Environmental and Resource Economics (2023) 86:1–27
https://doi.org/10.1007/s10640-023-00785-3

Investigating Consumer Preferences for Sustainable Packaging Through a Different Behavioural Approach: A Random Regret Minimization Application

Giovanna Piracci[1] · Fabio Boncinelli[1] · Leonardo Casini[1]

Accepted: 26 May 2023 / Published online: 18 June 2023

Abstract

Plastic pollution causing the near-permanent contamination of the environment is a preeminent concern. The largest market sector for plastic resins is packaging, and the food industry plays a major role in producing plastic packaging waste. Therefore, the gradual switch of the food system towards pro-environmental packaging strategies is required to contain the plastic packaging waste issue. To this extent, this study aimed to investigate how food consumers relatively value the provision of different sustainable packaging alternatives, namely the unpackaged option and bioplastic packaging. Moreover, to shed light on the behavioural mechanism underlying the decision-making process for sustainable packaging, we considered two different decision paradigms: the traditional random utility maximization and random regret minimization framework. Overall, our results indicate that consumer tastes are highly heterogeneous and that preference patterns change according to the behavioural approach assumed by individuals. Policymakers and marketers of food industries need to carefully consider the differences in the decision mechanism of consumers when implementing strategies to encourage pro-environmental food choices. Notably, our findings elucidate on the importance to embrace other perspectives as well, and not simply limit to utility maximization, to fully comprehend the decision-making process of consumers for sustainable foods.

Keywords Sustainable food choices · Bioplastic packaging · Unpackaged food · Choice experiment · Hybrid latent class · Pro-environmental behaviour

Abbreviations

DCE	Discrete choice experiment
RRM	Random regret minimization

✉ Fabio Boncinelli
fabio.boncinelli@unifi.it

Giovanna Piracci
giovanna.piracci@unifi.it

Leonardo Casini
leonardo.casini@unifi.it

[1] Department of Agriculture, Food, Environment and Forestry, University of Florence, Piazzale delle Cascine, 18 – 50144 Florence, IT, Italy

RUM Random utility maximization
MNL Multinomial logit
RPL Random parameter logit
LC Latent class

1 Introduction

The irreversible intrusion of plastics in the environment is a serious threat contributing to climate change (Ford et al. 2022), biodiversity loss (Gall and Thompson 2015) and risks to human health (Waring et al. 2018). The total amount of virgin plastics manufactured from 1950 to 2015 was 7800 million metric tons (Geyer et al. 2017). Consequently, plastics constitute the largest share of marine debris (between 60 and 80%) and are ingested by organisms in the marine ecosystem, thus being transferred in the food chain (Setälä et al. 2014; Gall and Thompson 2015). Nonetheless, global plastic production is forecasted to double in the next 20 years (World Economic Forum 2016).

The largest market sector for plastic resins is packaging (Jambeck et al. 2015; Barnes 2019). In Europe, the packaging industry covers the 40% of plastic material demand (Plastics Europe 2020), and the plastic packaging waste reached a total of 15.4 million tonnes in 2019, an increase of 26.4% compared to 2009 (Eurostat 2019). The reuse and recycling of these materials still remain under-implemented (European Commission 2018). As a result, the development of sustainable solutions in the packaging industry is urgently needed to mitigate the global externality of plastic pollution.

In this context, food-related packaging like drinking bottles, food wrappers, lids, takeaway containers, and grocery bags are among the most common plastic waste products (UNEP 2018). Food companies employ single-use plastic taking advantage of its durability, reduced weight, and low cost to prevent waste and guarantee food safety while ensuring high throughput (Leal Filho et al. 2019; Phelan et al. 2022). Given its major role in producing plastic packaging waste, the food industry is required to orientate towards packaging solutions alternative to plastic to improve the environmental performance of the supply chain (Phelan et al. 2022). To this end, packaging-free products and bioplastic packaging may represent convincing strategies to contrast the plastic pollution issue (Fogt Jacobsen et al. 2022). Previous research explored the consumer preferences and valuation for both bioplastic packaging (Herbes et al. 2018; Klein et al. 2019; De Marchi et al. 2020; Wensing et al. 2020) and the absence of packaging (Fernqvist, et al. 2015; van Herpen et al. 2016; Marken and Hörisch 2019) in the food domain. However, most studies concentrate solely on one type of environmental-friendly packaging (Herbes et al. 2018). Scarce attention has been paid on the assessment and comparison of consumer acceptance for different sustainable packaging configurations (Herrmann et al. 2022). Therefore, further evidence on the interplay among multiple pro-environmental packaging solutions is needed.

Moreover, consumer pro-environmental choice behaviours have been traditionally investigated under the utility maximization decision rule, which postulates that people are rational and choose to maximize their expected utility. As a result, the vast majority of Discrete Choice Experiment (DCE) applied in literature makes use of the associated Random Utility Maximization (RUM) models (McFadden 1974) to analyse choice data. Nevertheless, different behavioural paradigms departing from utility maximization have been implemented so far to capture the cognitive aspects left out from this classic framework. Among the others, Chorus (2010) proposed the Random Regret Minimization (RRM) approach, the underlying assumption of which is that individuals act to minimize their anticipated regret. This mechanism relies on the anticipated emotion (i.e., regret) that may be experienced as a consequence of individual decision outcomes (Loomes and Sugden 1982). Regret arises when a foregone option outperforms the chosen one according to one or more attributes.

RRM models have been adopted in several research fields, yet there are only few applications in the food context (Biondi et al. 2019). Furthermore, to date, RRM models have never been used in the frame of sustainable food choices. In this situation, anticipated regret is suspected to afflict individual choices in a twofold manner. On the one hand, choosing the pro-environmental alternative may arise regret from the immediate benefits waived by discarding the anti-environmental alternative, e.g., the one with more convenience features or lower price (Zhang et al. 2021). Conversely, deciding for the anti-environmental option may generate regret due to the loss in potential long-term benefits for the environment and social welfare from not engaging in an environmental-friendly choice (Zhang et al. 2021). For this reason, we hypothesized that regret minimization could play a role in consumer decision-making process for sustainable foods, along with the well-established utility maximization paradigm.

Based on these premises, the primary objective of the study was to investigate how food consumers relatively value the provision of different pro-environmental packaging alternatives, namely the bioplastic packaging and loose format. Additionally, we aimed to understand consumer choice behaviour towards pro-environmental packaging alternatives, considering two different behavioural paradigms, i.e., utility maximization and regret minimization. Drawing upon these, we also intended to explore possible sources of heterogeneity in consumer preferences according to the choice mechanism followed by consumers.

The contribution of this study to the existing literature is twofold. Firstly, it provides new evidence on consumer acceptance of pro-environmental packaging options, whose deep knowledge is essential to achieve the market transition towards an alternative of sustainable solutions to the use of plastic packaging. A deeper understanding of the underlying decision mechanism for pro-environmental choices is expected to help the design of policy strategies aimed to address the effective reduction of plastic packaging waste. Additionally, we will derive implications for food companies that are interested in engaging in a more responsible use of plastics while remaining aligned to consumer demand to maintain profit. Secondly, this study expands food choice research by applying a behavioural paradigm different from the classic utility maximization approach to investigate consumer choices. Remarkably, our results elucidate on the need to embrace other perspectives as well, not simply limit to utility maximization, to fully comprehend the decision-making process of consumers for sustainable food attributes.

The remainder of this paper is organised as follows. The next section provides the background of this study, which relies both on the literature on consumer behaviour for sustainable packaging and the strand concerning the RRM framework. The following section describes the methodological approach adopted to conduct the study and the econometric analysis performed. The results are outlined in Sect. 4 and discussed in Sect. 5. Lastly, the closing section illustrates the conclusion and main implications stemming from this work.

2 Background

2.1 Consumer Preferences for Sustainable Food Packaging

2.1.1 Bioplastic Packaging

The conceptualization of sustainable packaging in consumer mind is largely dominated by material-related considerations (Lindh et al. 2016) and, consequently, by biodegradability, reusability, or recyclability issues (Herbes et al. 2018). Therefore, limiting the environmental impact of food packaging can be achieved by substituting plastics with more sustainable materials, such as bioplastics, or buying free- (or reduced-) packaging products (Fogt Jacobsen et al. 2022).

The possibility of replacing plastic with bioplastic materials has recently gained attention on the market (Wensing et al. 2020). According to European Bioplastics, the association representing the interests of the thriving bioplastics industry in Europe, bioplastic can be defined as any plastic that is either bio-based, biodegradable, or a combination of both. The term bio-based indicates that the material originates from biomass such as corn, sugarcane, or cellulose (European Bioplastics 2022). However, stemming from this definition, it is worth noting that bioplastics still contribute to the global waste production, as they are not always biodegradable despite being renewable (Rujnić-Sokele and Pilipović, 2017). Consistently, many consumers perceive bioplastic materials as the least sustainable alternative option to the traditional plastic (Herrmann et al. 2022). For instance, the study by Herbes et al. (2018) pointed out that biomethane-based packaging is not positively accepted among consumers because, on the one hand, it was presented as non-biodegradable and, on the other, it suffers from the lack of knowledge of people. The authors concluded on the prominent value placed by people on the biodegradability feature compared to the material being bio-based. Moreover, they outlined the importance of increasing consumer understanding and awareness of the biomass industry. Indeed, information provision seems to trigger consumers to select environment-friendly packaging. In this regard, De Marchi et al. (2020) observed the positive effect of information on consumer likelihood to choose the bioplastic packaging. Moreover, consumers were found to be willing to pay more for bioplastic bottled water with respect to the traditional plastic format. Similarly, Wensing et al. (2020) confirmed the presence of a premium for the bioplastic packaging presence and tested the effectiveness of different types of nudging, including information, in inducing the choice of bioplastic packaging option. Responses to nudges seem to depend on consumers' cognitive style. Intuitive decision-makers are more susceptible to label information or pictures, while information text or videos are more effective in increasing consumer willingness to pay for bioplastic among rational individuals. Other studies add to this by investigating further possible drivers and barriers of consumer acceptance for bioplastics. For instance, Russo et al. (2019) disclosed that individual, green self-identity mediates the relationship between the attitude and intention to purchase and switch to bio-based products. Klein et al. (2019) reported the importance of green consumer values in influencing the purchase intention for bioplastic products. Both works corroborate the positive relation between the individual ecological worldview and the preference for sustainable food attributes (see for instance, Steiner et al. 2017).

2.1.2 Loose Food

Less attention has been given so far to the unpackaged product strategy (Fuentes et al. 2019; Louis et al. 2021). The purchase of loose foods is a growing market trend (Rapp et al. 2017; Louis et al. 2021). Consumers are becoming increasingly concerned about their own waste production. Consequently, specific sections devoted to bulk product purchases are being installed in many supermarket chains (for example, Waitrose in United Kingdom, Albert Heijn in Netherlands, and Coop in Italy), along with the opening of grocery stores fully conceived for zero-packaging purchases (van Herpen et al. 2016; Rapp et al. 2017). However, a significant shift towards this specific pro-environmental behaviour requires substantial changes both from the supply- and demand-side (Marken and Hörisch 2019). Renouncing food packaging causes logistic and operational drawbacks for retailers, for instance, the need to consider the lack of the protective function of packaging during transport and distribution (Beitzen-Heineke et al. 2017). Instead, from the consumer perspective, potential limits include the reduction in consumer convenience and more time-consuming shopping (Beitzen-Heineke et al. 2017). Drawing upon a quantitative survey, Marken and Hörisch (2019) showed that the lack of awareness of the existing offer, the limited product-range available, and impracticality are the most relevant deterrents among consumers. Moreover, the study by Fuentes et al. (2019) stressed that the practice of package-free shopping is a completely different mode of shopping that requires a drastic reinvention of consumer habits. People are asked to acquire new competencies and change behaviours (e.g., reusing bags; jars and other containers that are to be brought with them to stores). However, in the context of difficult-to-break routines, materiality and norms may exert a key role in the adoption of new sustainable practices. Indeed, pro-environmental personal norms seem to be an important predictor of the packaging-free purchase behaviour (Fuentes et al. 2019). Furthermore, people perception and inclination towards this sustainable practice varies upon the food category being involved. For instance, Fernqvist et al. (2015) explored advantages and disadvantages of the presence of packaging in relation to fresh vegetable purchases by means of focus group interviews. Their qualitative analysis showed that familiar loose products, such as vegetables, hold a stronger position in consumer preferences with respect to their packaged counterpart. Respondents identified the possibility of buying only the desired amount, the lower price with respect to the packaged alternative, and the opportunity to select higher quality products as the main positive aspects favouring the purchase of bulk foods. Moreover, plastic packaging material was viewed negatively because of its environmental impact.

2.1.3 Comparison of Multiple Types of Packaging

Consumer relative appreciation for different types of packaging has received scarce attention in the scientific literature so far. Klaiman et al. (2016) explored consumer willingness to pay for several packaging materials and their recyclability. Their findings indicated that the least sustainable option, namely plastic, was preferred over the others, i.e., aluminium, glass, and carton. Nevertheless, consumers were willing to pay the highest premium for the recyclability of plastic, maybe due to a sort of compensatory effect arising from the awareness of the negative impact of plastic on the environment. Conversely, in the study by Friedrich (2020), innovative wood plastic composites, which constitute bio-based materials, were the most preferred compared to cardboard, PET, and aluminium. This result suggests that bioplastics can be a suitable substitute for plastic applications, notwithstanding the consumers' lack of any prior experience with the material.

Narrowing down to our case study, the work by Herrmann et al. (2022) is the only one focusing on the possible substitution of plastic packaging for food with either alternative material such as bioplastic, or through the availability of unpackaged option. They conducted DCE and qualitative text analysis to evaluate consumer willingness to pay and accept these strategies, along with other alternative materials (i.e., plastic, recycled plastic, and paper). Their findings revealed that bioplastic was the least preferred packaging alternative, whereas the unpackaged option ranked as the most preferred. Moreover, their qualitative analysis pointed out that respondents are strongly uncertain about the sustainability of bioplastic packaging, and, consistently, they are unwilling to pay more for this attribute. The authors emphasized that the general disagreement at the legislative and scientific level about what kind of packaging is actually sustainable exacerbates the possible confusion in consumer minds. However, consumer behaviour towards bioplastic packaging is still a controversial issue, as previously outlined before. Furthermore, their application considers only utility maximization as the underlying decision rule of consumer choices.

In this regard, our work expands the existing research in a twofold manner. Firstly, we provide additional evidence on the debate concerning individual acceptance for bioplastics and, more in general, towards the interplay among multiple pro-environmental packaging solutions. We hypothesized that, in contrast to the results of Herrmann et al. (2022), consumers are not drastically adverse to this kind of innovation rather tastes for bioplastics are heterogeneously distributed among consumers. Secondly, we incorporated an alternative behavioral approach in the analysis of sustainable food decisions an alternative behavioural approach: the RRM. We considered that individuals can behave by following diverse paradigms and that the application of distinct decision rules could possibly result in different preference structures. The aim is to provide insights on the preferences of different pro-environmental packaging solutions (i.e. loose and bioplastic) while simultaneously investigating the heuristics driving sustainable choices.

2.2 The Random Regret Minimization Framework

The RUM paradigm has been widely applied to achieve the two main objectives of choice modelling: predicting behaviour and eliciting individual willingness to pay and welfare measures (Hess et al. 2018). The fundamental axiom of this framework is that when discriminating among goods, individuals hold perfect information about the benefits and costs of their decisions and, consequently, choose what will provide them the highest utility, informally expressed as satisfaction (Savage 1954). However, behavioural economics and psychology drew attention on systematic deviations from purely rational behaviours (see for instance, Simon 1955; Kahneman and Tversky 1979; Thaler 2015). In this direction, Loomes and Sugden (1982) proposed the regret theory as an alternative to the expected utility theory. Regret theory has been extensively applied in the field of economics for risky choices. The underlying concept is that the individual's utility is not derived from the chosen alternative per se, but from the regret or rejoice experienced by comparing the chosen alternative to the forgone one. Regret arises when the forgone option is more desirable than the chosen one, whereas rejoice, as the opposite of regret, is felt if the selected option outperforms the non-chosen. The notion of regret as a determinant of choice behaviour has gained widespread attention in many research fields [for a detailed review see Thiene et al. (2012), Biondi et al. (2019)]. Recently, it has been incorporated in choice modelling by

Chorus (2010) through the implementation of RRM approach in discrete choice analysis. In this case, the behavioral assumption is that people choose to minimize their anticipated regret. Regret emerges from the process of trading off attribute-levels when making a decision (Chorus et al. 2014). According to this mechanism, a *regret minimizer* focuses on how the considered alternative compares to the competing ones in terms of every conceivable attributes, whereas a *utility maximizer* concentrates only on the performance of the considered option itself (Chorus 2012). For instance, considering the presence of the well-established attribute "no OGM" on a purchased candy bar, it would make the utility associated with the product increase, in absolute term, under the RUM rule; whereas it would lead to less anticipated regret as the non-chosen candy bars lack the claim according to the RRM framework.

Moreover, the shape of the regret function (see Sect. 3.4 for details) implies that the regret arisen from a loss (i.e., the chosen option performing poorer than the foregone) looms larger than the rejoice generated by a gain of the same magnitude (Chorus 2012). This asymmetry in the impact of losses and gains, along with the reference-dependency in the RRM framework, conceptually recalls prospect theory models (Kahneman and Tversky 1979) and the notion of loss aversion (Tversky and Kahneman 1991).[1] Furthermore, the RRM approach enables to capture semi-compensatory behaviour (in the sense that the better performance of one attribute of an alternative not necessarily compensate for an equally large decline in the performance of another attribute) and choice set composition effects (Chorus 2010, 2012; Chorus et al. 2014).

RRM models have been adopted in several fields, such as transportation (Hensher et al. 2016; Hess et al. 2014), healthcare choices (Boeri et al. 2013; De Bekker-Grob and Chorus 2013), environmental resources (Thiene et al. 2012), and energy programmes (Boeri and Longo 2017). In the food choice context, Biondi et al (2019) firstly introduced the application of RRM approach by focusing on a situation of anticipated social approval about a special food choice. They provided evidence that RRM model returns estimates consistent to the RUM counterpart and is not inferior in terms of goodness of fit and predictive ability, thus suggesting the effective application of RRM models to the decision-making process for foods. Moreover, their findings indicated that, based on differences in personality traits, the choice mechanism may vary among consumers. Drawing upon this study, we decided to extend RRM applications in the field of choices for sustainable foods, specifically for pro-environmental packaging alternatives. We approached our case study from a double behavioural perspective by incorporating possible heterogeneity among consumers according to the choice mechanism adopted.

3 Material and Methods

3.1 The Choice Experiment

To assess consumer preferences for sustainable packaging under different behavioural frameworks, we conducted a hypothetical DCE. This method has been extensively applied to elicit consumer preferences for food attributes (see, for instance, Butler and Vossler

[1] The reference points of RRM are given by the attribute level of non-chosen options, while the reference points of prospect theory are determined by the status quo.

Table 1 Experimental design

Alternatives	
Loose	
Plastic packaging	
Bioplastic packaging	
Attributes	*Levels*
Organic label	Presence, Absence
Price (€/500gr)	1.39, 1.89, 2.39, 2.89

2018; Hilger et al. 2019; Muller et al. 2019; Boncinelli et al. 2021; Piracci et al. 2022). Data were collected by applying a cross-sectional online survey incorporating the DCE among Italian consumers. The questionnaire was delivered in March 2021 by means of a panel recruitment agency (Pollfish).

We choose fresh cherry tomato as the reference product for the DCE since vegetables can be commonly found either loose or packaged in the market. Moreover, tomatoes are the most consumed fresh vegetables in Italy (ISMEA 2017). Accordingly, the target population for the experiment consisted of tomato consumers over 18 years of age, i.e., the legal age in Italy. Therefore, respondents who declared to never consume tomatoes (1%) were screened out from the survey. In total, we gathered 395 full responses.

We implemented a labelled design, as reported in Table 1, meaning that the alternatives of the product correspond to the three different packaging formats: loose, plastic packaging, and bioplastic packaging tomatoes. For the remaining attribute selection, we proceeded in a twofold manner. We considered the most common tomato attributes in the Italian market. On the other hand, we took also into account the most valuable tomato characteristics in the consumer decision-making process according to the literature (Alphonce and Alfnes 2017; Printezis and Grebitus 2018; De Salvo et al. 2020; Wensing et al. 2020). Therefore, we decided to include the organic certification (absence, presence) and price (1.39, 1.89, 2.39, 2.89 €/500 g) in the experimental design. The price levels were chosen to represent the Italian market price range for fresh cherry tomatoes at the time of the study. In addition, to improve the realism of the choice situation while preserving the ease of the choice task, the origin and weight attributes of tomatoes were included in each choice scenario but kept fixed across all the alternatives. Therefore, respondents were asked to make hypothetical buying decisions for 500 g of fresh cherry tomatoes of Italian origin.

Before answering the choice tasks, respondents were provided with detailed instructions and a cheap talk script with a budget constraint reminder as an ex-ante mitigation strategy to the hypothetical bias (Cummings and Taylor 1999). To favour the careful reading of these pieces of information, people were forced to remain in the instruction section for one minute before they were allowed to continue through the survey. Moreover, the alternatives within each choice task, as well as the choice tasks, were randomized among respondents to limit possible ordering effects.

3.2 Experimental Design

The attributes and attribute levels were allocated among the three alternatives applying a Bayesian D-efficient approach (Sándor and Wedel 2001; Scarpa et al. 2007) to reduce the number of choice tasks faced by respondents and avoid fatigue effect. The experimental

Fig. 1 Example of choice task

design was optimised for multinomial logit models and based on a main-effects utility function.

Van Cranenburgh et al. (2018) stressed that traditional RUM efficient designs proved to perform poorly if the prevailing decision rule underlying choice behaviours is based on regret minimization. Unfortunately, the application of RRM is rare between food behaviour studies, and, thus, we have a poor empirical evidence to make any a priori assumption on the true behavioural paradigm applied by decision-makers when purchasing food. Therefore, we generated a decision-rule robust design (van Cranenburgh and Collins 2019; van Cranenburgh et al. 2018) that simultaneously allows estimating RUM and RRM models. The chosen design is still the one minimizing the D-error as in traditional designs. However, in this case, the D-error statistics is constructed as the weighted sum of the D-errors associated with the different specifications of the model, one per behavioural rule. The resulting composite efficiency measure incorporates the probability of each decision rule being the best fitting model to describe individual choice behaviours (van Cranenburgh and Collins 2019; van Cranenburgh et al. 2018). We set the weights for the decision rules to be equal. The Bayesian priors were generated from a pilot study conducted on a sample of 108 respondents. The design was constructed using the software Ngene (ChoiceMetrics 2018).

The final experimental design consisted of 12 choice sets blocked in three groups. Therefore, participants faced 4 choice tasks, each including the three labelled tomato alternatives. Figure 1 shows an example of the choice task (Instructions and descriptionsin the original choice tasks were in Italian).

We applied a forced-choice format, meaning that respondents were not provided with the opt-out option as in many previous experiments (see, among the others, Aoki et al. 2019; Costanigro et al. 2014; Gerini et al. 2016; Scarpa et al. 2021). This methodological decision was based on the following reasons. Since the RRM approach is based on pairwise comparison between the alternatives for each of their shared attributes, the model performs poorly in discrete choice analysis in the presence of a no-choice option. This is due to the fact that such alternative is not described in terms of any relevant attribute, and it, thus, cannot be compared to other alternatives at the attribute level (Chorus 2012; Thiene et al. 2012). Moreover, Hess et al. (2014) demonstrated that depending on the framing of the opt-out option as either "none of these" or "indifferent", the performance of RRM or RUM, respectively, are expected to deteriorate. Therefore, excluding the opt-out allowed us to prevent such risks as we were going to apply both modelling approaches simultaneously.

Even if the inclusion of an opt-out option is a common practice in DCE designs, this methodological choice should be taken in light of the objective of the study rather than set by default (Hensher et al. 2015). For instance, the presence of the no-buy alternative is required when the focus of the study is to estimate the consumer demand for the product in absolute term (Haaijer et al. 2001; Dhar and Simonson 2003; Carlsson et al. 2007; Hensher et al. 2015).[2] We were confident that removing the no-buy option from the experimental design as it does not affect the preference ordering (Carlsson et al. 2007), and our main research objective was to assess the impact of the different alternatives on consumer choice and the underlying mechanism driving the decision-maker behaviour rather than eliciting the willingness to pay for the alternatives.[3]

3.3 The Survey Instrument

The survey opened with the DCE. After completing the 4 choice tasks, respondents were asked several further questions. First, consumers' pro-environmental orientation was measured through the 15-item version of the New Environmental Paradigm (NEP) scale developed by Dunlap et al. (2000). Participants provided their level of agreement with statements concerning the relationship between human beings and the earth and nature (e.g., "We are approaching the limit of the number of people the earth can support", "Humans have the right to modify the natural environment to suit their needs"). Responses were scored on a 5-point Likert scale from strongly disagree to strongly agree. The items are phrased such that the agreement with the eight odd-numbered items and the disagreement with the seven even-numbered ones signals a proecological worldview (Dunlap et al. 2000). Therefore, the even statements were reversed. We aggregated the answers into one single measure, following Steiner et al. (2017), and a higher total score indicated a stronger propensity towards pro-environmental attitudes and beliefs. Cronbach's alpha for the scale was 0.79, confirming the reliability of the scale.

Furthermore, we assessed the consumer concern for the plastic pollution issue through the items "to what extent do you think the plastic pollution is serious?" and "to what extent do you think you are worried for the plastic pollution?". Additionally, the consumer belief about the benefits of the use of bioplastic was collected through the question "to what extent do you think that bioplastic can be helpful to tackle the plastic pollution issue?". All responses were provided on a Likert scale ranging from 1 (not at all) to 5 (a lot). Lastly, we collected the socio-demographic characteristics of the sample.

3.4 Econometric Analysis

We assumed that consumers choose one of the packaging options either maximizing their own utility, i.e., following the classical RUM paradigm, or minimizing their anticipated regret, i.e., according to the RRM behavioural approach. The linear-additive utility

[2] For a deeper discussion on the inclusion or exclusion of the opt-out alternative, the reader can refer to Carlsson et al. (2007) and Kallas et al. (2013).

[3] After each choice task we included in the survey a follow up question to ask respondents if they would have confirmed their selection or preferred not to buy anything. In 31 over 1580 choices (2%) respondents declared that they would have opted for the no-buy alternative. To test the robustness of our results we run all the analysis excluding these 31 observations and we did not detect any difference from the estimates on the whole sample. The additional results are available upon request.

function underlying the RUM modelling framework can be written as follows (Thurstone 1927; Marschak 1960):

$$U_i = V_i + \varepsilon_i = \alpha_i + \boldsymbol{\beta}' \boldsymbol{X}_i + \varepsilon_i \tag{1}$$

where U_i is the utility the decision-maker n gains from alternative i, V_i is the deterministic portion of utility, ε_i is the stochastic component, α_i is an alternative-specific constant indicating the utility for each alternative i (i.e., loose tomatoes, plastic packaged tomatoes and bioplastic packaged tomatoes), X_i is the vector of attributes describing the alternative i and β is the vector of the associated estimated parameters. As per McFadden (1974), assuming that the errors are independent and identically distributed (i.i.d.) Extreme value type I distributed, the choice probability is derived through a Multinomial Logit (MNL) specification (RUM-MNL):

$$P_i^{RU} = \frac{e^{V_i}}{\sum_{j=1}^{J} e^{V_j}} \tag{2}$$

Likewise, the overall regret postulated in the RRM modelling approach Ψ is made up of a systematic portion of the regret R and a random error component δ. Van Cranenburgh et al. (2015) proposed the μRRM model as a generalization of the classical RRM model first introduced by Chorus (2010). This model allows the μ parameter to be estimated along with the alternative specific constants γ and the preference weights ρ_m. The regret function of the μRRM model is given by (Chorus 2012, p. 36; van Cranenburgh et al. 2015, p.97):

$$\Psi_i = R_i + \delta_i = \sum_{j \neq i} \mu \ln\left(1 + \exp\frac{1}{\mu}\left[\gamma_j - \gamma_i\right]\right) + \sum_{j \neq i} \sum_{m=1}^{M} \mu \ln\left(1 + \exp\frac{\rho_m}{\mu}\left[x_{jm} - x_{im}\right]\right) + \delta_i \tag{3}$$

The observed part of the regret is conceived as the sum of all so-called binary regrets associated with the pairwise comparison between the considered alternative i and each competitor alternative j in terms of the regret associated with each alternative and for all attributes M. R_i maps the differences between the alternatives $(\gamma_j - \gamma_i)$ and the attribute levels of the alternatives $(x_{jm} - x_{im})$ onto regret. ρ_m captures the slope of the regret function for attribute m and reflects its relative contribution to the regret. Moreover, μ determines the shape of the regret function and indicates the profundity of the regret, which refers to the degree of regret aversion in choice behaviour. It provides information about the extent to which the choice is driven by the relative importance between losses (regret) and gains (rejoice). In case μ equals one, the μRRM model shrinks to the classical RRM model. Estimating μ larger than one implies a mild profundity of the regret; specifically, when μ approaches infinity, the model provides the same choice probabilities as its RUM counterpart: regret and rejoice are equivalent. Conversely, if μ is smaller than one, the individual degree of the regret aversion is higher than that ascribed to the classical RRM. Lastly, if μ tends to zero, only regret matters and rejoice is irrelevant; in this case, the model collapses into the Pure RRM (PRRM) model (van Cranenburgh et al. 2015).[4]

[4] As underlined by Boeri and Longo (2017) and Geržinič et al. (2021), the μ parameter in the μRRM model should not be confounded with the μ scale parameter related to the variance of the error term in RUM models.

Assuming that the negative of the error component is i.i.d. extreme value type I distributed and that minimizing the random regret is mathematically equivalent to maximizing its negative, the choice probability can be estimated as a Multinomial Logit (μRRM-MNL):

$$P_i^{RR} = \frac{e^{(-R_i)}}{\sum_{j=1}^{J} e^{(-R_j)}} \tag{4}$$

The MNL models were specified to recognize the panel structure of the data by multiplying the probabilities across individual choice observations for the same individual. However, MNL models still assume homogeneity in preferences across respondents. To relax this assumption, we applied two different approaches, accounting for the different sources of heterogeneity, as proposed by Boeri and Longo (2017). First, we specified a Random Parameter Logit (RPL) model. This model allows us to investigate how taste variability affects consumer choices. Specifically, the coefficients of the attributes and alternatives are allowed to vary randomly across the individuals according to continuous probability distribution functions. RUM-RPL is derived by integrating the logit probabilities over the distribution of β (Train 2009). Consistently, we implemented the equivalent model, μRRM-RPL, within the RRM framework, as described by Boeri and Masiero (2014). In both cases, all the taste parameters were specified as normally distributed, except for the price, which was considered to follow a constrained (one-sided) triangular distribution. This distribution is consistent with economic theory (demand curve slopes downward) and its use is supported by many previous applications (e.g., Scarpa et al. 2013; Van Loo et al. 2020; Ortega et al. 2022). Furthermore, we implemented the posterior analysis of the random taste coefficients to investigate the estimated and conditional distributions across the RUM and RRM specifications, as per Hess (2007) and Train (2009).

In addition, to accommodate for the heterogeneity in the decision rule applied within the sample, we assumed to observe a mixture of RUM-driven choices and RRM behaviours rather than treat all the choices as based on either utility or regret. To this end, we estimated a two-class Latent Class (LC) model where the class embeds the behavioural approach underlying the choices of the respondents, following Hess et al. (2012). The LC model is the semi-parametric version of a mixed model in which the heterogeneity is modelled as discrete in C mass points, with C being the number of classes. In this case, each class represents a group of consumers, categorized in a way that the decision rule is homogeneous within the segment, whilst heterogeneous between the segments. Therefore, one class consists of RUM decision-makers, whilst the other is made up of people behaving consistently with the RRM paradigm. The probability that individual n belongs to class c can be modelled as a MNL (Greene and Hensher 2003), as follows:

$$\pi_{nc} = \frac{e^{(\alpha_c)}}{\sum_{c=1}^{C} e^{(\alpha_c)}} \tag{5}$$

where α_c is the class-specific constant. For identification purposes, only the C−1 set of constants can be independently identified, one must be normalized to zero and act as the reference level.

Choice probabilities are defined according to an RPL model to account for taste heterogeneity. Therefore, the probability, P_i, that individual n chooses alternative i, unconditionally on the class he belongs to, is obtained as:

$$P_i = \pi_v \int_{\beta} P_i^{RU} f(\boldsymbol{\beta}) d\boldsymbol{\beta} + \pi_r \int_{\rho} P_i^{RR} g(\boldsymbol{\rho}) d\boldsymbol{\rho} \quad (6)$$

where $\pi_r = (1 - \pi_v)$ and π_v and π_r are the membership probabilities for the RUM and RRM classes, respectively.[5] All random parameters are assumed to be normally distributed except for the price which is specified as one-sided triangular. The probability integrals do not have closed-form solution and are simulated using the maximum likelihood. All models were estimated specifying 1000 Modified Latin Hypercube Sampling draws (Hess et al. 2006). The analyses were performed through the Apollo package in R (Hess and Palma 2019).

4 Results

4.1 Description of the Sample's Characteristics

The sample's characterization in terms of socio-demographic information and personal features is reported in Table 2. Females were slightly predominant in the sample (56.96%), while the median age of the respondents was 38. Regarding education, 54.43% of the sample held a university degree or a higher education degree, 37% held a high-school diploma, and the remaining had completed middle school. Considering the income, about 50% of the sample stated to have a low income, 26% reported a medium income, 4% declared they had a high-income level, and 20% preferred not to disclose this information. Furthermore, concerning their consumption habits, more than half of respondents (66.33%) stated to consume cherry tomatoes at least once a week or more, whilst 26.33% stated they consume the product once or twice per month. On the other hand, only a few respondents (7.34%) stated to consume cherry tomatoes less than once a month or rarely. A substantial proportion of the respondents (18.48%) were on vegan or vegetarian diet regimes, and the vast majority of the sample (89.87%) was responsible for the grocery shopping in the household. Moreover, the respondents were highly concerned about plastic pollution and believed in the positive contribution of bioplastics in tackling this issue. Accordingly, the participants showed high pro-environmental orientation.

4.2 Discrete Choice Experiment Results

The majority of the previous studies applying the RRM framework have focused on the MNL form. Therefore, to present our findings, we aligned to the traditional literature approach, starting from the MNL outcomes. In all the models, the alternative specific constant for the plastic option is normalized to zero due to identification purposes.

Table 3 reports the model estimates for RUM-MNL and RRM-MNL. As expected, the coefficient signs are consistent in both RUM and RRM specifications, confirming the robustness of the results. In terms of goodness of fit, the RUM version fits the data slightly better than its RRM counterpart, as indicated by the Log-Likelihood, Akaike Information Criterion, and Bayesian Information Criterion. Nonetheless, the difference between the

[5] For a deeper econometric description of the Latent Class model, the readers can refer to the works of Hess et al. (2012) and Boeri et al. (2014).

Table 2 Socio-demographic characteristics and personal traits and habits of the sample (n = 395)

Variable	n	%
Gender		
Female	225	56.96
Male	170	43.04
Class age		
18–24	62	15.7
25–34	108	27.34
35–44	96	24.3
45–54	84	21.27
> 54	45	11.39
Education		
Middle school	33	8.35
High school	147	37.22
Bachelor degree or higher	215	54.43
Income		
Low income	197	49.87
Medium income	101	25.57
High income	18	4.56
Not disclosed	79	20.00
Consumption frequency of cherry tomatoes		
Once per week or more	262	66.33
Once or twice per month	104	26.33
Less than once per month	14	3.54
Rarely	15	3.80
Vegan or vegetarian diet	73	18.48
Responsible for food purchase	355	89.87
Concern for plastic pollution issue—mean, SD	4.34	0.73
Belief in the benefits of the use of bioplastic—mean, SD	3.73	0.93
Pro-environmental attitude—mean, SD	3.81	0.53

SD standard deviation

two models can be considered negligible, as suggested by the rho-squared values (0.14 for RUM-MNL and 0.14 for RRM-MNL). Since the models were estimated assuming two different paradigms, the coefficients cannot be compared, as the interpretation differs.

Under the traditional RUM setting, the alternative specific constants indicate the utility of each packaging alternative relative to the plastic option. The coefficients for the loose and the bioplastic attribute are both statistically significant and positive, meaning that the consumers' utility increases when they buy products wrapped in pro-environmental packaging alternatives instead of products wrapped in plastic packaging, *ceteris paribus*. The coefficient of organic is not statistically significant, suggesting that the presence of the label does not affect consumer choices for tomatoes. Conversely, the price coefficient is statistically significant and negative. This reflects a decrease in utility with increasing price, which is consistent with the economic theory.

On the other hand, the RRM estimates signal the potential contribution of the alternatives and the attributes to regret. The regret parameter is significant and smaller than

Table 3 RUM-MNL and μRRM-MNL model estimates

	RUM-MNL		μRRM-MNL	
	Coeff	Std. err	Coeff	Std. err
Loose	1.03***	0.07	0.73***	0.05
Bioplastic	0.80***	0.08	0.21**	0.09
Organic	0.05	0.05	0.08**	0.04
Price	− 0.68***	0.04	− 0.56***	0.04
μ			0.74**	0.38
Log-likelihood	− 1488.04		− 1488.94	
Adjusted Rho-squared	0.14		0.14	
Akaike information criterion	2984.08		2987.88	
Bayesian information criterion	3005.54		3014.71	
Parameters	4		5	
Choices	1580		1580	

(***) and (**) indicate significance at a 1% and 5%, respectively. Coeff. denotes coefficient, and Std. err. means standard error

one signalling a considerable degree of regret aversion in the sample. The alternative specific constants capture the average of the unobserved regret associated with that alternative compared to the reference level, namely the tomatoes packaged in plastic. Therefore, the positive and statistically significant coefficient of the two sustainable packaging alternatives indicates that not choosing them will lead to significantly higher anticipated regret than the regret associated with the plastic packaging option. A positive and significant coefficient of the organic attribute means that the regret increases as the attribute is present in a non-chosen competing alternative but absent in the chosen option. Moreover, the negative and significant coefficient of the price attribute means that regret decreases as the non-considered alternative becomes more expensive than the selected option. As regards the packaging alternatives, the two models provide similar qualitative descriptions of the consumers' preferences. Under both paradigms, the loose alternative ranks higher than the bioplastic one, and the plastic tends to be discarded. However, the results differ for the organic coefficient which is not significant under the RUM and significant following the RRM rule.

We estimated the RPL models to account for the heterogeneity in tastes among the consumers. Results are presented in Table 4. The preference structure for the alternatives is similar to that found in the MNL specifications. The loose tomatoes are the most valuable format for the consumers, followed by the bioplastic option, whereas the plastic alternative is the least preferred. The standard deviations of the constants are highly significant, indicating high variability in preferences for sustainable packaging formats, namely the loose and the bioplastic. Furthermore, under both paradigms, the mean and standard deviation of the organic coefficients are not significant, reflecting that the attribute did not affect buying decisions for cherry tomatoes. The regret parameter in the μRRM-RPL model is also not significantly different from zero, which indicates a high degree of regret aversion in the sample. Only regret drives consumer behaviour, whereas rejoice associated with choice is irrelevant.

Based on the RPL estimates, we derived the predicted market share for each packaging alternatives under both decisional paradigms. The two models provided the same results.

Table 4 RUM-RPL and μRRM-RPL model estimates

	RUM-RPL		μRRM-RPL	
	Coeff	Std. err	Coeff	Std. err
Loose	1.13***	0.12	0.75***	0.08
Bioplastic	0.82***	0.11	0.54***	0.07
Organic	0.08	0.07	0.05	0.04
Price	−0.51***	0.03	−0.35***	0.02
μ			1.33×10^{3}	1.58×10^{4}
Standard deviation of random parameters				
Loose	1.67***	0.15	1.12***	0.10
Bioplastic	1.27***	0.15	0.85***	0.10
Organic	0.02	0.05	0.01	0.11
Price	0.51***	0.03	0.35***	0.02
Log-Likelihood	−1376.11		−1374.67	
Adjusted Rho-squared	0.14		0.14	
Akaike Information Criterion	2766.22		2765.33	
Bayesian Information Criterion	2803.78		2808.26	
Parameters	7		8	
Choices	1580		1580	

(***), (**) and (*) indicate significance at 1%, 5% and 10% respectively; Coeff. denotes coefficient, and Std. err. refers to standard error

Table 5 Summary statistics for estimated distributions and distributions of conditional means for the taste coefficients

	RUM-RPL		RRM-RPL	
	Loose	Bioplastic	Loose	Bioplastic
Estimated				
Mean	1.13	0.82	0.75	0.54
SD	1.67	1.27	1.12	0.85
Conditional means				
Mean	1.13	0.82	0.76	0.54
SD	1.24	0.79	0.83	0.54
Min.	−1.42	−1.04	−0.91	−0.67
Max.	3.21	2.46	2.14	1.65
Perc. > 0	77.72	88.61	76.96	88.10

SD denotes Standard Deviation; Min. denotes minimum; Max. denotes maximum, and Perc. denotes percentage

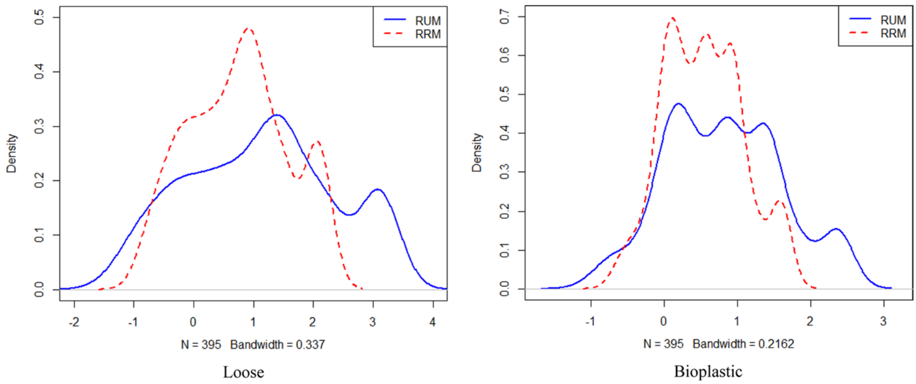

Fig. 2 Comparison of the kernel densities of the conditional means distributions between RUM and RRM

The predicted market share of the loose product is the largest (46%), followed by the bioplastic option (38%) and the plastic-packaged alternative (16%).

The two RPL models were used to compute the individual conditional distributions for the loose and bioplastic random taste coefficients.[6] The summary statistics of the distributions of the conditional means across the 395 respondents are listed in Table 5 along with the corresponding statistics for the estimated distributions. The mean values for the two coefficients are almost exactly the same whether considering the conditional or estimated distributions, in both the RUM and RRM. The range variation for the estimated distributions is unbounded considering a normal distribution, whereas for the distribution of the conditional means, the range is much narrower. Indeed, the standard deviations of the conditional means are significantly lower in RUM as well as in RRM. These occurrences are expected for a correctly specified and consistently estimated model (Train 2009).

A further comparison between the two RPL models is displayed in Fig. 2, using the kernel densities estimated on the conditional mean distributions of the loose and bioplastic coefficients. In addition to presenting the same shape, the RUM distributions tend to be less spread and report shorter tails around the mean values than the RRM curves. The proportion of the distribution in the negative domain for both attributes is similar across RUM and RRM: 22.28% vs 23.04% for the loose coefficient and 11.39% vs 11.90% for the bioplastic coefficient. This indicates that the part of respondents who would experience a loss of utility from choosing a pro-environmental packaging option is close to the share experiencing a decrease in regret when opting for a sustainable format.

To consider further sources of heterogeneity, we allowed for the coexistence of different decision-making processes within the sample. To this end, we applied an LC modelling approach with one class per behavioural rule and incorporated random taste heterogeneity within each class. Table 6 provides the results. In both classes, the coefficient estimates for the packaging alternatives are consistent with the findings from the MNL and RPL models. Both the loose and the bioplastic options are chosen over the plastic alternative. In the

[6] The organic coefficient was not considered for the posterior analysis as the mean and standard deviation resulted not significantly different from 0. The price, instead, was not included as assumed to follow a constrained triangular distribution. Only normally distributed coefficients allow us to derive general conclusions comparing the results obtained from the estimated and conditional distributions (Hess 2007).

Table 6 LC model estimates

	Class 1		Class 2	
	RUM class		μRRM class	
	Coeff	Std. err	Coeff	Std. err
Loose	1.41***	0.33	0.76***	0.12
Bioplastic	0.68**	0.27	0.71***	0.11
Organic	0.09	0.19	0.01	0.03
Price	0.01	0.03	−0.95***	0.08
μ			4.90×10^2	7.28×10^2
Standard deviation of random parameters				
Loose	3.13***	0.48	0.74	0.19
Bioplastic	2.39***	0.39	0.40	0.11
Organic	0.90***	0.27	0.02	0.09
Price	0.01	0.03	0.95***	0.08
Intercept	–		−0.02	0.05
Class membership probability	0.51		0.49	
Log-likelihood	−1324.75			
Adjusted Rho-squared	0.17			
Akaike information criterion	2681.50			
Bayesian information criterion	2767.34			
Parameters	16			
Choices	1580			

(***), (**) and (*) indicate significance at a 1%, 5% and 10% respectively. Coeff. denotes coefficient, and std. err. denotes standard error

RRM class, the loose is slightly preferred over the bioplastic. On the other hand, in the RRM class, the preference ranking is more pronounced. The loose coefficient is, indeed, almost twice the bioplastic's. This indicates that for the consumers who choose by minimizing their regret, the loose alternative is not as important as it is for those driven by the maximization of their utility. Another difference is that the price attribute is not influential in the decision-making process of the RUM respondents, whilst it significantly affects buying decisions for the RRM class as seen in the magnitude and significance of the estimated coefficient. Therefore, the LC model provided evidence for several discrepancies in individual behaviours that would have not been captured by considering homogeneity in the decision rule underlying choices, as assumed in the MNL and RPL approaches. The class allocation probabilities show that choices for cherry tomatoes are almost equally explained by the utility maximization tendency (51%) and the regret minimization paradigm (49%). Furthermore, the regret parameter of the RRM class is not significantly different from zero reflecting a high degree of regret aversion among the individuals included in this group. Through the posterior class allocation probabilities estimated with the LC model, we further inspected the pro-environmental attitude of each class.[7] The RRM class displays,

[7] We were not able to include the pro-environmental attitude or socio-demographic information of respondents as class membership predictors since the estimation process did not converge.

on average, a higher pro-environmental attitude (3.92) than its RUM counterpart (3.73), ($t = -3.59$, $P < 0.001$).

5 Discussion

In evidence, this study introduces the RRM framework in the context of sustainable food choices. The outcomes from the RRM models (MNL and RPL specifications) proved to be consistent from an empirical perspective, as they provide the same preference structure as the RUM models, coherently with previous applications (see, for instance, De Bekker-Grob and Chorus 2013; Boeri and Longo 2017; Mao et al. 2020). This can be seen as a sign of robustness for the resulting managerial and political implications (Thiene et al. 2012; Boeri and Masiero 2014).

Our findings indicate that the pro-environmental packaging options in the food context, namely the absence of the packaging and the presence of bioplastic packaging, are valuable among consumers. These alternatives were always preferred to the plastic option, and both the investigated behavioural paradigms confirmed this. Furthermore, the observed preferences for the sustainable packaging alternatives were considerably heterogeneous across the sample. These outcomes are corroborated by van Herpen et al. (2016), De Salvo et al. (2020), and Kocak Yanik et al. (2020), who previously observed the positive inclination of consumers towards unpackaged vegetables. In line with our results, De Marchi et al. (2020) and Wensing et al. (2020) pointed out that consumers are willing to pay premium prices for bioplastic-packaged products. However, our results are partially in contrast with Herrmann et al. (2022), who reported that consumers need an incentive to accept buying bio-based packaged foods since they elicit a negative willingness to pay for the attribute. A reason for this can be that their consumer sample was found to be strongly uncertain about the sustainability of bioplastic packaging and declared to perceive it as the least sustainable packaging format alternative to plastic packaging. Conversely, our sample, on average, exhibits a positive perception of this material and its beneficial contribution to mitigating the plastic pollution issue.

Accounting for the heterogeneity in the consumers' decision-making processes allowed us to capture different behavioural patterns among the respondents. The loose format was highly important among those who choose to maximize their utility. A plausible motivation for this behaviour can be rooted in the consumer prerogative of quality control during the purchasing phase. Unpackaged vegetables allow consumers to discriminate and choose according to search attributes (e.g., colour, size, appearance, physical defects, and degree of ripeness), which are considered extremely relevant during the buying stage (Ragaert et al. 2004). This seems to justify why the loose option is strongly preferred by those driven by the utility they can directly gain from their chosen alternatives. Moreover, a loose alternative implies no packaging disposal and is perceived by consumers as a more sustainable option (Herrmann et al. 2022). Accordingly, the class of utility maximization decision-makers was found to include respondents with a higher degree of environmental consciousness. This supports the findings of Boeri and Longo (2017), illustrating that being involved in environmental organizations makes a respondent more likely to behave according to the utility maximization paradigm rather than the regret minimization rule.

On the other hand, the regret minimization class appreciated both sustainable packaging alternatives, and the loose format was not strongly prevalent over the other. It appears that the consumers belonging to this group placed particular emphasis on the price attribute, which was found to be remarkably influential in driving their choice behaviours. We would conclude that the RRM decision-makers consider the economic outcomes related to their food choices as determinant. These empirical findings are consistent with the general notion that the minimization of the anticipated regret is a pivotal driver when the choice is perceived by the individual-as important or difficult (Zeelenberg and Pieters 2007), such as the budget evaluations for food expenditure. Our results related to the price parameter corroborate those obtained in the hybrid LC approach applied by Boeri and Longo (2017), reporting a non-significant coefficient for the RUM class and a significant value for the RRM class.

Without considering the heterogeneity in the decision rule within the sample, our results would have not captured the differences in the choice patterns among the consumers. Most notably, when allowing for the coexistence of multiple behavioural paradigms, we found that a considerable share of the choices (49%) are consistent with the RRM mechanism. The presence of a balanced proportion of RRM and RUM decision-makers has been previously observed also in the context of choices for air quality improvement policies (Mao et al. 2020), renewable energy programmes (Boeri and Longo 2017), and traffic calming projects (Boeri et al. 2014). Therefore, our findings corroborate the idea that the utility maximization rule should not be regarded as the only driver of consumer choices in all possible choice contexts.

Notwithstanding the contributions of the current study, the following limitations should be considered. Firstly, our LC approach incorporates both the decision rule and taste heterogeneity. We did so as these two sources of variability cannot be independently assessed. Furthermore, the model assumes all the choices as being taken following either the RUM or RRM paradigm, not allowing for the existence of other behavioural mechanisms or a mixture of the two. We acknowledge that this is a strong assumption. However, our aim was to propose a more flexible approach than that commonly applied, that is, to consider only utility maximization. We did not intend to demonstrate that individual choices can be exclusively regarded as being driven by either regret or utility. Further research could investigate the adoption of decision rules other than RRM or RUM, and assess how these different behavioural mechanisms guide individuals' decision-making. In addition, it would have been valuable if we had included the WTP analysis and assessed the difference between RUM- and RRM-based welfare measures. Nonetheless, these aspects were not consistent with the research objectives as well as already been addressed in previous research [as extensively treated in Chorus et al. (2014), Dekker (2014)].

Second, we relied on a hypothetical stated preference method. Hypothetical DCEs are known to suffer from hypothetical biases that may lead to misrepresented results. Further studies may apply incentive-compatible methods (e.g., real choice experiments and experimental auctions) or scanner data to support our findings and elicit the consumers' willingness to pay for sustainable packaging formats. The market shares retrieved from our experiment could eventually be compared with the actual market shares to prove the validity of our results. Third, to investigate preferences for different pro-environmental packaging options, we centred the experiment on tomatoes. This methodological choice derives from the evidence that consumers are used to the presence of fruits and vegetables without packaging since these items are commonly available in the market in bulk. Therefore, our results need to be interpreted as behaviours towards the absence or presence of packaging in the context of learned preferences (van Herpen et al. 2016). People might have reacted differently if they had been asked to make purchase decisions for other less common, unpackaged foods. The next step in research might be to understand the effect of the absence of packaging, considering other food categories that were only recently introduced as loose (e.g., pasta, cereals, and beans). Furthermore, in our study, we concentrated on preferences for the bioplastic packaging without incorporating how this should be signalled to the consumers to make it recognizable. Possible research directions could test the effectiveness of labelling and information provision in increasing consumer acceptance of this new alternative to plastic. Lastly, the extent to which the packaging strategies considered in this experiment should actually be acknowledged as more sustainable than plastic is still a controversial debate. For instance, in the case of loose food, the literature is not concordant on whether it is more important to reduce packaging production or minimize the risk of food spoilage (Beitzen-Heineke et al. 2017). Nevertheless, the broad array of bioplastics gives rise to a conspicuous list of adverse effects threatening sustainability, such as competition with food production, hygienic issues, or problems in waste management, depending on the renewable sources they originate from (European Commission 2018; Rujnić-Sokele and Pilipović, 2017). Although these considerations are positioned far beyond our research's scopes, further evidence from Life Cycle Assessment studies on food packaging is required to investigate the "degree of sustainability" of the different packaging options available that can be alternatively utilised to gradually substitute plastics.

6 Conclusion

The transition of the food industry towards more sustainable patterns has been increasingly advocated in political and academic debates (Phelan et al. 2022). Tackling the plastic pollution issue, this study investigated consumer acceptance of multiple pro-environmental packaging strategies under different behavioural rules by conducting a DCE. Overall, our findings reveal that consumer tastes are variable and that preference patterns change, depending on the behavioural paradigm assumed by an individual. In other words, we found that the heterogeneity in consumer choices lies in at least two different dimensions: taste and decision rule.

Consumers following the utility maximization mechanism attach great importance to the possibility of buying loose vegetables instead of plastic-packaged products. Moreover, they also exhibit a positive, albeit less pronounced, orientation towards the use of bioplastic packaging. Rather, individuals choosing according to the regret minimization process similarly value the provision of both sustainable packaging options. Surprisingly, a considerable proportion of the sample (49%) adopted the RRM decision rule in the context of sustainable food choices.

Our results provide both practical and policy implications. First, the study supports the idea that promoting pro-environmental packaging strategies as substitutes for plastic applications can contribute to limiting the environmental impact of the food system, since consumers were positively prone to their application. Several food companies tend to ignore plastic pollution in their sustainability agenda (Beitzen-Heineke et al. 2017). Moreover, they mention only waste management and recycling in their corporate sustainability reports, whilst neglecting sustainable packaging solutions aimed at systemic change (Beitzen-Heineke et al. 2017). Consumers' acceptance of sustainable packaging solutions can trigger firms to gradually orientate towards the use of bioplastic applications. As consumer demand for sustainable products grows rapidly, this orientation can be a potential reward strategy for food industries. In addition, marketers should consider that according to the different behavioural paradigms consumers follow, multiple market segments can be identified. These, in turn, present heterogeneous preference structures. Therefore, specific marketing strategies should be conceived for each target group. For instance, since utility maximizers were found to be more sensitive to the loose alternative, companies could benefit from the choice of supplying their products unpackaged to this group. In this case, the companies' promotion and advertising campaigns should emphasize the advantages of the packaging-free format for both the consumers (i.e., the possibility to select only high-quality products and in the desired amount) and the environment (i.e., no plastic packaging to dispose of after the purchase). On the other hand, as regret minimizers appreciated both sustainable packaging formats and did not favour one over the other, either bioplastic packaging or the unpackaged strategy can be profitably achieved. However, communication with the consumers should highlight the benefits of these products in comparison to the available competing alternatives. Furthermore, the price should be carefully set, as this group of consumers exhibited a high sensitivity to this attribute. In line with the previous considerations, policy interventions and tools aimed at encouraging sustainable consumption, specifically a reduction in plastic packaging waste, should also be tailored to the consumers, taking into account the heterogeneity in the behavioural approaches they apply when making choices. For instance, nudging strategies or information tools leveraging loss aversion principles may influence individuals following the RRM mechanism. Conversely, policy instruments based on environmental information or aimed to stimulate the individual's ecological worldview can prompt the individuals who take decisions through the RUM process. Future studies may test these considerations by exploring the effectiveness of different kinds of nudges, as per the decision rule adopted by consumers.

Lastly, our findings are relevant to scholars in the field of food consumer behaviour. We demonstrated that choices for sustainability attributes are driven by regret feelings. *Ceteris paribus*, we observed that the eco-friendly packaging strategies were preferred among people driven by regret minimization principles, indicating that sustainable consumption behaviour should be considered under the regret lens. Considering that the packaging format influences only the product's environmental footprint and not the food quality characteristics, a large share of consumers opt for the pro-environmental packaging strategies to avoid the regret of having chosen an identical product with packaging that promotes pollution.

Moreover, combined with the solid and well-established RUM, the RRM framework enabled to achieve a broader overview of the consumers' decision-making process for sustainable foods, as it allows them to take into account the choice phenomena that diverge from the classical RUM assumptions. We provided evidence that the behavioural patterns in the context of pro-environmental choices do not seem to be described solely by utility maximization mechanisms, rather regret minimization underlies about half of the decisions. Therefore, heterogeneity in consumers' choices relies also on the decision rule applied by the consumers, and not only on their tastes. Evaluating all decision-makers and their choices as driven by utility maximization considerations can lead to incomplete conclusions. Instead of choosing either of the two paradigms (RUM or RRM), it is more appropriate to consider both of them as well as a hybrid specification assuming heterogeneity in the decision rule across individuals to gain a comprehensive insight into a phenomenon from a behavioural perspective. Thus, expanding the theoretical foundation in modelling the choices is required, and further studies should test the regret framework for different applications or, alternatively, should consider the integration of RUM in other behavioural approaches.

Acknowledgements We would like to thank the anonymous reviewers for their helpful comments which improved the quality of our manuscript.

Author Contributions Conceptualization: GP, FB, LC; Methodology: GP, FB, LC; Formal analysis and investigation: GP, FB; Writing—original draft preparation: GP; Resources: LC; Supervision: FB, LC.

Funding Open access funding provided by Università degli Studi di Firenze within the CRUI-CARE Agreement. Funding provided by University of Florence.

Declarations

Conflict of interest The authors have no competing interests to declare that are relevant to the content of this article.

References

Alphonce R, Alfnes F (2017) Eliciting consumer WTP for food characteristics in a developing context: application of four valuation methods in an African market. J Agric Econ 68:123–142. https://doi.org/10.1111/1477-9552.12170

Aoki K, Akai K, Ujiie K et al (2019) The impact of information on taste ranking and cultivation method on rice types that protect endangered birds in Japan: non-hypothetical choice experiment with tasting. Food Qual Prefer 75:28–38. https://doi.org/10.1016/j.foodqual.2018.11.021

Barnes SJ (2019) Understanding plastics pollution: the role of economic development and technological research. Environ Pollut 249:812–821. https://doi.org/10.1016/j.envpol.2019.03.108

Beitzen-Heineke EF, Balta-Ozkan N, Reefke H (2017) The prospects of zero-packaging grocery stores to improve the social and environmental impacts of the food supply chain. J Clean Prod 140:1528–1541. https://doi.org/10.1016/j.jclepro.2016.09.227

Biondi B, Van der Lans IA, Mazzocchi M et al (2019) Modelling consumer choice through the random regret minimization model: an application in the food domain. Food Qual Prefer 73:97–109. https://doi.org/10.1016/j.foodqual.2018.12.008

Boeri M, Longo A (2017) The importance of regret minimization in the choice for renewable energy programmes: evidence from a discrete choice experiment. Energy Econ 63:253–260. https://doi.org/10.1016/j.eneco.2017.03.005

Boeri M, Masiero L (2014) Regret minimisation and utility maximisation in a freight transport context. Transp A Transp Sci 10:548–560. https://doi.org/10.1080/23249935.2013.809818

Boeri M, Longo A, Grisolía JM et al (2013) The role of regret minimisation in lifestyle choices affecting the risk of coronary heart disease. J Health Econ 32:253–260. https://doi.org/10.1016/j.jhealeco.2012.10.007

Boeri M, Scarpa R, Chorus CG (2014) Stated choices and benefit estimates in the context of traffic calming schemes: utility maximization, regret minimization, or both? Transp Res Part A Policy Pract 61:121–135. https://doi.org/10.1016/j.tra.2014.01.003

Boncinelli F, Piracci G, Casini L (2021) Understanding the role of information and taste heterogeneity in consumer preferences for functional beef: the case of the omega-3 enriched burger. Meat Sci 181:108614. https://doi.org/10.1016/j.meatsci.2021.108614

Butler JM, Vossler CA (2018) What is an unregulated and potentially misleading label worth? The case of "Natural"-labelled groceries. Environ Resour Econ 70:545–564. https://doi.org/10.1007/s10640-017-0132-9

Carlsson F, Frykblom P, Lagerkvist CJ (2007) Consumer willingness to pay for farm animal welfare: mobile abattoirs versus transportation to slaughter. Eur Rev Agric Econ 34:321–344. https://doi.org/10.1093/erae/jbm025

ChoiceMetrics (2018) Ngene 1.2 user manual and reference guide

Chorus CG (2010) A new model of random regret minimization. Eur J Transp Infrastruct Res. https://doi.org/10.18757/ejtir.2010.10.2.2881
Chorus CG (2012) Random Regret-based discrete choice modeling: a tutorial. Springer
Chorus C, van Cranenburgh S, Dekker T (2014) Random regret minimization for consumer choice modeling: assessment of empirical evidence. J Bus Res 67:2428–2436. https://doi.org/10.1016/j.jbusres.2014.02.010
Costanigro M, Appleby C, Menke SD (2014) The wine headache: consumer perceptions of sulfites and willingness to pay for non-sulfited wines. Food Qual Prefer 31:81–89. https://doi.org/10.1016/j.foodqual.2013.08.002
Cummings RG, Taylor LO (1999) Unbiased value estimates for environmental goods: a cheap talk design for the contingent valuation method. Am Econ Rev 89:649–665. https://doi.org/10.1257/aer.89.3.649
De Bekker-Grob EW, Chorus CG (2013) Random regret-based discrete-choice modelling: an application to healthcare. Pharmacoeconomics 31:623–634. https://doi.org/10.1007/s40273-013-0059-0
De Marchi E, Pigliafreddo S, Banterle A et al (2020) Plastic packaging goes sustainable: an analysis of consumer preferences for plastic water bottles. Environ Sci Policy 114:305–311. https://doi.org/10.1016/j.envsci.2020.08.014
De Salvo M, Scarpa R, Capitello R, Begalli D (2020) Multi-country stated preferences choice analysis for fresh tomatoes. Bio-Based Appl Econ 9:241–262. https://doi.org/10.13128/bae-7928
Dekker T (2014) Indifference based value of time measures for Random Regret minimisation models. J Choice Model 12:10–20. https://doi.org/10.1016/j.jocm.2014.09.001
Dhar R, Simonson I (2003) The effect of forced choice on choice. J Mark Res XL:146–160
Dunlap RE, Van Liere KD, Mertig AG, Jones RE (2000) Measuring endorsement of the new ecological paradigm: a revised NEP scale. J Soc Issues 56:425–442. https://doi.org/10.1111/0022-4537.00176
European Bioplastics (2022) What are bioplastics? https://www.european-bioplastics.org/bioplastics/. Accessed 28 Apr 2022
European Commission (2018) Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions—a European strategy for plastics in a circular economy
Eurostat (2019) Packaging waste statistics. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Packaging_waste_statistics#Waste_generation_by_packaging_material. Accessed 21 Apr 2022
Fernqvist F, Olsson A, Spendrup S (2015) What's in it for me? Food packaging and consumer responses, a focus group study. Br Food J 117:1122–1135. https://doi.org/10.1108/BFJ-08-2013-0224
Fogt Jacobsen L, Pedersen S, Thøgersen J (2022) Drivers of and barriers to consumers' plastic packaging waste avoidance and recycling—a systematic literature review. Waste Manag 141:63–78. https://doi.org/10.1016/j.wasman.2022.01.021
Ford HV, Jones NH, Davies AJ et al (2022) The fundamental links between climate change and marine plastic pollution. Sci Total Environ 806:150392. https://doi.org/10.1016/j.scitotenv.2021.150392
Friedrich D (2020) Consumer behaviour towards Wood-Polymer packaging in convenience and shopping goods: a comparative analysis to conventional materials. Resour Conserv Recycl 163:105097. https://doi.org/10.1016/j.resconrec.2020.105097
Fuentes C, Enarsson P, Kristoffersson L (2019) Unpacking package free shopping: alternative retailing and the reinvention of the practice of shopping. J Retail Consum Serv 50:258–265. https://doi.org/10.1016/j.jretconser.2019.05.016
Gall SC, Thompson RC (2015) The impact of debris on marine life. Mar Pollut Bull 92:170–179. https://doi.org/10.1016/j.marpolbul.2014.12.041
Gerini F, Alfnes F, Schjøll A (2016) Organic- and animal welfare-labelled eggs: competing for the same consumers? J Agric Econ 67:471–490. https://doi.org/10.1111/1477-9552.12154
Geržinič N, van Cranenburgh S, Cats O et al (2021) Estimating decision rule differences between 'best' and 'worst' choices in a sequential best worst discrete choice experiment. J Choice Model. https://doi.org/10.1016/j.jocm.2021.100307
Geyer R, Jambeck JR, Law KL (2017) Production, use, and fate of all plastics ever made. Sci Adv 3:25–29. https://doi.org/10.1126/sciadv.1700782
Greene WH, Hensher DA (2003) A latent class model for discrete choice analysis: contrasts with mixed logit. Transp Res Part B Methodol 37:681–698. https://doi.org/10.1016/S0191-2615(02)00046-2
Kallas Z, Escobar C, and Gil JM (2013) Analysis of consumers' preferences for a special-occasion red wine: A dual response choice experiment approach. Food Qual Prefer 30(2):156–168. https://doi.org/10.1016/j.foodqual.2013.05.008
Haaijer R, Kamakura W, Wedel M (2001) The "no-choice" alternative in conjoint choice experiments. Int J Mark Res 43:93–106. https://doi.org/10.1177/147078530104300105
Hensher DA, Rose JM, Greene WH (2015) Applied choice analysis. Cambridge University Press

Hensher DA, Greene WH, Ho CQ (2016) Random regret minimization and random utility maximization in the presence of preference heterogeneity: an empirical contrast. J Transp Eng 142:1–10. https://doi.org/10.1061/(ASCE)TE.1943-5436.0000827
Herbes C, Beuthner C, Ramme I (2018) Consumer attitudes towards biobased packaging—a cross-cultural comparative study. J Clean Prod 194:203–218. https://doi.org/10.1016/j.jclepro.2018.05.106
Herrmann C, Rhein S, Sträter KF (2022) Consumers ' sustainability-related perception of and willingness-to-pay for food packaging alternatives. Resour Conserv Recycl. https://doi.org/10.1016/j.resconrec.2022.106219
Hess S (2007) Posterior analysis of random taste coefficients in air travel behaviour modelling. J Air Transp Manag 13:203–212. https://doi.org/10.1016/j.jairtraman.2007.03.004
Hess S, Palma D (2019) Apollo: a flexible, powerful and customisable freeware package for choice model estimation and application. J Choice Model 32:100170. https://doi.org/10.1016/j.jocm.2019.100170
Hess S, Train KE, Polak JW (2006) On the use of a Modified Latin Hypercube Sampling (MLHS) method in the estimation of a Mixed Logit Model for vehicle choice. Transp Res Part B 40:147–163
Hess S, Stathopoulos A, Daly A (2012) Allowing for heterogeneous decision rules in discrete choice models: an approach and four case studies. Transportation 39:565–591. https://doi.org/10.1007/s11116-011-9365-6
Hess S, Beck MJ, Chorus CG (2014) Contrasts between utility maximisation and regret minimisation in the presence of opt out alternatives. Transp Res Part A Policy Pract 66:1–12. https://doi.org/10.1016/j.tra.2014.04.004
Hess S, Daly A, Batley R (2018) Revisiting consistency with random utility maximisation: theory and implications for practical work. Theory Decis 84:181–204. https://doi.org/10.1007/s11238-017-9651-7
Hilger J, Hallstein E, Stevens AW, Villas-Boas SB (2019) Measuring willingness to pay for environmental attributes in seafood. Environ Resour Econ 73:307–332. https://doi.org/10.1007/s10640-018-0264-6
ISMEA (2017) Il mercato del pomodoro da mensa
Jambeck JR, Geyer R, Wilcox C et al (2015) Plastic waste inputs from land into the ocean. Science 347:768–771
Kahneman D, Tversky A (1979) Prospect theory: an analysis of decision under risk. Econometrica 47:263–292
Klaiman K, Ortega DL, Garnache C (2016) Consumer preferences and demand for packaging material and recyclability. Resour Conserv Recycl 115:1–8. https://doi.org/10.1016/j.resconrec.2016.08.021
Klein F, Emberger-Klein A, Menrad K et al (2019) Influencing factors for the purchase intention of consumers choosing bioplastic products in Germany. Sustain Prod Consum 19:33–43. https://doi.org/10.1016/j.spc.2019.01.004
Kocak Yanik D, Elik A, Istanbullu Y, Gogus F (2020) Fruits and vegetables purchasing attitudes in turkey: packaging and loss reduction. Int J Sci Technol Res 6:39–45. https://doi.org/10.7176/JSTR/6-08-05
Leal Filho W, Saari U, Fedoruk M et al (2019) An overview of the problems posed by plastic products and the role of extended producer responsibility in Europe. J Clean Prod 214:550–558. https://doi.org/10.1016/j.jclepro.2018.12.256
Lindh H, Olsson A, Williams H (2016) Consumer perceptions of food packaging: contributing to or counteracting environmentally sustainable development? Packag Technol Sci 29:3–23. https://doi.org/10.1002/pts.2184
Loomes G, Sugden R (1982) Regret theory: an alternative theory of rational choice under uncertainty. Econ J 92:805–824
Louis D, Lombart C, Durif F (2021) Packaging-free products: a lever of proximity and loyalty between consumers and grocery stores. J Retail Consum Serv 60:102499. https://doi.org/10.1016/j.jretconser.2021.102499
Mao B, Ao C, Wang J et al (2020) Does regret matter in public choices for air quality improvement policies? A comparison of regret-based and utility-based discrete choice modelling. J Clean Prod 254:120052. https://doi.org/10.1016/j.jclepro.2020.120052
Marken GH, Hörisch J (2019) Purchasing unpackaged food products. In: Sustain manag forum Nachhalt, vol 27, pp 165–175. https://doi.org/10.1007/s00550-020-00490-5
Marschak J (1960) Binary-choice constraints and random utility indicators. In: Marschak J (ed) Economic information, decision and prediction: Selected essays (1974), vol 1. D. Reidel, Dordrecht
McFadden D (1974) Conditional logit analysis of qualitative choice behavior. In: Zarembka P (ed) Frontiers in econometrics. Academic Press, New York, pp 105–142
Muller L, Lacroix A, Ruffieux B (2019) Environmental labelling and consumption changes: a food choice experiment. Environ Resour Econ 73:871–897. https://doi.org/10.1007/s10640-019-00328-9
Ortega DL, Sun J, Lin W (2022) Identity labels as an instrument to reduce meat demand and encourage consumption of plant based and cultured meat alternatives in China. Food Policy 111:102307. https://doi.org/10.1016/j.foodpol.2022.102307
Phelan A, Meissner K, Humphrey J, Ross H (2022) Plastic pollution and packaging: corporate commitments and actions from the food and beverage sector. J Clean Prod 331:129827. https://doi.org/10.1016/j.jclepro.2021.129827

Piracci G, Boncinelli F, Casini L (2022) Wine consumers' demand for social sustainability labeling: evidence for the fair labor claim. Appl Econ Perspect Policy. https://doi.org/10.1002/aepp.13260

Plastics Europe (2020) Plastics—the Facts 2020. An analysis of European plastics production, demand and waste data

Printezis I, Grebitus C (2018) Marketing channels for local food. Ecol Econ 152:161–171. https://doi.org/10.1016/j.ecolecon.2018.05.021

Ragaert P, Verbeke W, Devlieghere F, Debevere J (2004) Consumer perception and choice of minimally processed vegetables and packaged fruits. Food Qual Prefer 15:259–270. https://doi.org/10.1016/S0950-3293(03)00066-1

Rapp A, Marino A, Simeoni R, Cena F (2017) An ethnographic study of packaging-free purchasing: designing an interactive system to support sustainable social practices. Behav Inf Technol 36:1193–1217. https://doi.org/10.1080/0144929X.2017.1365170

Rujnić-Sokele M, Pilipović A (2017) Challenges and opportunities of biodegradable plastics: a mini review. Waste Manag Res 35:132–140. https://doi.org/10.1177/0734242X16683272

Russo I, Confente I, Scarpi D, Hazen BT (2019) From trash to treasure: the impact of consumer perception of bio-waste products in closed-loop supply chains. J Clean Prod 218:966–974. https://doi.org/10.1016/j.jclepro.2019.02.044

Sándor Z, Wedel M (2001) Designing conjoint choice experiments using managers' prior beliefs. J Mark Res 38:430–444. https://doi.org/10.1509/jmkr.38.4.430.18904

Savage LJ (1954) The foundations of statistics. Wiley, New York

Scarpa R, Campbell D, Hutchinson WG (2007) Benefit estimates for landscape improvements: sequential Bayesian design and respondents' rationality in a choice experiment. Land Econ 83:617–634. https://doi.org/10.3368/le.83.4.617

Scarpa R, Zanoli R, Bruschi V, Naspetti S (2013) Inferred and stated attribute non-attendance in food choice experiments. Am J Agric Econ 95:165–180. https://doi.org/10.1093/ajae/aas073

Scarpa R, Bazzani C, Begalli D, Capitello R (2021) Resolvable and near-epistemic uncertainty in stated preference for olive oil: an empirical exploration. J Agric Econ 72:1–35. https://doi.org/10.1111/1477-9552.12398

Setälä O, Fleming-Lehtinen V, Lehtiniemi M (2014) Ingestion and transfer of microplastics in the planktonic food web. Environ Pollut 185:77–83. https://doi.org/10.1016/j.envpol.2013.10.013

Simon HA (1955) A behavioral model of rational choice. Q J Econ 69:99–118

Steiner BE, Peschel AO, Grebitus C (2017) Multi-product category choices labeled for ecological footprints: exploring psychographics and evolved psychological biases for characterizing latent consumer classes. Ecol Econ 140:251–264. https://doi.org/10.1016/j.ecolecon.2017.05.009

Thaler RH (2015) Misbehaving: The making of behavioural economics. Norton, New York

Thiene M, Boeri M, Chorus CG (2012) Random regret minimization: exploration of a new choice model for environmental and resource economics. Environ Resour Econ 51:413–429. https://doi.org/10.1007/s10640-011-9505-7

Thurstone LL (1927) A law of comparative judgment. Psychol Rev 34:273

Train KE (2009) Discrete choice methods with simulation. Cambridge University Press

Tversky A, Kahneman D (1991) Loss aversion in riskless choice: a reference-dependent model. Q J Econ 106:1039–1061

UNEP (2018) Single-use plastics: a roadmap for sustainability

van Cranenburgh S, Collins AT (2019) New software tools for creating stated choice experimental designs efficient for regret minimisation and utility maximisation decision rules. J Choice Model 31:104–123. https://doi.org/10.1016/j.jocm.2019.04.002

van Cranenburgh S, Guevara CA, Chorus CG (2015) New insights on random regret minimization models. Transp Res Part A Policy Pract 74:91–109. https://doi.org/10.1016/j.tra.2015.01.008

van Cranenburgh S, Rose JM, Chorus CG (2018) On the robustness of efficient experimental designs towards the underlying decision rule. Transp Res Part A Policy Pract 109:50–64. https://doi.org/10.1016/j.tra.2018.01.001

van Herpen E, Immink V, van den Puttelaar J (2016) Organics unpacked: the influence of packaging on the choice for organic fruits and vegetables. Food Qual Prefer 53:90–96. https://doi.org/10.1016/j.foodqual.2016.05.011

Van Loo EJ, Caputo V, Lusk JL (2020) Consumer preferences for farm-raised meat, lab-grown meat, and plant-based meat alternatives: does information or brand matter? Food Policy 95:101931. https://doi.org/10.1016/j.foodpol.2020.101931

Waring RH, Harris RM, Mitchell SC (2018) Plastic contamination of the food chain: a threat to human health? Maturitas 115:64–68. https://doi.org/10.1016/j.maturitas.2018.06.010

Wensing J, Caputo V, Carraresi L, Bröring S (2020) The effects of green nudges on consumer valuation of bio-based plastic packaging. Ecol Econ 178:106783. https://doi.org/10.1016/j.ecolecon.2020.106783
World Economic Forum (2016) The new plastics economy: rethinking the future of plastics
Zeelenberg M, Pieters R (2007) A theory of regret regulation 1.0. J Consum Psychol 17:3–18
Zhang Y, Gao Y, Jiang J (2021) An unpredictable environment reduces pro-environmental behavior: a dynamic public goods experiment on forest use. J Environ Psychol 78:101702. https://doi.org/10.1016/j.jenvp.2021.101702