's choices can differ based on common traits like age or gender; when tastes vary systematically in the population in relation to observed variables, the variation can be incorporated into MNL models through interaction terms (see Section 3.2.1) (Train, 2009). However, sometimes the value attached to attributes can be different based on unobserved or unobservable characteristics of people or choice situations, i.e. there is *random taste variation*.

Random taste variation cannot be captured by MNL models. This is because in MNL models $\beta$ coefficients are fixed among people, representing the average taste. This average values tell nothing about how much the coefficients vary among people, and the same value of $\beta$ can come from very different distributions. Information on the distribution of tastes can be important in many situations, for instance when a researcher is interested to uncover the tastes of a minority of people, e.g. a niche market for a new product. To incorporate random taste variation in discrete choice models, a Mixed Multinomial Logit model can be used (Train, 2009).

The Mixed Multinomial Logit (MMNL) model, also called Random Parameter Logit (RPL) model, is a flexible logit model which allows for random taste variation. In mixed logit models, $\beta$s vary across decision makers, with a pre-specified density $f(\beta)$. Therefore, the mixed logit probability is obtained as the integral of the logit probability in Equation 3.10 for RUM models and Equation 3.11 for RRM models, over a density of parameters. Considering the RUM model[7], the choice probability for the alternative $i$ by the decision-maker $n$ is:

$$P_{ni} = \int \frac{e^{\beta_n x_{ni}}}{\sum_j e^{\beta_n x_{nj}}} f(\beta)\, d\beta \tag{3.14}$$

where $\beta_n$ is an $M$-dimensioned vector of estimated coefficients, specific for the individual $n$, $\forall n = 1, \ldots, N$.

Equation 3.14 represents a weighted average of the logit equation evaluated at different values of $\beta$, with weights given by $f(\beta)$ – the latter is called *mixing distribution*

7 The same formulation of choice probabilities can be obtained for the RRM model, using the specification in (3.11).

(Train, 2009).
The mixing distribution can be discrete or continuous[8], MMNL models are also called continuous mixture models and assume continuous parametric densities for the $\beta_n$; whereas discrete random taste variation is implied by finite mixture models or the Latent class model (presented in Section 3.2.3).
In MMNL models, $\beta$s are given a distribution $f(\beta)$, which is defined by a group of parameters, typically its mean $b$ and covariance $W$. Accordingly, two sets of parameters enter the formulation of mixed logit models, the taste parameters $\beta_n$ for each individual and the parameters describing $f(\beta)$. Normal, lognormal, triangular, gamma mixing distributions for the parameters $\beta$ are among the most used. The researcher chooses the distribution that most adequately describes the real distribution among population. Hence, the choice of the mixing distribution must follow assumptions based on previous evidence or hypothesis, and in any case it will be an approximation of the actual randomness in population.
MMNL can be used without a random tastes interpretation (i.e. with $\beta$s that vary across respondents), but representing error components that create correlations among the utilities for different alternatives (i.e. with $\beta$s that vary across alternatives) (see Train, 2009, pag. 158). By allowing the taste parameter to vary across choice sets, the MMNL model relaxes the IIA property[9]. This contribute to the added flexibility of this model if compared to the MNL model.

### 3.2.3 Latent class model

The Mixed Logit model described in Section 3.2.2 is specified with continuous mixing distributions for the $\beta$s, following the hypothesis that each respondent can have different taste parameters. Nonetheless, discrete mixing distributions can be specified, where $\beta$s can take a finite set of values. In the latter case, the underlying hypothesis is that homogeneous-in-tastes segments exist within the population.
However, one must always remember that market segments represent sub-groups "artificially" created by researchers and exploited by companies as targets for their

8 The standard logit formulation is a special case with $f(\beta) = 1$ for $\beta = b$ and $f(\beta) = 0$ for $\beta \neq b$

9 Other logit formulations exist that accommodate for the violation of the IIA hypothesis in a RUM framework; for instance the Nested logit model, which captures the correlation between alternatives and group similar alternatives into a nest. In this case the IIA holds whithin each nest, but it does not hold for alternatives in different nests (Train, 2009).

strategies (Wedel and Kamakura, 2000, 2002). Segmentation has a practical relevance as it allows to meet specific consumer needs, increasing profit for the firm. Thus, models that approximate market heterogeneity are appealing by many actors in the marketing field, despite the fact that segments are not real entities in the market (Wedel and Kamakura, 2000, 2002).
In the so-called Latent Class (LC) model, discrete distributions are used to define the underlying latent structure of preference (Hensher et al., 2015). The discrete mixing distribution upon which the LC model is built can be seen as an approximation of the underlying continuous distribution specified in the MMNL model, which in turn is an approximation of the real heterogeneity among individuals.
In estimating the LC model, the distribution of the coefficients in the population does not have to meet any specific assumption (Hensher et al., 2015); only the number of classes has to be pre-specified. The researcher does not know a priori which respondent belong to a class, i.e. classes are *latent*, and a probability of class membership is estimated instead.

In LC models, the $\beta$s assume different values, one for each class or segment. If $Q$ classes (i.e. groups of individuals) are specified, $\beta$ can take $Q$ distinct values $\beta_1, \beta_2 \ldots \beta_Q$. In the standard version of the LC model parameters are fixed whithin classes but vary between classes[10]. The specification of the LC model within each class follows the MNL logit probability for the individual choice. The probability for the individual $n$ of choosing the alternative $i$ among $J$ available alternatives given the membership to a class $q$ resembles the MNL probability in Equation 3.10:

$$P_{ni|q} = \frac{e^{\beta_q x_{ni}}}{\sum_j e^{\beta_q x_{nj}}} \tag{3.15}$$

However, $q$ is unknown. The (3.15) can be re-written as the sum of the probabilities that the decision maker $n$ belongs to class $q$, called *prior probabilities*, multiplied by the probabilities that $i$ is chosen given the class $q$:

$$P_{ni} = \sum_{q=1}^{Q} H_{nq} \, P_{ni|q} \tag{3.16}$$

10 It is also possible to specify random parameters instead of fixed parameters within each class through more advanced LC models.

The prior probability $H_{nq}$ is unknown and is typically obtained through a class membership model, specified as a logit model, which is a function of the explanatory variables $z_n$ (e.g. socio-demographic characteristics), where $\theta_q$ denotes a vector of class-membership parameters that need to be estimated:

$$H_{nq} = \frac{e^{z_n' \theta_q}}{\sum_q e^{z_n' \theta_q}} \tag{3.17}$$

It is not strictly necessary to include covariates into the class membership model, it is also possible to have constant prior probabilities, which sum to one, where $z_n$ is a vector full of constant terms 1.

Estimates of the parameters of the model, $\beta_q$, and the parameters of the submodel, $\theta_q$, are obtained via maximum likelihood. Once estimates of the parameters are obtained, the *posterior probability* that consumer *n* belongs to latent class *q* can be calculated as:

$$\hat{H}_{q|in} = \frac{\hat{H}_{nq}\, \hat{P}_{ni|q}}{\sum_{q=1}^{Q} \hat{H}_{nq}\, \hat{P}_{ni|q}} \tag{3.18}$$

Hence, the latent classes are conceived as groups of people with similar tastes. But this is not the only possible interpretation. In fact, the heterogeneity among people can be related not only to different importance attached to attributes, but also to actual differences in the choice process by individual respondents (Hess et al., 2012). To account for different behavioural processes as latent classes, classes can be defined that correspond to different decision rules. Here, each class might refer to a probabilistic decision rule (e.g. regret minimization or utility maximization), or even a deterministic one. For instance, coefficients could be fixed to zero in a random-responder class.

In the present study, a discrete choice experiment has been carried out on a food choice, with particular interest put on the underlying behavioural process. Several models have been estimated and compared in their RUM and RRM formulations, including multinomial logit, mixed logit and latent class models.

The next section presents an overview of applications of DCEs carried out in the food literature, and the main topics covered.

## 3.3 An overview of Discrete Choice Experiments in the food literature

DCEs are extensively used in the food choice literature. More than four hundred DCE applications on food choice can be found in peer-reviewed journals. More specifically, searching for the keywords "choice experiment" and "consumer" and "food", 428 scientific articles can be found. Figure 3.3 displays the categories in which choice experiments are applied: Economics, Food Science Technology and Agricultural and Economics Policy are the main primary fields of applications of DCEs in the food consumption domain.

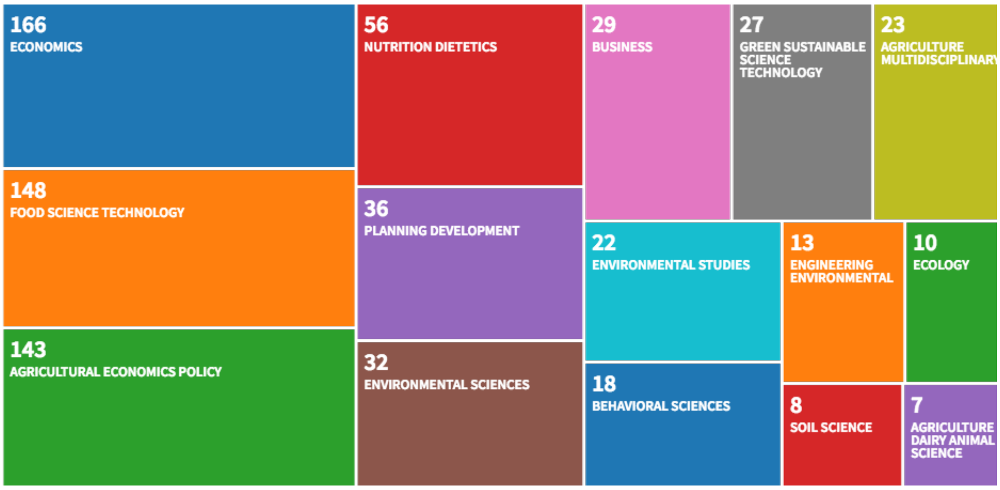



Figure 3.3. Scientific categories of DCE applications in food.

It is interesting also to look at the distribution per year-of-publication of articles using DCEs on food consumers (Figure 3.4). The interest in this type of methodology for studying consumer food choice has grown constantly in the past fifteen years, with more than sixty publications published per year since 2016.

DCEs allow to analyze the trade-offs consumers make between attributes of a product, resulting in the estimation of the value attached to each attribute. Moreover, through DCEs is possible to estimate the willingness to pay for an attribute, even for attributes that are not yet implemented such as new labels or certifications.

Existing studies mainly focus on the value attached to:

- *Nutritional composition* (e.g., Koistinen et al., 2013; Jurado and Gracia, 2017; Balcombe et al., 2010; Barreiro-Hurle et al., 2010)

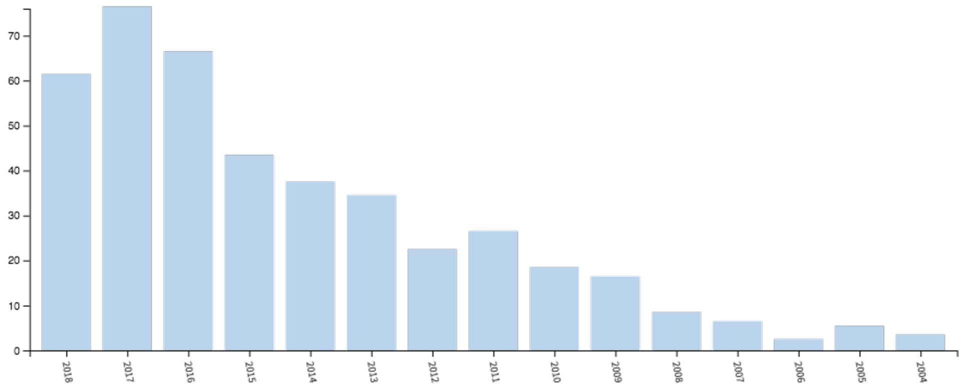



Figure 3.4. Publication year distribution of DCE applications in food.

- *Organic production* (e.g., Kim et al., 2018; Janssen and Hamm, 2012; Hasselbach and Roosen, 2015)
- *Local production* (e.g., Gracia et al., 2014; Hempel and Hamm, 2016; Holmes and Yan, 2012; Mugera et al., 2017)
- *Sustainability* (e.g., Emberger-Klein and Menrad, 2018; Grebitus et al., 2015; Aizaki et al., 2013; Sporleder et al., 2014; Grebitus et al., 2016)
- *Genetic-modification technology* (e.g., Yue et al., 2015; Edenbrandt et al., 2018; Ison and Kontoleon, 2014)
- *Food safety* (e.g., Marra et al., 2017; Raun Mørkbak et al., 2010; Owusu-Sekyere et al., 2014; Grunert et al., 2018)
- *Traceability* (e.g., Yin et al., 2017; Wu et al., 2017; Kehagia et al., 2017; Ubilava and Foster, 2009)
- *Country of origin* (e.g., Balcombe et al., 2016; Pouta et al., 2010; Bienenfeld et al., 2016)
- *Fortified/enriched food* (e.g., Pambo et al., 2017; Chowdhury et al., 2011; Moro et al., 2015; Baba et al., 2016)

These are usually evaluated in combination with one another. In each experiment, the evaluation of these aspect is specific for one food product. In the literature on DCEs, products more used in the experiments are: meat products, fruit (apple, bananas), yogurt, snacks, milk, bread, seafood, tomatoes, olive oil, and cheese.

All the published studies adopt DCMs based on the Utility theory. However, some studies deviate from the traditional framework of maximization of utility to explore more simple heuristics. For instance, Aizaki et al. (2012) used a discrete choice model developed by Swait (2001) to accommodate for a non-compensatory valuation, with regard to food safety attributes in beef products. Also, Caputo et al. (2018b) explored attribute non-attendance (i.e. respondents ignoring one or more attributes when deciding across DCE attributes) in a DCE on poultry meat with sustainability labels. The same author explored price reference-dependence in DCEs, finding that reference-dependent models are better in describing the choice data, and that the price evaluation is consistent with Prospect theory (Caputo et al., 2018a).
Discrete choice experimentation is evolving, especially concerning DCE's hypothetical nature. Some applications in the literature use the so-called real or non-hypothetical choice experiment to analyze the choice of food, which aims to reduce the hypothetical bias that derives from choosing in a non-real setting. Real choice experiments introduce an economic incentive for the participation of respondents, which they have to spend buying the alternative they choose, at the price indicated in the choice task[11] (see Gracia et al., 2014; Olesen et al., 2010; Wu et al., 2015).
Furthermore, DCEs are starting to be used in combination with other methodologies, in particular eye-tracking and scanner data. By registering participants' eye path is possible to re-construct the flow of choice process, detecting which information has been taken into account, and how thoroughly (see Balcombe et al., 2017; Bialkova et al., 2014). The joint use of DCE and scanner data allows to determine consumer preferences for specific attributes of a product, as well as to determine whether stated choices are consistent with revealed choices given by scanner data (Brooks and Lusk, 2010).

The aim of this section was to breafly present and describe how DCEs are applied in the literature on consumer food choice, providing some references that stand out for methodological advancements. Indeed, the great number of applications of DCEs that can be found in the literature make it rather complicated to provide a

11 In other words, one of the choice tasks in the experiment is binding, and participants are required to actually buy the product they choose, paying the corresponding price for the product in this scenario.

detailed overview of all the studies, which, in any case, is out of the scope of the present study.

The next chapter provides an overview of the performances of the RUM and RRM formulations for discrete choice models, taking into account comparisons carried out in the literature so far.

# Chapter 4

# RRM and RUM models comparisons: a review of empirical results

Since its conception in 2010, the performance of the RRM model has been mainly tested in the transportation field, most frequently with route choices for car drivers, car type choice and travel mode choice. Studies compare the performance of the RRM model with its RUM-based counterpart. The overview of empirical comparisons between the RRM and RUM based logit models by Chorus et al. (2014) provides a summary of results based on goodness of fit and prediction of the two models. No clear evidence on the superiority of either one of them emerges, as performances seem to be linked to the choice context and statistically significant differences (if any) are always rather small.

In their overview, Chorus et al. summarize which model has the best fit and gives the best prediction in the considered studies; they classify the studies based on the choice context and provide information about which type of model is estimated (whether MNL or Mixed MNL) and whether the data collection is based on revealed or stated choices. However, nothing is said about the experimental setting of the experiments, which is likely to affect the validity of results. More importantly, the overview does not provide the models' $\rho$-squared values nor predictions' hit rates, it only reports which model is superior, if any. Therefore, the reader is not able to fully understand the magnitude of the reported results.

Based on these premises, a review of previous comparisons between RRM and RUM logit models has been carried out in order to critically evaluate existing experiments.

The tables included in this section contain information for the retrieved studies[1] and reports the $\rho$-squared values[2] for the estimated models. In the following tables, each row refers to an empirical comparison of RRM and RUM models, whereas the columns include several charachteristics of the studies. *ID* refers to the ID used in Chorus et al. (2014) paper and *Paper ref.* is the reference of the paper in which the study is reported. Then, information about the settings of the DCEs is outlined: *SS* is the Sample Size in the DCE; *Exp. Design* is the experimental design used to build the DCE; *CT* indicate the number of Choice Tasks that each respondent faced; *N alt* represents the number of alternatives shown in each choice set; *No choice option* displays the type of questions in the DCE, whether respondents were forced to make a choice in each choice task or they were given possibility to not choose; *Attributes; Levels* displays the number of attributes and levels used in the DCE and *Attributes* provide a description of the attributes. Lastly, information about which models have been estimated, the *Number of parameters* and the *$\rho$-squared* values of RUM and RRM models are displayed, together with additional information on specific issues examined in the reviewed studies.

Concerning the choice contexts in which the RRM model has been applied, a vast number of studies are found in contexts of route choice for car drivers, travel mode choice and car type choice. With reference to the analysis of route choice for car drivers, ten experiments have been carried out in the literature. Comparisons' results are reported in Table 4.1. In these studies, the choice of the best route is mainly based on attributes concerning time and money spent (i.e. total travel time, travel time spent in traffic jams, travel-time variability, running costs, and toll costs); either four or five attributes are used in the experiments, which are mainly treated as continuous. Eight out of ten studies are based on forced choices with status quo option; these DCEs required individuals to make sixteen repeated choices, which could result in biased results due to fatigue of respondents. However, studies on respondents' fatigue in choice experiments have given conflicting results, either finding decreasing attention after six, nine or ten choice tasks (Caussade et al., 2005; Raffaelli et al., 2009; Hu et al., 2006). All the experiments estimate a MNL-model.

1 Only studies based on stated preferences have been considered (40 studies). Plus, five new studies published after Chorus et al. (2014) have been taken into account.

2 Only the $\rho$-squared values concerning the fit of the models have been reported, no information about the prediction is provided since the scarce evidence existing (in Chorus et al.'s table, only seven out of fortythree studies reported a measure of prediction ability).

| ID | Paper ref. | SS | Exp. Design | CT | N alt | No choice option | Attributes; Levels | Attributes | Model estimated | Number of parameters | ρ-square | Additional info |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 9 | Chorus (2012a) | Two samples of 167 and 196 respondents | Optimal orthogonal in the differences | 9 | 3 | Forced choice | 4; 3 levels each (all treated as continuous) | average door-to-door travel time, percentage of travel time spent in traffic jams, traffic fatalities per year on that route, total costs | MNL-model | 4 | (a) RRM 0.34; RUM 0.34. (b) RRM 0.34; RUM 0.34 | For each choice set asked the desirability-rate (a); for each choice set asked the satisfaction-rate (b). RUM and RRM estimated separately on the two sub-groups (a, b) |
| 13 | (Chorus et al., 2013b) | 300 | na | 16 | 3 | Forced choice with status quo option | 5 (all treated as continuous) | free-flow travel time, slowed-down travel time, travel-time variability, running costs, toll costs | MNL-model | 5 + ASC =6 | RRM 0.229; RUM 0.237 | Hybrid model that allows for different attributes to be processed using different rules was estimated |
| 14* | (Chorus and Bierlaire, 2013) | 390 | Optimal orthogonal in the differences | 9 | 3 | Forced choice | 4; 3 levels each (all treated as continuous) | average door-to-door travel time, percentage of travel time spent in traffic jams, traffic fatalities per year on that route, total costs | MNL-model | 4 | RRM 0.323; RUM 0.321 | Compromise variable added in the RUM model |
| 30-36 (Study 1) | (Leong and Hensher, 2015) | 280 | D-efficient | 16 | 3** | Forced choice with status quo option | 5; (levels na) | free flow time, slowed down time, stop/start/crawling time, running cost, toll cost | MNL-model | na | na | Relative Advantage Maximisation (RAM) model was also estimated |
| 30-36 (Study 2) | (Leong and Hensher, 2015) | na | D-efficient | 16 | 3** | Forced choice with status quo option | 4; (levels na) | free flow time, congested time, running cost, toll cost | MNL-model | na | na | Relative Advantage Maximisation (RAM) model was also estimated |
| 30-36 (Study 3) | (Leong and Hensher, 2015) | na | D-efficient | 16 | 3** | Forced choice with status quo option | 4; (levels na) | free flow time, slowed down time, stop/start/crawling time, running cost, toll cost | MNL-model | na | na | Relative Advantage Maximisation (RAM) model was also estimated |
| 30-36 (Study 4) | (Leong and Hensher, 2015) | na | D-efficient | 16 | 3** | Forced choice with status quo option | 4; (levels na) | free flow time, slowed down time, stop/start/crawling time, running cost, toll cost | MNL-model | na | na | Relative Advantage Maximisation (RAM) model was also estimated |
| 30-36 (Study 5-7) | (Leong and Hensher, 2015) | 57 in Study 5; na studies 6 and 7 | D-efficient | 16 | 3** | Forced choice with status quo option | 4; (levels na) | free flow time, congested time, running cost, toll cost | MNL-model | na | na | Relative Advantage Maximisation (RAM) model was also estimated |

* Same panel used in Study 9 but different respondents were selected.

** Alternatives in the choice set are made of a recent trip (info asked to the respondent), and unlabelled alternatives defined by attribute levels pivoted off of the recent trip profile.

Table 4.1. RUM/RRM comparisons on route choice for car drivers

Sample size ranges between 57 and 390, although in half of the studies the number of respondents is not explicitly indicated, which represents an important information gap. But an even greater gap is represented by the missing $\rho$-squared values in all the studies by Leong and Hensher (2015), which makes impossible for the reader to appropriately interprete the results. For the studies that provide the information about the $\rho$-squared values, the fit of the models lie between 0.24 and 0.34. Moreover, despite the statistically significant difference in fit indicated in Chorus et al. (2014), it is clear that RUM and RRM model have a quite similar goodness of fit to the data, their difference only showing in the third digit behind the decimal point.

For what concerns applications on travel mode choice (Table 4.2), nine experiments have been found. The choice of the transport is usually linked to travel time, punctuality of the transport, travel costs, waiting time and seat availability. The number of attributes considered in each DCE varies between three and eight, this also gives rise to estimated models which differ in terms of the number of estimated parameters. Both MNL and Mixed logit models are estimated, the latter also with two different types of distribution for the errors (normal and triangular). The $\rho$-squared values of RRM and RUM models vary betweeen 0.144 and 0.539, the lower ones being associated with MNL models. Therefore, in this context the estimation of a Mixed logit model greatly increases the fit to the data, which means that there is random heterogeneity in the data that the MNL model cannot capture. Again, the difference in fit between RRM and RUM models barely reaches one percentage point, the RRM model having the best fit most of the times.
Note that the DCE from Boeri and Masiero (2014) was carried out on only 27 respondents; this is due to the particular context involved in the study: respondents were not consumers but logistic managers of manufactoring firms located in a small area of Northern Italy, and they had to choose among alternatives of freight transport modes. This also explains the obtained $\rho$-squares above 0.5, which might be due to the homogeneity across respondents.

Six studies can be found that explore the choice of a car (Table 4.3). Vehicles are typically described based on purchase price, country of manufacture, fuel price and efficiency, seating capacity, emissions charge, engine size. For the special case of the choice of an alternative fuel vehicle, also monthly contribution, tax percentage charge, recharge/refueling time, number of available brands/models and policy measure have been considered. In these studies, the $\rho$-squared values are always

| ID | Paper ref. | SS | Exp. Design | CT | N alt | No choice option | Attributes; Levels | Attributes | Model estimated | Number of parameters | ρ-square | Additional info |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 37 (Study 8) | (Leong and Hensher, 2015) | 269 | Bayesian D-efficient | 6 | 5 labelled | Forced choice | na | Access and egress modes, one-way cost, and attributes that attempt to capture travel time variability | MNL-model | na | na | Relative Advantage Maximisation (RAM) model was also estimated |
| 1 | (Chorus, 2010) | 280 | na (simulator) | na | na (simulator) | Forced choice | 8 (7 cont., 1 dummy) | Travel time, travel time uncertainty, travel costs, travel costs uncertainty, waiting time, waiting time uncertainty, seat availability, seat availability uncertainty | MNL-model | 8+ ASC =9 | RRM 0.433; RUM 0.440 | |
| 24,26,27 | (Boeri and Masiero, 2014) | 27 | na | 15 | 3 labelled | Forced choice with status quo option | 3; two with 5 levels and one with 3 levels (all treated as continuous) | Transport time, transport cost, punctuality of the transport | MNL-model; Mixed MNL1; Mixed MNL2** | 3+2 ASC=5 | MNL-RRM 0.147; MNL-RUM 0.144; MXMNL-RRM1 0.531; MXMNL-RUM1 0.526; MXMNL-RRM2 0.538; MXMNL-RUM2 0.539 | |
| 25,28,29 | (Boeri and Masiero, 2014) | 27 | na | 15 | 3 labelled | Forced choice with status quo option | 3; two with 5 levels and one with 3 levels (all treated as continuous) | Transport time, transport cost, punctuality of the transport | MNL-model; Mixed MNL1; Mixed MNL2** | 3+3 ASC=6 | MNL-RRM 0.208; MNL-RUM 0.200; MXMNL-RRM1 0.467; MXMNL-RUM1 0.461; MXMNL-RRM2 0.469; MXMNL-RUM2 0.458 | |
| 42 | (Hess and Stathopoulos, 2013) | 368 | D-efficient | 10 (6 blocks) | 3 labelled* | Forced choice with status quo option | 6; (all treated as continuous) | Travel time, travel cost, rate of crowded trips, rate of delays, average length of delays, provision of a delay information service with different pricing | MNL-model | 6+ASC=7 | na | Mixed RU-RR structure, where the allocation to a given class is driven in part by a latent variable which at the same time explains respondents' stated satisfaction with their real world commute journey |

* Alternatives in the cs are made of a recent trip (info asked to the respondent), and unlabelled alternatives defined by attribute levels pivoted off of the recent trip profile.
**Mixed MNL1= errors normal distributed; Mixed MNL2 errors triangular distributed

Table 4.2. RUM/RRM comparisons on travel mode choice

| ID | Paper ref. | SS | Exp. Design | CT | N alt | No choice option | Attributes; Levels | Attributes | Model estimated | Number of parameters | ρ-square | Additional info |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 12 | (Chorus et al., 2013a) | 616 | Efficient | 8 | 3 | Forced choice | 9; attrxlevels: 3x3,4x4,1x5, 1x6 (car type dummy coded with 5 dummies) | Car type (i.e., type of Alternative fuel vehicle), purchase or catalogue price, monthly contribution, tax percentage charge, driving range, recharge/refueling time, additional detour time for refueling, number of available brands/models, policy measure | MNL-model | 14 | RRM 0.225; RUM 0.225 | |
| 16 | (Beck et al., 2013) | 131 (individual choices) | D-efficient | 8 | 3 labelled | Forced choice | 9; attrxlevels: 3x3, 5x5, 1x6 | Purchase price, Country of manufacture, Fuel price, Seating capacity, Registration, Annual emissions charge, Variable emissions charge, Engine size, Fuel efficiency | MNL-model | 10 + 3 interactions | RRM 0.137; RUM 0.137 | Compares choices of groups and individuals, exploring the influence household members have within an interactive agency choice experiment. |
| 17 | (Beck et al., 2013) | 235 (primary respondents) | D-efficient | 4 | 3 labelled | Forced choice | 9; attrxlevels: 3x3, 5x5, 1x7 | Purchase price, Country of manufacture, Fuel price, Seating capacity, Registration, Annual emissions charge, Variable emissions charge, Engine size, Fuel efficiency | MNL-model | 7 + 2 interactions | RRM 0.108; RUM 0.105 | Compares choices of groups and individuals, exploring the influence household members have within an interactive agency choice experiment. |
| 18 | (Beck et al., 2013) | 235 (Secondary respondents) | D-efficient | 4 | 3 labelled | Forced choice | 9; attrxlevels: 3x3, 5x5, 1x8 | Purchase price, Country of manufacture, Fuel price, Seating capacity, Registration, Annual emissions charge, Variable emissions charge, Engine size, Fuel efficiency | MNL-model | 8 | RRM 0.093; RUM 0.093 | Compares choices of groups and individuals, exploring the influence household members have within an interactive agency choice experiment. |
| 19 | (Beck et al., 2013) | 235 (group choices) | D-efficient | 4 | 3 labelled | Forced choice | 9; attrxlevels: 3x3, 5x5, 1x9 | Purchase price, Country of manufacture, Fuel price, Seating capacity, Registration, Annual emissions charge, Variable emissions charge, Engine size, Fuel efficiency | MNL-model | 10 + 1 interaction | RRM 0.145; RUM 0.143 | Compares choices of groups and individuals, exploring the influence household members have within an interactive agency choice experiment. |
| 22* | (Hensher et al., 2013) | na | D-efficient | 4 | 3 labelled | Forced choice | 9; attrxlevels: 3x3, 5x5, 1x10 | Purchase price, Country of manufacture, Fuel price, Seating capacity, Registration, Annual emissions charge, Variable emissions charge, Engine size, Fuel efficiency | MNL-model | 9 + 7 interactions | RRM 0.109; RUM 0.108 | |

* pooled dataset of 17 and 18

Table 4.3. RUM/RRM comparisons on car type choice

quite low, between 0.093 and 0.225, meaning that there is high variability which is not captured by the attributes used in the DCE and /or by the MNL model formulation of the models used. According to the results reported in Chorus et al. (2014), the RRM model obtains a significant better fit to the data in half of the cases, whereas in the other half the two models are tie in fit. Despite the significance of results, looking at absolute values of $\rho$-squared it is clear that the difference is always rather small.

According to Chorus et al. (2014), the RRM model has a better fit when people have to make an explicit trade-off between time spent to commute and a gain in salary (see Table 4.4: experiment 40 implied a choice regarding own workplace and experiment 41 included also the same reasoning for the partner's workplace relocation).

Four studies by Hess et al. (2014) explore this issue: in these experiments the sample size is rather high, paired with a small number of choice tasks per respondent[3]. These settings are ideal for the success of the data collection, minimizing the biases that can occur.

However, Study 1 (both in experiments 40 and 41) estimated the RUM and RRM models only on the subset of data where one of the two alternatives was chosen by respondents, leaving out the observations in which people decided not to choose. Looking at Table 4.4, results of Studies 1 regarding the fit of RUM and RRM estimated models provide identical fit for the two models in both studies. This identical fit is due to the fact that the RRM model collapse into the RUM model when only two alternatives are available (see Chorus, 2010). In this study, although the inclusion of the no-choice alternative in the choice set theoretically renders the choice task a multinomial choice, the comparison results based on a subset of data which leaves out the no choice observations are likely to be biased.

Indeed, the comparison is more accurate with at least three non-no choice alternatives in the choice set (Chorus and Rose, 2011). Thus, we believe the results of this comparison are not meaningful. On the other hand, Study 2 provides sizeable differences in fit between the two models, the RRM model reaching a better fit. These results could be linked to the explicit trade-off requested and to the particular

3 The choice experiment was designed according to a full-profile design. This is possible because of the small number of attributes and levels considered, only two attributes (commuting time and monthly net wage) with two levels each are considered in Study 40; whereas in Study 41, four attributes with two levels each are considered and the resulting choice sets were divided into two blocks. For detailed information on the data see Swardh and Algers (2009).

| ID | Paper ref. | SS | Exp. Design | CT | N alt | No choice option | Attributes; Levels | Attributes | Model estimated | Number of parameters | ρ-square | Additional info |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 40 (Study1) | (Hess et al., 2014) | 2358 | na | 4 | 2* | "I am indifferent" opt out | 2; (all treated as continuous) | One-way commuting trip, net wage per month | MNL structure with added panel effect error components | 2+ error component=3 | adj. RRM 0.479; RUM 0.479 | models estimated only on the subset of choices actually made (I am indifferent left out) |
| 40 (Study2) | (Hess et al., 2014) | 2358 | na | 4 | 2+ indifferent | "I am indifferent" opt out | 2; (all treated as continuous) | One-way commuting trip, net wage per month | MNL structure with added panel effect error components | 2 + ASC + error component=4 | adj. RRM 0.481; RUM 0.362 | models estimated including I am indifferent options chosen |
| 41 (Study1) | (Hess et al., 2014) | 2358 | na | 4 | 2* | "I am indifferent" opt out | 4; (all treated as continuous) | One-way commuting trip, net wage per month, one-way commuting trip of the spouse, net wage per month of the spouse | MNL structure with added panel effect error components | 4+ error component=5 | adj. RRM 0.497; RUM 0.497 | models estimated only on the subset of choices actually made (I am indifferent left out) |
| 41 (Study2) | (Hess et al., 2014) | 2358 | na | 4 | 2+ indifferent | "I am indifferent" opt out | 4; (all treated as continuous) | One-way commuting trip, net wage per month, one-way commuting trip of the spouse, net wage per month of the spouse | MNL structure with added panel effect error components | 4 + ASC + error component=6 | adj. RRM 0.535; RUM 0.438 | models estimated including I am indifferent options chosen |

* with only two option in the choice set the two models collapse in the same formulation.

Table 4.4. RUM/RRM comparisons on salary and travel time trade-offs

choice context; the choice of a farther workplace but with an increased wage is likely to trigger regret due to the increased time spent, and vice versa saving time but receiving less money is also likely to trigger regret.
Other experiments refer to choices of travel information (Table 4.5). In this context RUM has a significant better fit (Chorus et al., 2014), but the differences are again small in size, except for Experiment 39. In the latter study, panel effect error components were included in the MNL model. In the other contexts, i.e. choice of traffic calming scheme, choice of departure times for car drivers and choice of road pricing-policy by politicians, the two models have almost equal goodness of fit to the data. In these studies, MNL models were estimated and their $\rho$-squared values range between 0.08 and 0.173, which indicates that both RUM and RRM models perform poorly on the data.

A different field of application is related to healthcare: choice of lifestyle to prevent coronary heart disease, choice of medical treatments and choice of type of vaccination have been analyzed in existing studies (Table 4.6). In these contexts, similarly to the other contexts discussed so far, no clear evidence emerges on which model could better fit the data. Other contexts in which the model has been applied are related to leisure time, i.e. choice of recreational activities and choice of online-dating profiles. In these two experiments, $\rho$-squared values are again rather low, between 0.081 and 0.14.
More recent studies involve choices of travel mode, health and lifestyle programmes to reduce obesity, route, renewable energy programmes and evacuation travel behaviour (Table 4.7). In particular, Wang et al. (2017) recent experiment can be seen as an exception among all the comparisons carried out in the literature, in which $\rho$-squared values are above 0.6 and the differences in model fit between RRM and RUM models are remarkable, indicating that decisions taken in an emergency state are well explained by travel time, travel time uncertainty, perceived road damage probability and perceived service level, and are likely to be guided by anticipation of regret.

Overall, differences in performance between RUM and RRM models appear to be context- and dataset- specific. Only Hess et al. (2014) and Wang et al. (2017) obtained sizeable different results in models fit. Going into detail in their experimental settings, it is tricky to find similar features that can be responsible for the stronger results. Moreover, we do not have information about differences in predictions, so

| Choice context | ID | Paper ref. | SS | Exp. Design | CT | N alt | No choice option | Attributes; Levels | Attributes | Model estimated | Number of parameters | ρ-square | Additional info |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Travel information acquisition choices | 2 | (Chorus, 2010) | 104 | na | 9 | 3+ no choice | "none of these" option | 4; 2 continuous, 2 dummy coded | Type of provided information, who takes the initiative to get information, unreliability price | MNL-model | 6 | RRM 0.259; RUM 0.262 | Models estimated only on the subset of choices actually made (none of these left out) |
| Travel information acquisition choices | 38* | (Hess et al., 2014) | 104 | na | 9 | 3+ no choice | "none of these" option | 4; 2 continuous, 2 dummy coded | Type of provided information, who takes the initiative to get information, unreliability price | MNL structure with panel effect error components | 6+ error component=7 | adj. RRM 0.265; RUM 0.267 | Models estimated only on the subset of choices actually made (none of these left out) |
| Travel information acquisition choices | 39* | (Hess et al., 2014) | 104 | na | 9 | 3+ no choice | "none of these" option | 4; 2 continuous, 2 dummy coded | Type of provided information, who takes the initiative to get information, unreliability price | MNL structure with panel effect error components | 6 + ASC + error component=7 | adj. RRM 0.205; RUM 0.253 | Models estimated including none of these options chosen |
| Choice of traffic calming schemes | 43 | (Boeri et al., 2014) | 407 | Randomized set of profiles from the full factorial design | 8 | 2+ status quo | Forced choice with status quo option | 5; 2 dummy coded and 3 continuous | Annual cost, speed, noise, beauty, waiting time for crossing the road | MNL-model | 5+ ASC=6 | RRM 0.113; RUM 0.112 | Latent class RU and RR models with and without taste heterogeneity are also estimated |
| Choice of departure times for car drivers | 5 | (Chorus and de Jong, 2011) | na | na | na | 2+ status quo | Forced choice with status quo option | 5; (all treated as continuous) | travel time, time spent in traffic jams for both the morning and the evening commute, resulting amount of time at work | MNL-model | 5+ ASC=6 | adj. RRM 0.173; RUM 0.172 | Respondent could choose to depart at or close to their regular hour, or considerably earlier or later (and face reduced travel times) |
| Choice of road pricing policy-options by politicians | 6 | (Chorus et al., 2011) | 51 | na | 5 | 3 | Forced choice | 5; 5 levels each (all treated as continuous) | Operational costs, congestion reduction, emission reduction, acceptability among inhabitants and acceptability among retailers | MNL-model | 5 | RRM 0.09; RUM 0.08 | |

* same dataset as in 2

Table 4.5. RUM/RRM comparisons on other contexts

| Choice context | ID | Paper ref. | SS | Exp. Design | CT | N alt | No choice option | Attributes; Levels | Attributes | Model estimated | Number of parameters | ρ-square | Additional info |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Lifestyle-choices to prevent coronary heart disease | 11 | (Boeri et al., 2013) | 493 | Bayesian efficient | 10 | 2+ status quo | Forced choice with status quo option | 4, attrxlevels: 3x5, 1x7 (all treated as continuous) | Diet, amount of physical activity, risk of a fatal heart attack in the next ten years, cost | MNL-model | 4 | na | Respondent's tailored DCE questions built using answers given by the respondent in the initial part of the questionnaire |
| Choice of preventive Osteoporosis Drug Treatment | 20 | (De Bekker-Grob and Chorus, 2013) | 120 | Fold-over fractional factorial, efficiency 95% | 16 | 2+ no choice | "no drug treatment" option | 5; attrxlevels: 4x4, 1x2 (3 continuous, 2 dummy coded) | Effectiveness, side effects, total treatment duration, route of drug administration, out-of-pocket costs | Panel mixed logit model error component | 7+ 1rnd parameter(ASC)=8 | adj. RRM 0.359; RUM 0.359; Hybrid RRM-RUM 0.358 | Hybrid RUM–RRM model was estimated |
| Choice of papillomavirus vaccination | 21 | (De Bekker-Grob and Chorus, 2013) | 312 | Near optimal fractional factorial, efficiency 79% | 9 (6 blocks) | 2+ no choice | "no vaccination" option | 5; 3 levels each (all treated as continuous) | Degree of protection against cervical cancer, protection duration, serious side effects, chance of mild side effects, age at vaccination | Panel mixed logit model error component | 5+ 1rnd parameter(ASC)=6 | adj. RRM 0.356; RUM 0.370; Hybrid RRM-RUM 0.370 | Hybrid RUM–RRM model was estimated |
| Choice of natural park services | 7 | (Thiene et al., 2012) | 480 | Efficient Bayesian | 12 | 2+ status quo | Forced choice with status quo option | 10, 3 levels each (8 continuous, 2 dummy coded) | Thematic itineraries, Network of trails , Trail signs, Managed trails excursions, Climbing routes, Via ferrata, Shelters, Congestion, Information, Entrance fee | MNL-model | 12 +ASC=13 | RRM 0.081; RUM 0.084 | |
| Choice of online date profile | 15 | (Chorus and Rose, 2011) | 661 | na (8 different experimental designs) | 9 | 3+ no choice | no choice option | 6, 3 levels each (all treated as continuous) | Drinking Habit, Smoking Habit , Children, Looks, Job, Cost to contact | MNL-model | 6+ASC=7 | RRM 0.14; RUM 0.13 | |

Table 4.6. RUM/RRM comparisons in other contexts (2)

| Choice context | ID | Paper ref. | SS | Exp. Design | CT | N alt | No choice option | Attributes; Levels | Attributes | Model estimated | Number of parameters | ρ-square | Additional info |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Travel mode choice | 101 | (Hensher et al., 2016) | 670 | Bayesian-efficient | 6 (40 blocks) | 3 (of 4 labelled alternatives) | Forced choice | 8, See Hensher et al. (2011) for a detailed description of the CE | In-vehicle travel time, travel cost, access, and egress times, frequency, crowding, getting a seat, number of transfers | both MNL and mixed-MNL (RPL) | 9+3 ASC=12; 12+6 SD=18 | RRM 0.444; RUM 0.444; Mixed-RRM=0.551;Mixed-RUM=0.549 | Preference heterogeneity is accounted for through random parameters |
| Health and lifestyle programmes to reduce obesity | 102 | (Ryan et al., 2017) | 58 | na | 10 | 2+ status quo | Forced choice with status quo option | 7, attrxlevels: 5x4 (continuous), 2x2 (dummy) | Comprehensiveness, Goal, Weight reduction, Reduction in risk of diabetes,Reduction in risk of high blood pressure, Time per day, Cost per week | MNL-model (RUM); MNL model with search measure index | 7; 11 | na | The CE was completed and eye movements were recorded to examine how transitions are linked to choices |
| Route choice | 103 | (Guevara and Fukushi, 2016) | 134 | na | 8 | 3 | Forced choice | 2; (all treated as continuous) | Travel time, travel cost | MNL-model | 2+2 ASC=4 | RRM 0.348; RUM 0.344 | Six models are compared. MNL-RUM, Emergent Value (EV) model,Weigh Change (WC), MNL-RRM, RBA, CCM |
| Evacuation route choice | 104 | (Wang et al., 2017) | 521 | Optimal orthogonal in the differences | 3 | 3 | Forced choice | 4; 3 levels each (all treated as continuous) | Average Travel Time, travel Time Uncertainty, perceived road damage probability, perceived service level | MNL-model | 4+ interactions=12 | RRM 0.787; RUM 0.643; Hybrid RRM-RUM 0.794 | Perceived road damage probability interacted with socio-demographics |
| Preferences for policies for the promotion of renewable energy | 105 | (Boeri and Longo, 2017) | 300 | Fractional factorial efficient | 6 (6 blocks) | 2+ status quo | Forced choice with status quo option | 4, attrxlevels: 3x3, 1x4 | Annual percentage reduction in greenhouse gas emissions, duration of energy disruptions (black-outs), variation in the number of people employed in the energy sector,electricity bill increase | MNL-model (RUM, RRM, λRRM), RU-RPL, RR-RPL | 4 | na | Sub-sample 2 received some additional information on the effects of black-outs compared to sub-sample 1 |

Table 4.7. RUM/RRM comparisons not included in Chorus et al. (2014)

we cannot really say that one model is better than another.

In order to further summarize the evidence outlined so far, tables displaying the frequencies of the main characteristics of the studies are presented. Tables 4.8 and 4.9 show a summary of the collected information.

Overall, one experiment out of three is based on a sample of less than 200 respondents; moreover, 36 percent of the studies are based on data collected through more than ten repeated choice tasks per respondents.

The D-efficient experimental design, with reference to the RUM model, is used in 30% of the applications. Indeed, efficient designs towards a utility maximizing choice behaviour may not be as efficient when people choose according to regret minimization, as recently established by van Cranenburgh et al. (2018). To overcome this limitation, van Cranenburgh et al. derived efficient experimental designs for DCEs that are robust towards the underlying decision rule.

Providing three alternatives in the choice set seems to be the rule, with the majority of them being articulated as two alternatives plus the status quo option. Seventy percent of the studies included up to five attributes in the DCE and most of them were treated as continuous in estimating the models.

Table 4.9 summarizes the information concerning estimated models, showing how the majority of the comparisons were based only on the estimation of the MNL model; these models, both for RUM and RRM specifications, often fail to reach a satisfactory $\rho$-squared value.

What appears evident from Tables 4.8 and 4.9 is the lack in the provided information in existing comparisons beween RUM and RRM models: in 44 percent of the studies is not indicated which experimental design the researcher used to build the DCE; in 27 percent of the studies the $\rho$-squared values are not provided in the papers.

The present chapter has given an overview of the empirical evidence concerning performances of the RUM and RRM model formulations of logit models. The following chapter outlines the empirical study carried out in the food domain and displays the results.

Table 4.8. Characteristics of the collected studies: A summary (1)

| Characteristic | n of applications | % of applications (N=45) |
|---|---|---|
| **Sample size** | | |
| <200 | 16 | 36% |
| 201-600 | 15 | 33% |
| >600 | 7 | 16% |
| na | 7 | 16% |
| **Experimental Design** | | |
| Bayesian D-efficient | 4 | 9% |
| D-efficient | 14 | 31% |
| Optimal orthogonal in the differences | 3 | 7% |
| Other designs | 4 | 9% |
| na | 20 | 44% |
| **Choice tasks per respondent** | | |
| 3-5 | 10 | 22% |
| 6-10 | 17 | 38% |
| 11-16 | 16 | 36% |
| na | 2 | 4% |
| **N alt. in the choice set** | | |
| 3 | 39 | 87% |
| 4 | 4 | 9% |
| 5 | 1 | 2% |
| na | 1 | 2% |
| **No choice option** | | |
| Forced choice | 14 | 31% |
| Forced choice with status quo option | 21 | 47% |
| "I am indifferent" opt out | 4 | 9% |
| "none of these" opt out | 6 | 13% |
| **N attributes** | | |
| 2-3 | 9 | 20% |
| 4-5 | 23 | 51% |
| 6-10 | 12 | 27% |
| na | 1 | 2% |
| **Attributes' coding** | | |
| Continuous | 28 | 62% |
| Continuous and categorical | 9 | 20% |
| na | 8 | 18% |

Table 4.9. Characteristics of the collected studies: A summary (2)

| Characteristic | n of applications | % of applications (N=45) |
|---|---|---|
| **Estimated models** | | |
| MNL-model | 29 | 64% |
| Both MNL and mixed-MNL | 8 | 18% |
| MNL structure with added panel effect error components | 8 | 18% |
| **ASC included** | 20 | 44% |
| **$\rho$-squared RRM MNL** | | |
| <0.30 | 21 | 47% |
| 0.31-0.50 | 10 | 22% |
| >0.50 | 2 | 4% |
| na | 12 | 27% |
| **$\rho$-squared RUM MNL** | | |
| <0.30 | 21 | 47% |
| 0.31-0.50 | 11 | 24% |
| >0.50 | 1 | 2% |
| na | 12 | 27% |
| **$\rho$-squared RRM Mixed (N=8)** | | |
| <0.50 | 3 | 38% |
| >0.50 | 4 | 50% |
| na | 1 | 13% |
| **$\rho$-squared RUM Mixed (N=8)** | | |
| <0.50 | 3 | 38% |
| >0.50 | 4 | 50% |
| na | 1 | 13% |

# Chapter 5

# Empirical study

## 5.1 Objective of the study

The aim of the empirical study is to compare performances of RUM and RRM based logit models in explaining and predicting food consumer choices. This study represents the first application of the RRM model in the food domain.
A second objective is to analyze the heterogeneity in food choices, based on personality traits. In particular, the personality traits taken into account are assumed to be linked to the choice strategy; by means of a segmentation analysis, it will be possible to see whether and how latent traits influence the way in which the choice is made.
A consumer survey has been carried out, encompassing a choice experiment and the scales to measure personality traits. Several logit models have been estimated on the sample in order to achieve the desired results.
The next sections outline the procedure and methods used for the survey, the measures and the analyses performed, and the obtained results, along with a final discussion.

## 5.2 Experimental settings

### 5.2.1 Participants, survey administration and questionnaire

Data have been collected in February 2017 by means of a web-based survey; 300 students from Wageningen University were recruited as participants by advertising the study in an education building. The online survey was managed and administered through Qualtrics software. In order to avoid any distraction, the questionnaire was administered in a controlled setting in a computer lab of the university. Completion of the questionnaire took an average of about 10 minutes. Students received a snack as a (pre-announced) reward for participating in the study. Key characteristics of the sample are displayed in Table 5.1.

Table 5.1. Demographic characteristics of the sample

| Characteristics | | Percentages |
|---|---|---|
| **Gender** | Females | 79.67 |
| | Males | 20.33 |
| **Type of student** | Bachelor | 68.33 |
| | Master | 30.0 |
| | Other | 1.67 |
| **Age (mean; std dev)** | | 20.45; 2.02 |

The selected food product for the experiment was cheese. Since the sample is made up by students in a Dutch university, cheese has been chosen as the object of the experiment because it is a product familiar and affordable for students, is a relevant part of their diet, and has many alternatives available on the shelves.

The questionnaire included the discrete-choice experiment based on stated preferences and questions to measure the personality traits that were hypothesized to influence the relative performance of the RRM and RUM -based models. Moreover, liking and consumption habits of cheese and socio-demographic variables were investigated (see the full questionnaire in Appendix A).

The questionnaire started with the questions pertaining to the discrete-choice experiment on cheese. Respondents had to choose a single alternative of cheese among the three presented, of which they (imagined to) buy a single unit. Respondents were asked to choose a cheese from each of ten different choice sets included in the questionnaire.

Before being asked to choose cheeses from the choice sets, the participants were briefed about a scenario that they had to imagine themselves to be in while choosing one out of three pieces of cheese.

It reads as follows: *"Imagine you have invited some friends to your home, everybody will bring something nice to eat or drink, you agreed to contribute with some cheese. You* *do not know for sure when your friends will come, but it is going to be within a week. You are at the supermarket, you know you are going to be busy during the next days, therefore you want to do the shopping today. Assume that you are only expected to bring one type of cheese".*

In order to increase the likelihood for anticipated regret to emerge, we tried to make the choice of cheese more important than usual, introducing other people – friends, whose opinion is likely to be taken into account – in the scenario. Moreover, the uncertainty about the day of the meeting might also introduce some regret, especially with respect to trade-offs involving preservability of cheese.

After having read the scenario, participants saw a detailed explanation of attributes and levels in terms of which the cheeses could differ from each other (see next section for attributes and levels included in the experiment). Then, the choice tasks were displayed one at a time. Respondents had to choose one cheese from the presented alternatives, according to their preference.

### 5.2.2 Choice experiment

Choice sets consisted of three cheese alternatives defined in terms of four attributes. Relevant attributes considered for the choice of cheese were: Quality, Price, Preservability and Sustainability of the packaging.

The attribute selection was guided by the desire to enhance regret emergence, in line with the study aim. Specifically, quality and price were included as these tend to be relevant attributes for most consumer choices. In order to make the presented alternatives of cheese more realistic to consumers, each quality level had its own reference price. The price attributes referred to deviations from these reference prices.[1]

Preservability expressed through the days until the best-by date was included because it implies different levels of uncertainty about the products' suitability at the consumption moment. It relates both to food safety issues and social norm, thus regret is likely to be taken into account when trading-off different options. Preference for recyclable packaging is one of the dimensions of sustainable consumption (Mancini et al., 2017), the related attributed was included because environment-friendliness of product packaging has proven to be a relevant product attribute in

1 Respondents only saw the resulting price.

consumer food choice (Rokka and Uusitalo, 2008) and to explore a moral dimension of food choice (Chorus, 2015).
Attributes and levels are shown in Table 5.2.

Table 5.2. Attributes and levels in the choice experiment

| Attributes | Levels |
|---|---|
| **Quality (reference price)** | No star (€ 1.40)<br>* (€ 1.90)<br>** (€ 2.40)<br>*** (€ 2.90) |
| **Price** | - € 0.40<br>- € 0.20<br>+ € 0.00<br>+ € 0.20<br>+ € 0.40 |
| **Preservability (best by date)** | 2 days<br>7 days<br>14 days |
| **Packaging sustainability (% of recyclable components)** | A (80 – 100)<br>B (20 – 80)<br>C (0 – 20) |

Choice sets were generated by a (in terms of the RUM model) D-efficient fractional-factorial main-effects design, following Rose and Bliemer (2009).
Prior simulations revealed that, as far as the two 3-level attributes are concerned, a (3x3x4x5) D-efficient design rules out any difference in the performance of the RRM and RUM models. The reason for this is that all three levels of each 3-level attribute occurred exactly once across the alternatives in each choice set, with the consequence that the RRM model becomes a mere re-parametrization of the RUM model. Therefore, a (6x6x4x5) D-efficient fractional-factorial main-effects design was generated first, using SAS 9.3 software. This design had a relative D-efficiency of 82.13%. Subsequently, the levels of the two 6-level attributes in the design were collapsed into three levels, obtaining a (3x3x4x5) design with relative D-efficiency of 85.05% (for comparison, the highest relative D-efficient we obtained by directly generating a (3x3x4x5) design was 90.57%).
The experimental design contains 60 choice sets, which were divided into six blocks

with ten choice sets each. Each respondent was confronted with a single block, i.e. ten choice sets. Respondents were randomly assigned to the blocks in a balanced way.

In each choice set, respondents selected one alternative from the three displayed (see Figure 5.1).

**According to your preferences, choose one option from the three shown below:**

| ***Cheese 1*** | |
|---|---|
| **Quality** | ** |
| **Sust. of pack.** | C |
| **Price** | € 2.60 |
| **Preservability** | 14 days |

| ***Cheese 2*** | |
|---|---|
| **Quality** | no star |
| **Sust. of pack.** | C |
| **Price** | € 1.20 |
| **Preservability** | 7 days |

| ***Cheese 3*** | |
|---|---|
| **Quality** | *** |
| **Sust. of pack.** | B |
| **Price** | € 2.90 |
| **Preservability** | 14 days |

Figure 5.1. Example of choice set

Following Dhar and Simonson (2003), respondents were forced to make a choice, without offering them a no-choice option. The inclusion of the no-choice option can affect some alternatives more than others, taking greater shares of choice away from safer or compromise options (Dhar and Simonson, 2003), i.e. options that people would choose to avoid regret and thus diminish the relevance of the RRM model.

To be able to compare the RRM and the RUM model in the presence of no-choice options, respondents saw a subsequent scenario in which they were allowed to reconsider each (forced) choice they made, "confirming" if they would actually buy the product even when they would have had the option to buy nothing and postpone the shopping.

Research has shown different effects of the inclusion of the so-called no-choice option on RRM and RUM models (Chorus, 2012b; Hess et al., 2014; Thiene et al., 2012), due to its formulation in the questionnaire. In particular, the formulation of the no-choice option in the questionnaire as "none of these" or "indifferent" could have ambiguous effect on the models. Empirical results have shown that RRM model is negatively affected by none of these framing, on the other hand RUM is more affected by the indifferent option (Hess et al., 2014). In our scenario, we did not make the difference between "none of these" and "indifferent" as reasons for the no-choice explicit.

### 5.2.3 Personality traits

In the present study, people heterogeneity in choice patterns is explored, based on personality traits. The underlying assumption is that personality traits affect people's choices; specifically, it is assumed that personality traits can lead people to act more as utility-maximizer or as regret-minimizer. Hence, personality traits such as regret sensitivity, need for acceptance, and type of regulatory focus are likely to drive people more towards one of the two principles.

Sensitivity to regret refers to the degree to which a person might regret a decision once made. The underlying hypothesis is that people that are more regret sensitive will be more likely to minimize regret than to maximize utility in choice situations. For measuring regret sensitivity, the five-item scale developed by Schwartz et al. (2002) was used.

Need for acceptance is defined as the desire to be accepted from others, concerning with being valued and accepted by individuals. A strong desire for acceptance might lead people to take the social norm – which has proven to be a determinant of choice of food (Herman et al., 2003; Ivanic, 2016) – into account in their everyday decisions. Since Beck et al. (2013) found support for the idea that the RRM performs better when people know they will have to defend their choice to others or when they bear a high degree of responsibility for the choice (as previously theorized by Zeelenberg and Pieters, 2007), it seems plausible that people that have a strong need for acceptance will be more likely to minimize regret than to maximize utility in choice situations. In the experiment, need for acceptance was measured with a reduced version of the need-to-belong scale by Leary et al. (2013). The original scale includes ten items aimed to measure two domains of need to belong: the need for social support and the need for acceptance. In the present study, we only consider the latter.

According to regulatory-focus theory, self-regulation can be promotion focused (acting towards gains) or prevention focused (acting towards avoiding losses) (Hall et al., 1997; Higgins et al., 2001; Higgins, 1997, 1998). Regulatory focus has been found to influence how people evaluate products and their choice motives. In particular, researchers found that prevention-focused individuals attach more importance to products' features related to purposes of safety, whereas promotion-focused people place greater importance to features related to comfort (Werth and Foerster, 2007). Considering that safety is about avoiding losses, and comfort typically can be seen as a gain, it would be straightforward to assume that prevention-focused individuals are more likely to act as regret minimizers, and promotion-focused people as utility maximizers. However, according to Leder et al. (2013), the overall intensity of anticipated regret does not differ between prevention- and promotion-focused individuals, but they differ in what triggers regret, i.e. the types of negative outcomes that are most relevant to them. Florack et al. (2013) describe the two types of regret: prevention-related regret is experienced when people did not think carefully enough about their choice and end up with an inferior product; whereas promotion-related regret is connected to the situation in which a better result could have been obtained if they had made a different choice. The anticipated regret connected to consumer choice and modelled by the RRM model depends on the foregone options, arising when a better result could have been obtained by choosing a different option (i.e. the promotion-related regret). Therefore, we hypothesize that the RRM model performs better than its RUM-based counterpart on promotion-oriented individuals.

In the present study, the prevention-promotion focus was measured by two subscales, one of which measures promotion goals and one of which measures prevention goals. Short versions of the subscales by Lockwood et al. (2002) were used in this study in order to reduce the burden for respondent (six items in total, three for each subscale).

Table 5.3 gives an overview of the 7-point Likert-scale items that were used in the experiment. Each item was rated from Strongly disagree to Strongly agree.

Table 5.3. Personality traits: Scales and items

| Scales | Items |
|---|---|
| **Regret sensitivity**<br>(Schwartz et al., 2002) | - Whenever I make a choice, I'm curious about what would have happened if I had chosen differently<br>- Once I make a decision, I don't look back (Reversed item)<br>- When I think about how I'm doing in life, I often assess opportunities I have passed up<br>- If I make a choice and it turns out well, I still feel like something of a failure if I find out that another choice would have turned out better<br>- Whenever I make a choice, I try to get information about how the other alternatives turned out |
| **Need for Acceptance**<br>adapted from (Leary et al., 2013) | - My feelings are easily hurt when I feel that others do not accept me<br>- If other people don't seem to accept me, I don't let it bother me (Reversed item)<br>- I try hard not to do things that will make other people avoid or reject me<br>- I want other people to accept me |
| **Promotion/Prevention Focus**<br>adaped from (Lockwood et al., 2002) | - I often think about how I will achieve academic success<br>- I typically focus on the success I hope to achieve in the future<br>- I frequently imagine how I will achieve my hopes and aspirations<br>- I often worry that I will fail to accomplish my academic goals<br>- I am anxious that I will fall short of my responsibilities and obligations<br>- I frequently think about how I can prevent failures in my life |

## 5.3 Methodological approach

### 5.3.1 RUM and RRM logit models estimation and comparison

For model estimations, Biogeme 2.5 Software package has been used (Bierlaire, 2016). In the model estimations, Quality, Sustainability of the packaging and Preservability were treated as categorical (dummy coded) predictors, whereas the effect of Price was assumed to be linear.

First, MNL models have been estimated (See Equation (3.3) for RUM and Equation (3.6) for RRM based models).

Despite the two models sharing the same MNL formulation and being equally parsimonious, a direct comparison between the parameter values of the two models is not meaningful. Firstly, in the RRM model the effect that unitary changes on attributes have on random regret does not only depend on the estimated taste parameters, but also on the other available alternatives[2]. Secondly, the magnitude of the estimates in the RRM model depends on the number of the available alternatives, i.e. on the choice set size. Larger choice sets give rise to smaller RRM-parameter estimates, and vice versa (Chorus, 2012a). This happens because the RRM model formulation involves a sum of all the binary comparisons between the available alternatives. With fixed parameters' magnitude, in a larger choice set one would obtain regret-levels and choice probabilities that are more sensitive to changes in attribute values, which is not the case in the real world. It is much more realistic for the degree of sensitivity of regret-levels and choice probabilities to changes in attribute values to be invariant with respect to the choice set size. This means that in the context of larger choice sets, smaller RRM-parameter estimates should be obtained and vice versa (Chorus, 2012a).

Given the impossibility to directly elicit meaningful results from the parameters' comparison, an indirect comparison of the RUM and RRM models estimates is sometimes useful. More specifically, a meaningful comparison can be performed on parameter ratios of the RRM model with their RUM counterparts. This is worthwhile because the ratios of parameters does not suffer from the abovementioned choice set size-effect, since the latter affects each parameter to the same extent. Therefore, by comparing parameters ratios of RUM and RRM models one can get information on the differences between model types in terms of the relative importance of one attribute over another attribute taken as reference (typically the price).

Based on existing applications, the overall performance of the RUM and RRM models are compared in terms of goodness of fit to the data and predictive ability

2 Contrary to the linear in parameter specification of the RUM model, the RRM model does not imply the IIA assumption.

Table 5.4. Prediction *vs* real choices in the validation sample

| | | Actual Choices | | |
|---|---|---|---|---|
| | | **1** | **2** | **3** |
| Predicted choices | **1** | a | b | c |
| | **2** | d | e | f |
| | **3** | g | h | i |

(Chorus, 2012a; Chorus et al., 2013a, 2014).
RUM and RRM logit models are not nested, having the same number of estimated coefficients, but different specifications. Therefore, the Ben-Akiva and Swait (BAS) test (Ben-Akiva and Swait, 1986) is used to compare the goodness of fit of the two models (See Section 3.2.1 for the formula).
The predictive ability of each model can be assessed by looking at the cross-validated hit rate, i.e. the out-of-sample proportion of correctly predicted choices. In order to calculate the cross-validated hit rate, the sample of choice observations is randomly split into an estimation sample (i.e., two third of the observations) and a validation sample (i.e., the remaining one third of the observations). First, the models are estimated on the estimation sample. Then the estimated parameters are used to predict choices in the validation sample according to the largest predicted probabilities. Finally, the predicted choices are compared with actual choices across the validation sample, obtaining the hit rate. In Table 5.4 the correctly predicted choices are represented by *a*, *e* and *i*. Therefore the hit rate can be computed as

$$\frac{a+e+i}{M}$$

where M is the number of observation in the validation sample.
In addition to the hit rate value, in order to statistically compare the prediction ability of the two models, McNemar's test was calculated. It tests whether the difference on the number of incorrect predictions between the two models' predictions is statistically significant. The null hypothesis of the test is marginal homogeneity, i.e. the probabilities for each outcome (marginal frequencies) are the same. The McNemar's test compares the number of incorrect prediction of the two models in the following way:

$$\chi^2 = \frac{(inc_R - inc_U)^2}{inc_R + inc_U}$$

where *inc* represents the number of incorred prediction with Regret and Utility based models. Under the null hypothesis, $\chi^2$ has a chi-squared distribution with 1 degree of freedom. If the null hypothesis is rejected, the marginal proportions are significantly different, i.e. the model with the higher hit rate predicts significantly better.

MNL models are first estimated and compared on the overall sample. Then, the same models are estimated on the restricted sample of confirmed choices, in order to see whether models performances are affected by the presence of a no-choice option.

### 5.3.2 Segmentation

The previous mentioned analyses concern models estimated on the entire sample, under the assumption of homogeneity of taste within the population. Nonetheless, exploring and evaluating heterogeneity in choices is an important objective of the study. To do so, three methods have been used: a priori segmentation based on personality traits, mixed logit models that account for random taste variation, and latent class RUM–RRM model to explore heterogeneity in decision rules.

A priori segmentation is performed separately for the three personality traits considered. It is done through a split of the sample into three subsamples, based on the tertile scores on the personality traits. Then, RRM and RUM models are estimated in the first and third tertiles, leaving out observations around the mean.
The scores for the personality traits are obtained through ordinal Confirmatory Factor Analysis (CFA) on the validated scales items (Rosseel, 2012). One-factor models were estimated for regret sensitivity (all completely-standardized factor loadings above 0.5) and need for acceptance (all factor loadings above 0.6). A two-factor model was estimated for the two regulatory-focus subscales (all factor loadings above 0.6). However, concerning the regulatory focus, we found a positive and rather high (above 0.5) correlation between prevention and promotion scores. One could argue that people might not be solely promotion or prevention focused, but that the two dimensions can be present in varying degrees at the same time. To allow for this simultaneous presence, we subtracted the prevention CFA scores from the promotion scores, in line with the idea of ipsatizing scores (Ten Berge, 1999), calling the new scale Promotion-Prevention Discrepancy. In this new representation of an

Table 5.5. Results from the CFA

| Model | Chi-Square p-value | SRMR | RMSEA | CFI | TLI |
|---|---|---|---|---|---|
| Regret sensitivity | >0.05 | 0.02 | 0.00 | 1.00 | 1.00 |
| Need for acceptance | >0.05 | 0.02 | 0.03 | 1.00 | 1.00 |
| Prevention-Promotion discrepancy | >0.05 | 0.03 | 0.04 | 1.00 | 1.00 |

Table 5.6. Original-scale means (across participants) of the average (across items) score in each of the tertiles of the factor score distributions

| Trait | Tertile original scale means | | |
|---|---|---|---|
| | 1 | 2 | 3 |
| Regret sensitivity | 3.11 | 4.44 | 5.39 |
| Need for acceptance | 3.40 | 4.72 | 5.84 |
| Prevention focus | 3.50 | 4.16 | 5.17 |
| Promotion focus | 4.50 | 4.90 | 5.66 |

individual's self-regulatory orientation, positive values of promotion-prevention discrepancy mean that promotion is relatively high, whereas negative values of promotion-prevention discrepancy mean relative prevention focus (Chen et al., 2017). Table 5.5 shows that each model had a good fit.

In order to test the hypothesized moderating effects of regret sensitivity, need for acceptance, and promotion-prevention discrepancy, the sample of respondents was divided into tertiles based on their CFA factor scores on each of these traits separately. To have a clear distinction between respondents with a higher and respondents with a lower score, separate RRM and RUM models were estimated for the highest and the lowest tertiles, excluding observations around the mean. Table 5.6 displays the original-scale (7-points scale) means (across participants) of the average (across items) score in each of the tertiles of the factor score distributions; Table 5.7 shows the factor score ranges in the first and third tertiles.

Estimated MNL models are compared in terms of goodness of fit and prediction ability, in each of the tertiles.

Table 5.7. Factor score ranges for high and low tertiles

| Trait | Tertile factor score ranges | | | |
|---|---|---|---|---|
| | 1 | | 3 | |
| | Min | Max | Min | Max |
| Regret sensitivity | -2.77 | -0.30 | 0.36 | 2.63 |
| Need for acceptance | -2.32 | -0.36 | 0.37 | 2.49 |
| Promotion-prevention discrepancy | -2.28 | -0.29 | 0.26 | 1.65 |

Latent class models allow the use of different behavioural processes to explain the choices (Hess et al., 2012). In particular, in this study the estimated LC model assume the existence of two latent classes, one of the classes assumes a utility-based choice, whereas the other class assumes a choice based on minimization of regret. Two LC models have been estimated, one with a class membership function that is not dependent on any personal characteristic, and a different one in which the class membership function is linked to psychological traits. This will allow to link the membership to a class with specific psychological traits.

## 5.4 Results

### 5.4.1 Multinomial Logit model

In this experiment, the deterministic utility associated with an alternative $i$ is formulated as such:

$$\begin{aligned} U_i = \beta_{B_{2days}} * B_i^{2days} + \beta_{B_{7days}} * B_i^{7days} + \beta_{Price} * Price_i \\ + \beta_{Q_{NoStar}} * Q_i^{NoStar} + \beta_{Q_*} * Q_i^{*} + \beta_{Q_{**}} * Q_i^{**} + \\ \beta_{S_C} * S_i^C + \beta_{S_B} * S_i^B \end{aligned} \tag{5.1}$$

Where $B$, $Q$ and $S$ are dummy variables for the respective levels.
The deterministic regret is estimated with the following formula:

$$\begin{aligned} R_i = \sum_{j \neq i} [ & ln(1 + \exp(\beta_{B_{2days}} \ * \ B_j^{2days} + \beta_{B_{7days}} \ * \ B_j^{7days} \\ & \qquad - (\beta_{B_{2days}} \ * \ B_i^{2days} + \beta_{B_{7days}} \ * \ B_i^{7days}))) \\ & + ln(1 + \exp(\beta_{Price} \ (Price_j - Price_i))) \\ & + ln(1 + \exp(\beta_{Q_{NoStar}} \ * \ Q_j^{NoStar} + \beta_{Q_*} \ * \ Q_j^* + \beta_{Q_{**}} \ * \ Q_j^{**} \\ & \qquad - (\beta_{Q_{NoStar}} \ * \ Q_i^{NoStar} + \beta_{Q_*} \ * \ Q_i^* + \beta_{Q_{**}} \ * \ Q_i^{**}))) \\ & + ln(1 + \exp(\beta_{S_C} \ * \ S_j^C + \beta_{S_B} \ * \ S_j^B - (\beta_{S_C} \ * \ S_i^C + \beta_{S_B} \ * \ S_i^B)))] \end{aligned} \tag{5.2}$$

In both equations, the baseline levels for each qualitative attribute are: three star quality, 14 days until the best by date, and sustainability of the packaging equal to A (80-100% recyclable).

Estimation results for MNL models are displayed in Table 5.8 and Table 5.9.
Estimated coefficients are in line with expectations: since the reference modality for each attribute is the best option (longer best by date, higher quality and higher sustainability of the packaging), the coefficients sign reflects a decrease in utility and an increase in regret, with respect to reference modes. The higher magnitude is represented by no star quality (compared to three stars) and 2 days until the best by date (compared to 14 days); these aspects are more important than (an increase of 1.00€ in) price.
In the RRM model, the relatively higher magnitude for quality and best by date attribute-levels means that for these attributes higher regret arises from a loss with respect to the rejoice arising from an equivalent gain. In other words, there is a higher profundity of regret, which means greater asymmetry between regret and rejoice. Thus, a more emphasized regret minimizing behaviour is observed for quality and best by date with respect to price and sustainability of the packaging, in the choice of cheese.
RUM and RRM models show almost the same pattern for the relative importance given to the cheese attributes. In order to better understand if any difference exist between models, since it is not possible to directly compare the parameter values of the two models (Chorus, 2012a), the relative importance of attributes with respect to price has been calculated. Results are plotted and displayed in Figure 5.2. Besides the

Table 5.8. RRM MNL estimation results

| Description | Coeff. estimate | Robust Asympt. std. error | $t$-stat | $p$-value |
|---|---|---|---|---|
| 2 days | 1.43 | 0.06 | 25.20 | <0.01 |
| 7 days | 0.12 | 0.04 | 2.79 | 0.01 |
| Price | 0.89 | 0.05 | 16.54 | <0.01 |
| No star | 1.60 | 0.09 | 18.16 | <0.01 |
| * | 0.76 | 0.07 | 10.38 | <0.01 |
| ** | 0.12 | 0.06 | 2.01 | 0.04 |
| C | 0.60 | 0.05 | 12.77 | <0.01 |
| B | 0.20 | 0.04 | 4.61 | <0.01 |

**Summary statistics**

Number of observations = 3000

Number of estimated parameters = 8

$$
\begin{aligned}
\text{AIC} &= 4625.865 \\
\text{BIC} &= 4673.916 \\
\mathcal{L}(\beta_0) &= -3295.837 \\
\mathcal{L}(\hat{\beta}) &= -2304.932 \\
-2[\mathcal{L}(\beta_0) - \mathcal{L}(\hat{\beta})] &= 1981.809 \\
\rho^2 &= 0.301 \\
\bar{\rho}^2 &= 0.298
\end{aligned}
$$

Table 5.9. RUM MNL estimation results

| Description | Coeff. estimate | Robust Asympt. std. error | $t$-stat | $p$-value |
|---|---|---|---|---|
| 2 days | -2.23 | 0.08 | -26.65 | <0.01 |
| 7 days | -0.13 | 0.05 | -2.44 | 0.01 |
| Price | -1.39 | 0.09 | -15.28 | <0.01 |
| No star | -2.63 | 0.15 | -16.99 | <0.01 |
| * | -1.03 | 0.11 | -9.83 | <0.01 |
| ** | -0.08 | 0.07 | -1.10 | 0.27 |
| C | -0.88 | 0.07 | -12.41 | <0.01 |
| B | -0.32 | 0.06 | -5.00 | <0.01 |

**Summary statistics**

Number of observations = 3000

Number of estimated parameters = 8

$$
\begin{aligned}
\text{AIC} &= 4627.942 \\
\text{BIC} &= 4675.993 \\
\mathcal{L}(\beta_0) &= -3295.837 \\
\mathcal{L}(\hat{\beta}) &= -2305.971 \\
-2[\mathcal{L}(\beta_0) - \mathcal{L}(\hat{\beta})] &= 1979.732 \\
\rho^2 &= 0.300 \\
\bar{\rho}^2 &= 0.298
\end{aligned}
$$

coefficient ratios being quite similar across the two models, in the quality attribute there is some weak evidence that intermediate levels gain importance within the RRM model.

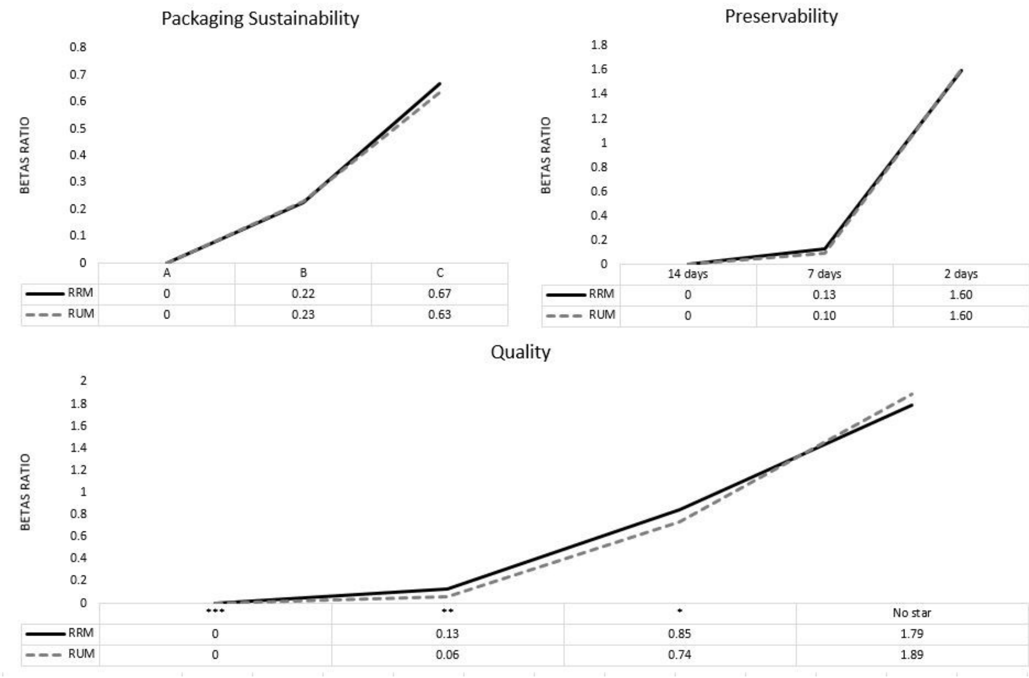



Figure 5.2. RUM and RRM coefficient ratios relative to price

Table 5.10 displays the results of the comparison in performance of the two models. No significant difference emerges neither for the goodness of fit to the data, nor for the prediction ability. In the general case, on the overall sample, the two specification of Multinomial Logit performs equally well.

Table 5.10. MNL comparison

| | RRM | RUM |
|---|---|---|
| $\bar{\rho}^2$ | 0.298 | 0.298 |
| BAS test | Not significant | |
| Cross-validated hit rate | 66.50% | 66.80% |
| McNemar test | Not significant | |

Table 5.11. RRM MNL estimation results on confirmed choices

| Description | Coeff. estimate | Robust Asympt. std. error | $t$-stat | $p$-value |
|---|---|---|---|---|
| 2 days | 1.83 | 0.09 | 19.69 | <0.01 |
| 7 days | 0.17 | 0.06 | 2.97 | <0.01 |
| Price | 1.07 | 0.07 | 16.06 | <0.01 |
| No star | 1.98 | 0.12 | 16.78 | <0.01 |
| * | 1.06 | 0.10 | 10.87 | <0.01 |
| ** | 0.25 | 0.08 | 2.92 | <0.01 |
| C | 0.85 | 0.07 | 12.92 | <0.01 |
| B | 0.26 | 0.06 | 4.34 | <0.01 |

**Summary statistics**

Number of observations = 1894

Number of estimated parameters = 8

$$\begin{aligned} \text{AIC} &= 2429.746 \\ \text{BIC} &= 2474.117 \\ \mathcal{L}(\beta_0) &= -2080.772 \\ \mathcal{L}(\hat{\beta}) &= -1206.873 \\ -2[\mathcal{L}(\beta_0) - \mathcal{L}(\hat{\beta})] &= 1747.798 \\ \rho^2 &= 0.420 \\ \bar{\rho}^2 &= 0.416 \end{aligned}$$

The overall sample includes the forced choices made by respondents. If the sample of choices is restricted to the choices that are confirmed (and not delayed) in the second round of choice tasks, a further comparison between regret and utility based models is possible. Table 5.11 and Table 5.12 display the estimation results.

The BAS test on the restricted sample of confirmed choice is significant with a p-value<0.005, whereas the difference in prediction is not significant (see Table 5.13). This means that in case of choices on which consumer are certain, utility specification has a better fit to the data, although RRM and RUM predict equally well. Therefore, the performance of the RRM model increase if we consider also choices on which people are not completely sure.

Table 5.12. RUM MNL estimation results on confirmed choices

| Description | Coeff. estimate | Robust Asympt. std. error | $t$-stat | $p$-value |
|---|---|---|---|---|
| 2 days | -2.87 | 0.14 | -20.81 | <0.01 |
| 7 days | -0.23 | 0.08 | -3.04 | <0.01 |
| Price | -1.85 | 0.12 | -14.78 | <0.01 |
| No star | -3.50 | 0.22 | -16.08 | <0.01 |
| * | -1.63 | 0.14 | -11.31 | <0.01 |
| ** | -0.28 | 0.10 | -2.81 | 0.01 |
| C | -1.22 | 0.10 | -12.20 | <0.01 |
| B | -0.37 | 0.09 | -4.24 | <0.01 |

**Summary statistics**

Number of observations = 1894

Number of estimated parameters = 8

$$
\begin{aligned}
\text{AIC} &= 2422.227 \\
\text{BIC} &= 2466.599 \\
\mathcal{L}(\beta_0) &= -2080.772 \\
\mathcal{L}(\hat{\beta}) &= -1203.114 \\
-2[\mathcal{L}(\beta_0) - \mathcal{L}(\hat{\beta})] &= 1755.316 \\
\rho^2 &= 0.422 \\
\bar{\rho}^2 &= 0.418
\end{aligned}
$$

Table 5.13. MNL comparison on confirmed choices

| | RRM | RUM |
|---|---|---|
| $\bar{\rho}^2$ | 0.416 | 0.418 |
| BAS test | RUM is the best model (p-value<0.005) | |
| Cross-validated hit rate | 76.86% | 77.50% |
| McNemar test | Not significant | |

### 5.4.2 Segmentation

To explore whether any difference exists in models performances based on personality traits, and thus to unveil different decision processes based on personality, the sample has been segmented. Subsamples were obtained based on the scores on personality traits; first and third tertiles have been considered, excluding the observations placed in the middle. RRM and RUM models are estimated in the first and third tertiles separately, for each of the considered personality traits. Models are compared in terms of goodness of fit and predictive ability. Results are displayed in Table 5.14.

Some significant differences between the two specifications are found in fit, but not in prediction. On subsamples made of people with high regret, high need for acceptance and high prevention-promotion discrepancy the RRM model specification has a significant better fit. The opposite happens in subsample with lower values in personality scales. Although being significant, the differences in fit are generally small.

Table 5.14. RUM RRM estimation results on subsamples

| | Subgroup | $\bar{\rho}^2$ | | Better fit | CV Hit rate (%) | | Better prediction |
|---|---|---|---|---|---|---|---|
| | | RRM | RUM | | RRM | RRM | |
| Regret sensitivity | High | 0.30 | 0.30 | RRM | 66.67 | 66.06 | Tie |
| | Low | 0.28 | 0.28 | RUM | 68.93 | 68.34 | Tie |
| Need for acceptance | High | 0.33 | 0.33 | RRM | 68.75 | 68.15 | Tie |
| | Low | 0.25 | 0.25 | RUM | 66.17 | 65.88 | Tie |
| Promotion-prevention discrepancy | High | 0.34 | 0.33 | RRM | 68.24 | 69.50 | Tie |
| | Low | 0.28 | 0.28 | RUM | 63.89 | 65.43 | Tie |

### 5.4.3 Mixed logit model estimation

Mixed logit models have been estimated with RUM and RRM behavioural specifications. Random errors have been assumed as normally distributed[3].

Table 5.15 and Table 5.16 display estimation results.

3 The smaller standard deviation of random coefficients is fixed at zero to ensure model identification, following Walker et al. (2007).

In the two estimated models, random taste heterogeneity is statistically significant. The mean coefficients for 2 days and no star quality attributes levels have the higher importance on utility and on regret, and the higher associated profundity of regret. But they have also the larger associated standard deviations. In order to interpret the results of estimated MMNL models more deeply, the size of $\sigma$ coefficients relative to $\mu$ coefficients has been calculated; also, the percentages of people with $\beta$s coefficients below zero for the RRM model and above zero for the RUM model are calculated. Table 5.17 displays the elaboration on the data.
When relating the estimated $\sigma$ with the estimated $\mu$ for one attribute, the relative size of $\sigma$ is obtained. For 2 days and Price attributes these relative sizes of $\sigma$ are bigger for the RRM model; on the contrary, for No star, One star and C level of recyclability of the packaging, the relative sizes of $\sigma$ are bigger for the RUM model. Coherent results are obtained looking at the shares of people with an estimated $\beta$ coefficient below/above zero; these shares of people are to be interpreted as having coefficients of an opposite sign with regards to the whole sample. In particular, more variability in taste is detected by the RRM model regarding Best by date and Price: a higher share of people feel rejoice from an higher price and a shorter best by date, compared with the share of people that attach positive utility to these levels. The opposite result is obtained for One star quality and C recyclability: higher shares of people attach a positive utility to these levels, compared to people that feel rejoice. The BAS test is significant, meaning that the RRM MMNL model has a statistically significant better fit to the data if compared to the RUM MMNL model. Therefore, including random taste variation through the Mixed MNL model changes the comparison result between the two behavioural specifications, leading to a significant difference. The improvement in fit gained using MMNL with respect to MNL can be seen also in the $\bar{\rho}^2$ values, which change from nearly 0.30 for both RUM and RRM -MNL models to nearly 0.40 for RUM-MMNL and 0.41 for RRM-MMNL model.

Table 5.15. RRM Mixed Logit estimation results

| Description | Coeff. estimate | Robust Asympt. std. error | $t$-stat | $p$-value |
|---|---|---|---|---|
| 2 days ($\mu$) | 3.43 | 0.26 | 13.34 | <0.01 |
| 2 days ($\sigma$) | 2.06 | 0.18 | 11.36 | <0.01 |
| 7 days ($\mu$) | 0.24 | 0.07 | 3.47 | <0.01 |
| Price ($\mu$) | 1.72 | 0.12 | 14.21 | <0.01 |
| Price ($\sigma$) | 1.32 | 0.11 | 11.67 | <0.01 |
| No star ($\mu$) | 2.93 | 0.18 | 16.77 | <0.01 |
| No star ($\sigma$) | 1.18 | 0.12 | 9.60 | <0.01 |
| * ($\mu$) | 1.37 | 0.12 | 11.81 | <0.01 |
| * ($\sigma$) | 0.41 | 0.11 | 3.80 | <0.01 |
| ** ($\mu$) | 0.25 | 0.09 | 2.80 | 0.01 |
| C ($\mu$) | 1.05 | 0.09 | 11.24 | <0.01 |
| C ($\sigma$) | 0.81 | 0.09 | 8.68 | <0.01 |
| B ($\mu$) | 0.28 | 0.07 | 4.01 | <0.01 |

**Summary statistics**

Number of observations = 3000

Number of excluded observations = 0

Number of estimated parameters = 13

$$
\begin{aligned}
\text{AIC} &= 3888.351 \\
\text{BIC} &= 3966.433 \\
\mathcal{L}(\beta_0) &= -3295.837 \\
\mathcal{L}(\hat{\beta}) &= -1931.175 \\
-2[\mathcal{L}(\beta_0) - \mathcal{L}(\hat{\beta})] &= 2729.323 \\
\rho^2 &= 0.414 \\
\bar{\rho}^2 &= 0.410
\end{aligned}
$$

Table 5.16. RUM Mixed Logit estimation results

| Description | Coeff. estimate | Robust Asympt. std. error | $t$-stat | $p$-value |
|---|---|---|---|---|
| 2 days ($\mu$) | -4.60 | 0.30 | -15.38 | <0.01 |
| 2 days ($\sigma$) | 2.57 | 0.22 | -11.48 | <0.01 |
| 7 days ($\mu$) | -0.20 | 0.08 | -2.48 | 0.01 |
| Price ($\mu$) | -2.37 | 0.17 | -14.38 | <0.01 |
| Price ($\sigma$) | 1.55 | 0.14 | -11.35 | <0.01 |
| No star ($\mu$) | -4.86 | 0.33 | -14.85 | <0.01 |
| No star ($\sigma$) | 2.15 | 0.26 | 8.25 | <0.01 |
| * ($\mu$) | -1.70 | 0.17 | -9.98 | <0.01 |
| * ($\sigma$) | 0.96 | 0.15 | 6.48 | <0.01 |
| ** ($\mu$) | -0.14 | 0.10 | -1.36 | 0.17 |
| C ($\mu$) | -1.46 | 0.14 | -10.61 | <0.01 |
| C ($\sigma$) | 1.25 | 0.13 | 9.33 | <0.01 |
| B ($\mu$) | -0.46 | 0.09 | -4.94 | <0.01 |

**Summary statistics**

Number of observations = 3000

Number of estimated parameters = 13

$$
\begin{aligned}
\text{AIC} &= 3967.092 \\
\text{BIC} &= 4045.175 \\
\mathcal{L}(\beta_0) &= -3295.837 \\
\mathcal{L}(\hat{\beta}) &= -1970.546 \\
-2[\mathcal{L}(\beta_0) - \mathcal{L}(\hat{\beta})] &= 2650.582 \\
\rho^2 &= 0.402 \\
\bar{\rho}^2 &= 0.398
\end{aligned}
$$

Table 5.17. Comparison between RUM and RRM MMNL models' estimates

| **Relative sizes of $\sigma$s** | **RRM** | **RUM** |
|---|---|---|
| 2 days | 60% | 56% |
| Price | 77% | 65% |
| No star | 40% | 44% |
| * | 30% | 56% |
| C | 77% | 86% |
| **Shares of people with a negative (RRM)/positive (RUM) $\beta$ coefficient** | **RRM** | **RUM** |
| 2 days | 5% | 4% |
| Price | 10% | 6% |
| No star | 1% | 1% |
| * | 0% | 4% |
| C | 10% | 12% |

Table 5.18. Mixed Logit comparison

| | RRM | RUM |
|---|---|---|
| $\bar{\rho}^2$ | 0.410 | 0.398 |
| BAS test | RRM is the best model (p-value<0.001) | |

### 5.4.4 Latent Class model

A latent class model has been estimated. The model assumed two latent classes, with different behavioural processes: one class was specified as following a utility-maximizing choice rule, and the other one followed a regret-minimizing decision rule. Using this type of specification for the LC model, we allow for the use of different underlying choice strategies for each respondent, using a probabilistic approach (Hess et al., 2012). The LC model estimates two sets of parameters for the choice model, in the two individual classes, and the probabilities to belong to each class. Results are displayed in Table 5.19, where LC 1 is utility based and LC 2 is regret based. The estimated coefficient $s$ represents the probability to belong to Class 2, and $1 - s$ is the probabilty to belong to Class 1. The obtained value for $s$ means that there is 49% probability to belong to the regret-based class.
To obtain information about which individual is more likely to belong to Class 1 or to Class 2, covariates have been included in the membership funcion ($s$). Through this formulation is possible to link features of the respondent to the membership probability. In particular, psychological scales have been included as covariates, obtaining one parameter for each scale. Unfortunately, the three parameters are not significant (see Table 5.20), meaning that none of the psychological traits affects the selection of the behavioural process underlying choice.

Table 5.19. Latent Class model estimation results

| Description | Coeff. estimate | Robust Asympt. std. error | $t$-stat | $p$-value |
|---|---|---|---|---|
| 2 days (LC 1) | -3.06 | 0.25 | -12.13 | <0.01 |
| 2 days (LC 2) | 1.27 | 0.22 | 5.68 | <0.01 |
| 7 days (LC 1) | -0.24 | 0.11 | -2.20 | 0.03 |
| 7 days (LC 2) | -0.04 | 0.05 | -0.84 | 0.40 |
| Price (LC 1) | -1.70 | 0.17 | -10.31 | <0.01 |
| Price (LC 2) | 0.68 | 0.11 | 6.41 | <0.01 |
| No star (LC 1) | -1.76 | 0.40 | -4.38 | <0.01 |
| No star (LC 2) | 3.27 | 0.47 | 6.98 | <0.01 |
| * (LC 1) | -0.72 | 0.24 | -3.05 | <0.01 |
| * (LC 2) | 0.54 | 0.12 | 4.41 | <0.01 |
| ** (LC 1) | -0.03 | 0.14 | -0.20 | 0.84 |
| ** (LC 2) | -0.02 | 0.07 | -0.31 | 0.75 |
| C (LC 1) | -1.16 | 0.18 | -6.39 | <0.01 |
| C (LC 2) | 0.50 | 0.10 | 4.72 | <0.01 |
| B (LC 1) | -0.37 | 0.10 | -3.57 | <0.01 |
| B (LC 2) | 0.26 | 0.08 | 3.26 | <0.01 |
| s | 0.49 | 0.11 | 4.56 | <0.01 |

**Summary statistics**

Number of observations = 3000

Number of estimated parameters = 17

$$
\begin{aligned}
\text{AIC} &= 4396.401 \\
\text{BIC} &= 4498.510 \\
\mathcal{L}(\beta_0) &= -3295.837 \\
\mathcal{L}(\hat{\beta}) &= -2181.201 \\
-2[\mathcal{L}(\beta_0) - \mathcal{L}(\hat{\beta})] &= 2229.272 \\
\rho^2 &= 0.338 \\
\bar{\rho}^2 &= 0.333
\end{aligned}
$$

Table 5.20. Latent Class model with covariates estimation results

| Description | Coeff. estimate | Robust Asympt. std. error | $t$-stat | $p$-value |
|---|---|---|---|---|
| 2 days (LC 1) | -3.05 | 0.25 | -12.17 | <0.01 |
| 2 days (LC 2) | 1.27 | 0.22 | 5.68 | <0.01 |
| 7 days (LC 1) | -0.23 | 0.11 | -2.07 | 0.04 |
| 7 days (LC 2) | -0.04 | 0.05 | -0.80 | 0.43 |
| Price (LC 1) | -1.69 | 0.17 | -10.22 | <0.01 |
| Price (LC 2) | 0.69 | 0.10 | 6.66 | <0.01 |
| No star (LC 1) | -1.74 | 0.41 | -4.24 | <0.01 |
| No star (LC 2) | 3.28 | 0.48 | 6.90 | <0.01 |
| * (LC 1) | -0.71 | 0.24 | -2.97 | <0.01 |
| * (LC 2) | 0.54 | 0.12 | 4.60 | <0.01 |
| ** (LC 1) | -0.03 | 0.14 | -0.22 | 0.82 |
| ** (LC 2) | -0.02 | 0.07 | -0.34 | 0.74 |
| C (LC 1) | -1.18 | 0.18 | -6.63 | <0.01 |
| C (LC 2) | 0.49 | 0.11 | 4.65 | <0.01 |
| B (LC 1) | -0.37 | 0.10 | -3.59 | <0.01 |
| B (LC 2) | 0.26 | 0.08 | 3.34 | <0.01 |
| NFA | 0.12 | 0.19 | 0.63 | 0.53 |
| Prom-prev | -0.21 | 0.23 | -0.91 | 0.36 |
| Regret | -0.24 | 0.17 | -1.42 | 0.15 |
| s | 0.95 | 0.43 | 2.21 | 0.03 |

**Summary statistics**

Number of observations = 3000

Number of estimated parameters = 20

$$
\begin{aligned}
\text{AIC} &= 4399.408 \\
\text{BIC} &= 4519.535 \\
\mathcal{L}(\beta_0) &= -3295.837 \\
\mathcal{L}(\hat{\beta}) &= -2179.704 \\
-2[\mathcal{L}(\beta_0) - \mathcal{L}(\hat{\beta})] &= 2232.266 \\
\rho^2 &= 0.339 \\
\bar{\rho}^2 &= 0.333
\end{aligned}
$$

## 5.5 Discussion

The present study tested the RRM model in the food choice domain through an empirical illustration. The empirical setting concerned the choice of cheese for a house party with friends; the attributes of cheese considered were quality, price, best-by-date and sustainability of the packaging. Several logit models were estimated.

The RRM-MNL model returns coherent estimates of anticipated regret and is not inferior to the RUM-MNL model in terms of goodness of fit and prediction. In fact, the goodness of fit to the data and the cross-validated hit rates are similar for the two models. This tie in model performance is in agreement with Chorus et al. (2014), who found that RUM and RRM perform equally in terms of model fit and prediction ability in nearly one third of the applications, mainly estimating MNL model. In those studies that do show statistically significant differences, these differences tend to be very small. Therefore, our results based on MNL estimation in a food context do not come as an exception, but are in line with previous findings. Moreover, the $\rho$-squared values of models are in line with previous estimations in the literature (see Table 4.9).

The RUM and RRM-MNL models have been estimated also on the restricted sample of people that, in a subsequent choice task, had confirmed they would buy the option previously chosen even if they had the possibility to postpone the shopping. On this subsample, the RUM model fits significantly better the data. This result confirms the association between anticipated regret and choice deferral (Beattie et al., 1994).

The estimation of Mixed logit models for RUM and RRM discloses significant random taste heterogeneity in the sample, which the MNL model cannot capture. Moreover, a statistically significant difference in fit between the two formulations is found, the RRM MMNL model providing a better fit to the data. Since the beta coefficients in the RRM model also reflect the degree of asymmetry between regret and rejoice, for this model the mixed logit formulation does not only imply different tastes in population, but also different regret minimization behaviours. Therefore, the estimation of the mixed logit model might favour the RRM model, increasing its fit in comparison to the RUM model.

In the MNL model estimation, the magnitude of parameters displays that the most important attribute levels that affect choice are no star quality with respect to three star quality, followed by 2 days until the best by date with respect to 14 days. These attribute levels produce the higher dis-utility and anticipated regret. This pattern of importance in utility and regret changes looking at estimated coefficients of MMNL models: in the RRM MMNL model, the attribute level affecting regret to the higher extent is two days compared to fourteen days until the best by date; in the RUM MMNL model, the highest (dis-)utility is provided by no star quality compared to three star. Therefore, taking into account taste heterogeneity in the sample, different behaviours are captured by the two models. If regret is modelled, the best by date has a higher impact meaning that higher regret is caused by losses (shorter best by date) than the rejoice provided by gains (longer best by date). On the other hand, if compensatory utility is modelled, the quality has an higher impact on choice.

Some evidence emerges showing that the RRM model can slightly outperform the RUM model when looking at sub-samples based on personality traits that are expected to be related to regret anticipation. This evidence is based on the obtained significant differences in fit of the models; however, this result is not supported by a difference in prediction of the models.

In particular RRM fits better to individuals with high regret sensitivity, need for acceptance, and stronger focus on promotion than on prevention. While intuitively it may seem odd that under promotion focus regret outperforms utility, our results align with earlier findings about what causes regret in different situations (Leder et al., 2013). More specifically, this result confirms that the RRM model captures promotion-related regret, arising when thinking that a non-chosen alternative could have provided a better result. This is a negative outcome that is highly relavant for promotion-oriented individuals (Florack et al., 2013).

Our results for individual regret sensitivity support the validity for the regret minimization model, which outperforms RUM on individuals that are highly sensitive to regret, and thus might wish to avoid it. This result supports the convergent validity of the RRM behavioural framework, which corroborates the findings of Connolly and Butler (2006) that show that there is moderate correspondence between self-reported emotions, including regret and disappointment, and choice behaviour in the context of real-money lotteries.

Despite evidence provided by segmentation, latent class model estimation does not confirm the effect of psychological traits on the use of decision rules taken into account in this study. Including psychological traits as covariates in the LC membership function does not result in any significant effect of these traits on the use of a regret-minimizing or utility-maximizing choice process. Moreover, assuming two latent classes that follow regret-minimization or utility maximization decision rule, the results of LC estimation are quite mixed, with a fifty-fifty percent to belong to one or the other class.

Focusing on the subset of confirmed choices, the RUM MNL model has a better fit than the RRM MNL model. When delaying is justifiable and when difficulty is experienced in trading-off important attributes, regret minimizers tend to defer choice, since they typically associate more regret with choosing than with deferring (Mourali et al., 2018). Accordingly, individuals that do not defer choice are more likely to choose guided by utility maximization, in line with our findings.

Overall, the application of the RRM behavioural process to the choice of food is promising; the larger difference with the linear-in-parameter RUM model appears when fitting the Mixed logit model. Significant heterogeneity among individuals concerning the value attributed to the product characteristics is found, and regret minimizing approach provides a better performance.

## Study limitations and directions for future research

The present study has a number of limitations. First of all, although the scenario was aimed to trigger deliberate comparisons of the alternatives and weighing of attributes, it may be questioned whether food choices, even for special occasions are fully deliberate, or rather rely on simple heuristics. For future research, it could be worthwhile to investigate and compare simultaneously more decision rules taking into account heuristics, in different situations.

Another limitation may come from the experimental settings, particularly from the forced choice format and the experimental design used. The decision to force the choice was made based primarily on the scenario, which referred to an imminent dinner; therefore, the shopping could not be postponed. Since we refer to a very frequently purchased consumer product there is no compelling need for a no-choice option (Carson et al., 1994). Moreover, with the addition of a no-choice option, no information is obtained on the relative attractiveness of the available alternatives in a given choice set when the no-choice option is chosen. This is especially relevant in the estimation of the RRM model, which is based on pairwise comparisons of alternatives: when the no choice option is chosen, it is not possible to trace back any information about the relative liking of available alternatives (Brazell et al., 2006). The experimental design was generated mainly based on consideration of D-efficiency for the RUM model, but not for efficiency in discriminating between the RUM and the RRM model. Prior to this study we ran some simulation studies with the experimental design we used. That is, we generated simulated observed choices according to RUM with hypothetical values for the attribute-level utility parameters and RRM with hypothetical values for the attribute-level regret parameters. Subsequently, both the RUM and the RRM model were estimated on each dataset with simulated choices, both with the attributes as categorical and with the attributes as linear predictors. We found coherence between the model that generated the simulated choices and the fit of the estimated models: the RUM model fit significantly better data generated according to RUM compared to RRM model, and vice versa (BAS test p-value<0.001 in all cases). Nevertheless, for further studies the use of the experimental design recently proposed by van Cranenburgh et al. (2018) is encouraged.

To the best of our knowledge, the current study is the first one to explore the possibility that food choices could be driven by regret minimization rule. Further research is needed to fully understand how people perceive the importance of food choices and how this is connected to regret minimization.
Further studies are encouraged to explore which psychological traits are likely to favour regret minimization in food related choice situations. The use of different formulations of the RRM model could provide more insights on individuals heterogeneity, i.e. hybrid RUM-RRM models and Generalized RRM model (Chorus, 2014; Chorus et al., 2013b).
It is quite difficult to distil some conclusions about those food contexts in which the RRM framework may better than the RUM framework account for consumer choices, especially given the weak evidence obtained in previous studies, showing that differences in performance between RUM and RRM models are mainly context- and dataset- specific (Chorus et al., 2014). Further research should explore other food products and contexts on which the RRM model may substantially outperform the RUM model.
Most promising contexts in which people more likely minimize regret when choosing could be: i) Situations where food risks may emerge from the choice (e.g. allergies, intolerance); ii) situation involving time constraints (e.g. time limited promotions)

such as in Wang et al. (2017); iii) contexts in which it is to be expected that others will also evaluate one's choice on a number of relevant attributes in comparison to other alternatives that are known to be available (e.g., choice of restaurant, buying a gift); iv) contexts with a strong moral component, as suggested by Chorus (2015) (e.g., different degrees of animal friendliness, see de Jonge et al. (2015)).

# Conclusion

The present study introduced the RRM model in the food choice domain through an empirical illustration. Furthermore, the food choice process and factors affecting it were discussed.
Assuming homogeneity in choices among individuals, the RRM model returns coherent estimates of anticipated regret and is not inferior to the RUM model in terms of goodness of fit and prediction. If heterogeneity in consumers' choices is allowed for, the RRM (mixed logit) model has a significantly better fit than its RUM counterpart.
These results can be helpful for driving strategies both in marketing and public policy making, to adapt products, messages, advertising to consumers that rely on different choice processes. Indeed, understanding how people make their food choices is important for effectively develop communication messages on healthy eating (Connors et al., 2001). Furthermore, market shares predictions and marketing actions are based on consumer choice modelling (Dieckmann and Dippold, 2009). In particular, segmentation based on consumers' choice process is of great interest for marketers and policy makers. For instance, when approaching loss-averse consumers, improving disadvantages will be more effective than further improve an advantage of an existing product (Neumann and Böckenholt, 2014). Also, knowing which kind of personal and situational features are more likely to trigger regret minimization allow to target specific groups or context that better respond to regret anticipation. This could be elicited through health or weight reduction in-store campaigns, accurate shelf displays that induce people to take into account helthier compromise alternatives, revisited restaurants' menu presentation.

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# Appendix A - Questionnaire

Dear student, thank you for agreeing to take part in this survey. The collected data will be helpful for a study on consumer choice of cheese. Collected data are completely anonymous and will only be reported at an aggregate level. Filling the questionnaire will take less than fifteen minutes. Press the bottom right button to start the survey.

Please, carefully read the text below.

Imagine you have invited some friends to your home, everybody will bring something nice to eat or drink, you agreed to contribute with some cheese. You do not know for sure when your friends will come, but it is going to be within a week. You are at the supermarket, you know you are going to be busy during the next days, therefore you want to do the shopping today. Assume that you are only expected to bring one type of cheese.

You will see ten assortment of three different cheeses to choose from.
Types of cheese differ based on 4 attributes: Quality, Sustainability of the packaging, Price and Preservability.
**Quality** has been rated by the Dutch Dairy Association, it is indicated with stars and refers to the general quality of the cheese: No stars quality refers to cheeses that are either not tested or do not comply with one or more standards of quality considered by the Association; * quality refers to cheeses that meet the basic quality standards considered by the Association; ** quality refers to average quality cheeses quality refers to high quality cheeses.
**Sustainability** of the packaging is indicated with three letter grades: A, B and C. A refers to packaging of which 80% to 100% of its components could be recycled; B refers to packaging of which 20% to 80% of its components could be recycled; C refers to packaging of which up to 20% of its components could be recycled.
**Price** is the price for 100 grams, it can vary between € 1.00 and € 3.30.
**Preservability** is expressed through the number of days left before the best by date, it ranges between 2 and 14 days.

You will see ten different assortments, each with three cheese alternatives. We ask you to make a choice from each of these assortments. Please, carefully consider every choice you make. Please, think about the choice you would make if you would be in the previously sketched scenario - get together with friends in your house sometime during the next seven days - in real life.

*General Quality has been rated by the Dutch Dairy Association; Sustainability of the packaging refers to the percentage of packaging components that can be recycled; Price for 100 grams; Preservability is indicated through the number of days left before the best by date.*

- According to your preferences, choose one option from the three shown below:

| ***Cheese 1*** | |
|---|---|
| **Quality** | ** |
| **Sust. of pack.** | C |
| **Price** | € 2.60 |
| **Preservability** | 14 days |

| ***Cheese 2*** | |
|---|---|
| **Quality** | no star |
| **Sust. of pack.** | C |
| **Price** | € 1.20 |
| **Preservability** | 7 days |

| ***Cheese 3*** | |
|---|---|
| **Quality** | *** |
| **Sust. of pack.** | B |
| **Price** | € 2.90 |
| **Preservability** | 14 days |

*[… Ten choice sets like the previous one were displayed]*

- Now imagine you have the possibility to buy nothing, and come back for the shopping another time, or in another shop, when or where there might be other cheeses available. Would you still buy the cheese you chose before? Below you can find the cheeses you have just chosen, please for each cheese indicate whether you would buy it or buy nothing.

| ***Cheese 3*** | |
|---|---|
| **Quality** | ** |
| **Sust. of pack.** | B |
| **Price** | € 2.20 |
| **Preservability** | 7 days |

○ Buy

○ Not buy

*[… Ten questions like the previous one were displayed, one for each option chosen]*

Please, give a rate of the **Quality** levels according to your preferences, indicate with 0 the least preferred level, and with 10 the most preferred level, the remaining level's ratings should stay somewhere in between:

| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| *** three stars | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| ** two stars | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| * one star | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| No star | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

How much is the difference between your most preferred and least preferred Quality level important in the choice? Indicate a value between 0 - not important at all, and 10 - extremely important.

0 1 2 3 4 5 6 7 8 9 10

Importance of the difference between the most preferred and least preferred level

*[… Replicated for price, sustainability and preservability]*

How much do you agree with the following statements?

| | Strongly disagree | Disagree | Somewhat disagree | Neither agree nor disagree | Somewhat agree | Agree | Strongly agree |
|---|---|---|---|---|---|---|---|
| If my guests will not appreciate the cheese I bought, I would regret the choice I made. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I like cheese. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| In general, I care about choosing the best cheese. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| To me, it was important to make the right decision in the choice tasks presented during the experiment. | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

The questionnaire is almost finished, now we ask you to answer some questions about yourself, these are not directly related to choice of cheese.

How much do you agree with the following statements?

| | Strongly disagree | Disagree | Somewhat disagree | Neither agree nor disagree | Somewhat agree | Agree | Strongly agree |
|---|---|---|---|---|---|---|---|
| I typically focus on the success I hope to achieve in the future. | | | | | | | |
| I often think about how I will achieve academic success. | | | | | | | |
| I am anxious that I will fall short of my responsibilities and obligations. | | | | | | | |
| I often worry that I will fail to accomplish my academic goals. | | | | | | | |
| I frequently imagine how I will achieve my hopes and aspirations. | | | | | | | |
| I frequently think about how I can prevent failures in my life. | | | | | | | |

How much do you agree with the following statements?

| | Strongly disagree | Disagree | Somewhat disagree | Neither agree nor disagree | Somewhat agree | Agree | Strongly agree |
|---|---|---|---|---|---|---|---|
| When I think about how I'm doing in life, I often assess opportunities I have passed up. | | | | | | | |
| Once I make a decision, I don't look back. | | | | | | | |
| If I make a choice and it turns out well, I still feel like something of a failure if I find out that another choice would have turned out better. | | | | | | | |
| Whenever I make a choice, I try to get information about how the other alternatives turned out. | | | | | | | |
| Whenever I make a choice, I'm curious about what would have happened if I had chosen differently. | | | | | | | |

How much do you agree with the following statements?

| | Strongly disagree | Disagree | Somewhat disagree | Neither agree nor disagree | Somewhat agree | Agree | Strongly agree |
|---|---|---|---|---|---|---|---|
| My feelings are easily hurt when I feel that others do not accept me. | | | | | | | |
| I try hard not to do things that will make other people avoid or reject me. | | | | | | | |
| I want other people to accept me. | | | | | | | |
| If other people don't seem to accept me, I don't let it bother me. | | | | | | | |

How often do you eat cheese?

- ❍ Every day or almost every day
- ❍ Once or twice a week
- ❍ Once a month
- ❍ More rarely

Do you follow any restricted diet or have allergy/intolerance to lactose?

- ❍ No
- ❍ Allergic/intolerant to lactose
- ❍ Vegetarian
- ❍ Vegan
- ❍ Other, namely ____________________

Gender

- ❍ Female
- ❍ Male

Age_____________________________

Are you a master or a bachelor student?

- ❍ I am a bachelor student
- ❍ I am a master student
- ❍ Other, namely ____________________

You reached the end of the questionnaire, a very last question we ask you to think to a situation in which you are choosing food from different products in the same category, and you feel that if you choose the wrong one you are going to regret the choice. Which product comes to your mind and why?

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