Learning the value of Eco-Labels: The role of information in sustainable decisions*

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Abstract

Sustainability ratings, such as EU energy ratings, provide consumers with credible and understandable information on product sustainability. Evidence from both the appliances and the housing markets shows that consumers not only use sustainability ratings for assessing the environmental impact of their choices, but also to be informed about private benefits such as reductions in future energy costs. These results question the potential effectiveness of sustainability ratings for other products, such as food or cleaning products, where the link between environmental and private benefits is less clear. In two incentivized experiments (N=749), we study how consumers use sustainability ratings when these labels are not associated with the products' quality. Participants made multiple choices between two products based on their quality and sustainability, which were presented in separate ratings, alongside the products' prices. In the middle of the experiment, we provide clear information regarding the attributes driving the quality and sustainability ratings. We vary the information provided across treatment conditions, making in some conditions certain products less appealing due to one specific attribute. We compare two treatments, where either the products are less appealing due to their quality or sustainability. The treatment comparison allows us to analyze to what extent participants use each type of new information provided. We use process-tracing methods to track the participants' attention and analyze potential heterogeneous usage of the information. Our findings indicate that while participants consider all attributes in their choices, they weigh quality more than sustainability on average. When provided with new negative information regarding one of the ratings, participants use the information differently depending on whether it regards quality or sustainability. Specifically, when a product's sustainability rating yields less than expected, participants choose products with both lower and higher ratings. When the quality of a product is less than expected, participants shift only towards higher quality products. Analyzing participants' attention patterns reveals significant heterogeneity in preferences, with greater variance observed in preferences for sustainability compared to quality.

Keywords: Attention, Sustainability ratings, conjoint analysis, information treatments, MouselabWeb
JEL Codes: D81, D83, D87, D91.

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1 Introduction

Global warming is a major problem affecting the majority of the world's societies. So far, efforts to reduce the global levels of CO2 emissions, and the rise in temperatures associated with that, have proven to be mostly ineffective (European Commission et al., 2021). Among all industries, the food industry has great mitigation potential. Of the total amount of emissions, about 21% to 37% come from the food industry (Ritchie and Roser, 2023). Although evidence shows strong consumers' attitudes towards sustainable consumption, this is not reflected in their actual consumption (El-Haffar et al., 2020). However, consumers might not follow through with their sustainable intentions because they are unaware of, or underestimate, the climate impact of their food choices due to the general lack of accessible information (Camilleri et al., 2019; Pace and van der Weele, 2020).

Eco-labels and sustainability ratings, such as the eco-score or the EU Energy labels, have been developed to provide consumers with credible and understandable information regarding the sustainability of their choices. Evidence shows that labels and ratings increase the sustainable choices for other types of purchases, such as buying a house (e.g., Chegut et al., 2020; Khazal and Sønstebø, 2020) or choosing appliances (e.g., Labandeira et al., 2020; European Commission, 2021). Although these results suggest that labels increase the sustainable choices of consumers, there is evidence that these decisions are driven by their private benefits instead of their attitudes toward sustainability. For example, in the context of the consumption of energy-efficient products, Stadelmann and Schubert (2018) show that the impact of energy labels is substantially larger when the labels are paired with information regarding the expected reduction in future energy costs. These results suggest that the private benefits associated with the energy rating might be driving most of their effects on consumption.

When considering other consumption goods found in supermarkets, such as food or cleaning products, it is not clear that sustainable products can be directly associated with direct personal benefits. For example, Luchs et al. (2010) show that more sustainable or socially responsible products are deemed as more "gentle" and less strong. Then, if the consumers' perceived quality is linked to the strength of the product (e.g., cleaning products), the consumers will have a negative association between quality and sustainability. In this study, we focus on investigating the role of sustainability ratings in the consumer's decision, when there is no association between quality and sustainability. This allows us to disentangle the private from the social incentives that lead to choosing a sustainable product.

Although ratings facilitate the acquisition of information that otherwise would be difficult to obtain, it is unclear how consumers process that information, particularly in real-world situations that are loaded with constant streams of information. On one hand, consumers are frequently exposed to news and information about sustainability, but also about practices like greenwashing (Delmas and Burbano, 2011; Yokessa and Marette, 2019). Both types of information will affect the preferences for choosing sustainable products, but on the other hand, they can also make the process of "understanding" which products to choose more complex. This adds a new layer of complexity to a task that is already increasingly complex. During purchasing decisions, consumers need to weigh a large number of attributes, such as price, product quality, and size, as well as information regarding product sustainability. When multiple sources of information are available, it is not clear how consumers will react. We aim to deepen the understanding of how consumers integrate the products' attributes to make a decision, and how external information affects this process.

We address these questions in the current study by developing an incentivized experimental task that simulates an online shopping experience. Participants choose between different pairs of products depending on three attributes, namely price, quality, and sustainability. While the products are not real, the attributes of the chosen product will have real consequences for the participants' outcomes: (1) participants receive a bonus payment depending on the quality level of the chosen product and the price they pay for it; (2) additionally, depending on the level of sustainability of the chosen product, a donation to plant trees is made on the participant's behalf. We also record how participants pay attention to the product attributes by capturing relevant components of the decision process, including what information is being processed, in which order, and for how long. We expect that individual preferences for the different attributes will be reflected by participants' attentional patterns.

The first goal of our experiment is to test what underlying assumptions participants have about the rating systems. When choosing which product to buy, participants are informed about the product's quality and sustainability via visual rating systems. After several decisions, we provide participants with precise information about how the different ratings affect their bonus payment and the donations for planting trees. Participants then make the same purchasing decisions in the second half of the experiment. A comparison of pre- and post-information decisions enables us to assess how participants' decisions are affected by precise knowledge about the consequences of their decisions via the rating system.

To test how participants react to new information regarding the rating systems, we change the value of the quality and sustainability ratings using a between-subjects design with three conditions. Specifically, in our baseline treatment, the values underlying both ratings increase linearly across the rating scale. In the other two treatments, we decrease the underlying value (quality or sustainability depending on the treatment) of some of the products with a specific rating. Hence, we can analyze how consumers change their consumption towards other available options when one product's value is decreased. We compare the treatments with decreased quality and decreased sustainability to compare if participants react differently to information regarding different attributes.

Using a random-utility model framework (RUM) we estimate the value attributed to each rating and for each attribute. Specifically, we estimate the decision weight for each attribute and then use these weights to estimate the willingness to pay (WTP) for each rating. Our results show that overall participants are willing to pay for higher quality (higher pay-offs) and sustainability (trees planted). We also observe that the willingness to pay (WTP) increases more steeply from low- to mid-level ratings than from mid- to high-level ratings suggesting a non-linear (concave) increase in WTP as the rating for each attribute increases. We also elicit beliefs about the underlying values driving these ratings and discard the possibility that the concave preferences for increasing the ratings are driven by beliefs.

After establishing the baseline behavior of the participants, we assess the effects of the different information treatments on the willingness to pay. Our results show that participants underreact to the information provided when compared to the optimal decisions. Namely, in the treatment conditions where the sustainability value of some products is reduced, we still find that participants have a large positive willingness to pay for these products. These results suggest that participants are "leaving money on the table" by choosing to buy more expensive products that provide little to no additional benefits. When we compare how the participants react towards negative information regarding the sustainability products compared to their quality, we find asymmetric reactions towards the information. When considering the sustainability of the products, participants shift from the negatively affected products towards products with both lower and higher sustainability ratings. On the other hand, when the negative information regards the quality of some products, participants shift only towards higher quality products.

Finally, we explore deeper on the mechanisms driving these results. Using the methods from (Hirmas et al., 2023), we show that participants are highly heterogeneous in the weight they allocate towards the different attributes. We find that most of this heterogeneity is driven by their differences in attention towards sustainability. Namely, participants who focus consistently more on the sustainability ratings, compared to the rest of the sample, show a significantly larger willingness to pay for sustainability. We do not find strong correlations between the differences in attention and any elicited sustainable measures or demographics. These results suggest that attention can provide strong additional information regarding the participants' decision process.

When assessing possible mechanisms for the underreaction towards the information treatments, we find that these differences are not driven by beliefs. By the end of the experiment, participants recall almost perfectly the additional information provided to them. On the other hand, there are low to no effects of the information treatments on the attention allocated to the different attributes. Therefore, we conclude that participants are aware of the new information, but do not fully incorporate it into their choices. These results are consistent with anchoring behavior (Tversky and Kahneman, 1974).

This paper presents a novel paradigm that mitigates the challenges of studying environmental decisions in an incentivized setting, which is suitable for both lab and online experiments. Using bundles (i.e., combining money and trees planted) framed as 'products', we distinguish between private and sustainable benefits associated with a 'product'. Our findings demonstrate how consumers make use of sustainability ratings when the ratings are not linked to private benefits. These results inform policymakers about the (heterogeneous) consumer attitudes. Importantly, our results suggest that consumers are more sensitive to negative information when it comes to sustainability rather than quality, which should be accounted for in information-driven policies aiming to increase sustainable consumption.

2 Related Literature

Classic economic theory works on the assumption that consumers use and process all information available to make their decisions. There is substantial evidence from the work on behavioral economics, cognitive psychology, and neuroeconomics that challenges such assumptions. Namely, we find that consumers do not use all the information available and misuse the information obtained (for reviews on the topic: Orquin and Mueller Loose, 2013; Mackowiak et al., 2021).

Nowadays, consumers face an increasing flow of information when making decisions, which hinders their capacity to process and integrate it all. Thus, consumers are more likely to avoid and neglect information that would have been valuable for their choice (Simon, 1971). This trade-off between the availability of information and the costs of attention has been extensively studied in the literature on "rational inattention" (e.g. Sims, 2003), which assumes that agents are aware of the costs of obtaining information. Rationally inattentive agents optimally decide their search rules for information such that the marginal cost of obtaining information equals the expected marginal value of the information obtained.

Parallelly, Empirical work in economics has demonstrated that consumers fail to incorporate fundamental information in multiple fields. When information is not easily available, consumers are less likely to use it in their decisions (e.g., Chetty et al., 2009; Allcott and Taubinsky, 2015). Moreover, if information becomes more salient (i.e., more striking compared to the rest), agents are more likely to 'over-weight' this information in their decisions (e.g., Bordalo et al., 2013; Hirmas et al., 2023). The literature in Marketing and cognitive psychology shows that there are multiple factors, not linked to the product's value, that still affect the decision. In the meta-analysis from Orquin et al. (2021), the authors compile evidence that factors in the spatial presentation of the options, such as the position, size, and overall salience of a product, have a strong impact on the consumers' choices.

These different strands of literature provide evidence that consumers' choices are not fully informed and that there are contextual factors, seemingly unrelated to the decision, that consistently influence choice. Therefore, helping consumers in their decision process can have a large impact on their decisions. Labels and ratings are a useful tool to aggregate information that otherwise would be too difficult to process. Consumers are exposed and affected by multiple types of labels and ratings, such as quality ratings when choosing service providers (e.g., hotels, transportation, restaurants), cost efficiency of appliances (i.e., EU energy labels; European Commission, 2021), nutritional value of food (e.g., Jürkenbeck et al., 2022; Barahona et al., 2023; Crosetto et al., 2024); and also sustainability (e.g., EU Eco-label Yokessa and Marette, 2019).

There is an extensive body of literature that studies the impact of sustainability labels or ratings on consumer choices (for reviews on the impact of sustainability ratings, see Yokessa and Marette, 2019; Bastounis et al., 2021; Majer et al., 2022). Nonetheless, most of these studies use hypothetical choices, where participants are primed to think of their purchasing experience and to state their preference for different products (e.g., Staples et al., 2020; Potter et al., 2022). There are significantly fewer studies that either use incentivized settings in the laboratory (e.g., Vecchio and Annunziata, 2015; Engel and Szech, 2020) or implement field studies in cafeterias, canteens, or supermarkets (e.g., Tilling, 2023; Vlaeminck et al., 2014). Hypothetical choices make the design and implementation of the experiments simpler at the cost of having real incentives. On the other hand, incentivized experiments regarding sustainability ratings are specific to their context, since the incentives require real products. Participants make choices based on their preferences for that specific product, which decreases the external validity of the results. Our design lies in between these two types of studies. First, we provide an incentivized choice paradigm, but without having to incorporate any specific product into the design. Moreover, the implementation of our paradigm is rather simple and cost-effective, as opposed to lab experiments with products or field experiments.

Within the experimental literature, several studies that have assessed the impact of labels or ratings in combination with other attributes. Some of these studies compare the impact of different labels/information (e.g., Andor et al., 2019; Sigurdsson et al., 2022; Kolber and Meixner, 2023). Parallelly, some studies test the provision of direct information regarding how sustainable the products are (e.g., Steiner et al., 2017). De Bauw et al. (2021), the authors study the role of a sustainability rating called eco-score in combination with the Nutri-score, a nutritional rating. While the Nutri-score directly informs the participants about the quality of the product, the eco-score informs them about the sustainability of said product. In this specific context, the authors find that the combination of both scores still enhances the nutritional value of the participants' choices, but does not affect the sustainability of their choices. These results suggest that when more information is available, participants decrease their levels of attention to the sustainability ratings.

Providing sustainability ratings helps to ensure that consumers have information regarding the environmental impact of their choices. This information will only affect choices if attended and considered important. Thus, the study of the attention allocated to these labels is relevant to understanding their (seemingly heterogeneous) impact on the consumers' choices. In two hypothetical food choice studies (Van Loo et al., 2015, 2021), the authors show that (1) participants pay more attention to nutritional information than the environmental impact of the products and (2) more attention to the labels increases their importance in their choice. Another study shows that informing participants about the underlying information of sustainability labels increases their attention toward the label. Our study further explores the role of attention in consumption choices with sustainability ratings. In our incentivized experiment, we analyze within-subject variations in attention and choices when providing clear and understandable information about the underlying attributes driving the ratings. Moreover, we explore how this information can be taken differently when the underlying attribute represents the product quality, which provides private benefits, compared to when the attribute represents the environmental impact of the product.

3 Experimental design

3.1 Participants

We recruited participants via the online platform Prolific. As preregistered, we excluded participants who did not pass attention and manipulation checks; or who took too long to finish the task (see Appendix section A for a detailed description of the exclusion criteria). Our final database includes 291 participants (153 females, 2 non-binary, average age = 29.96). Most of the participants belong to the United Kingdom (N=68) and continental Europe (N=167). The experiment lasted 26 minutes on average. Participants received a participation fee of 2.3 pounds and they were told that depending on their choices, they could earn additional bonus payments and trees planted on their behalf in a location of their choosing. On average, participants earned 1.91 pounds as a bonus payment and we donated 1.47 trees (USD$486) to the organization One Tree Planted, which will plant trees in locations specified by our participants around the globe (See locations in appendix section B). All procedures were approved by the Ethics Committee of Economics and Business (EBES), University of Amsterdam.

3.2 Materials and Procedure

The experiment was programmed using the web-based software oTree. The front end of the experiment was web-based (i.e., programmed using a combination of HTML, JavaScript, and CSS)[1]. Since our experiment relied heavily on how participants perceive visual stimuli, participation from smartphones and tablets was blocked to ensure that visual stimuli were presented on a sufficiently large screen (i.e., on desktop and laptop computers). Moreover, participants were instructed to keep their Fullscreen mode on and not to switch to other pages. Participants were not able to continue with the experiment if their page was not on Fullscreen. Additionally, we told participants that if they jumped to other pages repeatedly, we reserved the right to exclude them from payment (and analysis).

Participants began by signing an informed consent; then they were instructed to set their browser to Fullscreen mode. Following this, they read the instructions and answered several comprehension check questions. After answering all questions correctly, they proceeded to the main

[1] code available here.

task, consisting of two decision blocks. Between the decision blocks, participants received additional information regarding the sustainability and quality labels. After completing both decision blocks, participants answered a questionnaire with demographics, comprehension questions, questions regarding their behavior in the experiment, and the Connectedness to Nature scale (Mayer and Frantz, 2004). We also included the question "How do you see yourself: are you generally a person who is prepared to behave sustainably, even when this is inconvenient or costly to you?" (Likert scale 1-5). Three attention checks were included within the questionnaire to ensure that participants were paying attention. These questions prompted participants to give a specific answer (e.g., 'Please answer 2'). Participants who failed to answer two out of the three attention checks were also excluded from payment.

Main Task

The main task consisted of a series of purchasing choices. Participants chose between two fictitious products depending on their attributes, which included price, quality, and sustainability. While the products were not real, the decisions had real outcomes for the participants. Choosing products with a higher price resulted in a lower bonus payment, while products with higher quality yielded a higher bonus. Choosing products with higher sustainability ratings meant more trees were planted on their behalf. At the end of the experiment, one decision was randomly selected to be payout relevant, and participants received the two-part bonus associated with that decision: 1. a bonus payment calculated as the private value of the product (reflected by the quality) minus the price, and 2. they were informed of how many trees will be planted on their behalf. The value of the products ranged from 60 to 90 quality points (10 points = 0.5 pounds), resulting in a range of 3 to 4.5 pounds. The price of the products ranged between 1 to 3 pounds. Therefore, the products never had a cost more than their monetary value. Participants were aware that the bonuses would never be negative. The products' sustainability ranged between 0 to 30 sustainability points (10 points = 1 tree planted). To personalize the sustainability attribute, participants could choose a specific location, or choose 'anywhere' if they had no preferences (See Appendix B for more information about the selected locations).

The quality and sustainability values were presented to participants as two distinct three-tier ratings. Quality was presented as a one-to-three 'star' rating, while sustainability would be presented as a one-to-three 'leaf' rating. Participants were informed that a higher tier in the rating represented higher values of the respective attribute, but they were not informed about the actual value underlying each tier.

Figure 1 shows an example of the information provided to participants during a decision trial. For illustration purposes, Panel A displays all the information available. Of note, participants never observed all the information simultaneously because we hid this information behind grey cells (Panel B) to record how participants paid attention to different attributes while they made their decisions. Participants could reveal the information by hovering their cursor over the attribute's row, which made the information of that attribute available as shown in Panel C. This method is similar to, but differs from, standard approaches, such as used via MouselabWeb (e.g., Willemsen and Johnson, 2011), as the information is presented simultaneously for an entire row. When developing the task, we noticed that participants took significantly longer if the information was revealed one by one (about five times more). Since longer studies lead to fatigue and boredom (Miller, 2023), and because our main focus is to analyze the changes in decisions after the information treatments, we opted for revealing the attributes simultaneously, thus facilitating the comparison between products. Importantly, since the scales and dimensions of the attributes were significantly different, we expected saccades (shifts of visual attention from one stimulus to the other), to be prominently within-attributes more than between. Evidence shows that when participants are exposed to more attributes than options, which is our case, then they are more likely to compare products attribute-wise instead of integrating the information product-by-product(Meißner et al., 2020; Jenke et al., 2021). It is pertinent to note that our empirical strategy only requires the time spent looking at an attribute, not at each specific value, eliminating the need for fixation times on individual values. Therefore, we concluded that our *row-wise Mouselab* approach is more fitting for our paradigm.

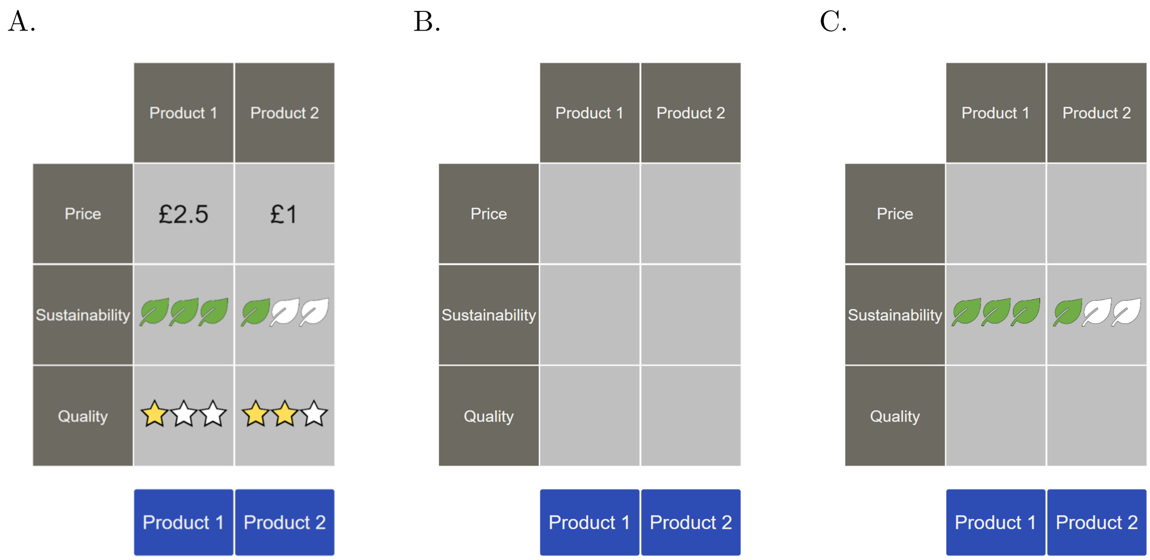


Figure 1: Example of a decision screen

This figure shows an example of the decision screen. Panel A provides all the information that participants could observe on a trial. Participants never observed all the information at the same time. When the trial started, participants have all the information covered (Panel B). If a participant hovers the mouse over an attribute, the attribute is revealed for both options (Panel C).

The order of the attributes was randomized at the participant level, remaining constant for each participant throughout the experiment. The price was always on the top for external validity, as it is most common to have the price first in online webshops. Quality and Sustainability were randomized in the second and third positions. Between every decision, participants clicked on a button to continue to the next trial. The button was positioned in the middle of the vertical axis (y=0.5 screen height), while the position of the horizontal axis was randomized within trials on either left (x=10% of the screen width) or right (x=90% of the screen width). This intermediate button ensured that the participant's cursor was never on top of any attribute before the beginning of a trial. By randomizing the horizontal location, we minimize the risk of priming the products on one specific side.

Participants performed 17 trials for each block of decisions, before and after the information treatment. The attribute values for each trial were pseudo-randomized to maximize the power of our estimations and increase the external validity (see Appendix C for a detailed description). Every participant completed 5 trials for each combination of sustainability ratings (bottom vs. mid, mid vs. top, and bottom vs. top) plus two trials with the same value of sustainability for both products. The product with the highest sustainability was randomized between left and right. We did not present trials where any choice was strictly dominated (i.e., more Quality and Sustainability and lower price for the same product).

Information treatment and belief elicitation

After the first decision block, we elicited the participants' beliefs about the underlying values of the quality and sustainability rating scales. We asked participants to guess how many sustainability points they would obtain for a product of each tier. Similarly, we asked how many quality points they would obtain for each tier of the quality rating[2]. Participants were reminded of the range for both quality (60 to 90) and sustainability (0 to 30) points. They had to answer in steps of 2.5 points and received 0.1 extra for each correctly estimated rating.

After eliciting the participants' beliefs about the ratings, we provided clear information regarding the underlying values for both ratings. Each participant observed two graphs, one for sustainability and one for quality. The graphs showed the amount of points they could obtain by choosing products with a specific rating. Figure 2 shows the graphs presented to participants. With this information, participants knew exactly how many points they would obtain for each tier of both quality and sustainability ratings. To assess how sensitive the participants are to the information, we assigned participants to three between-subject treatment conditions, each with different underlying values for either the sustainability or quality rating scale that were communicated via the graphs shown in Figure 2. 1. In the baseline condition, which we refer to as the *linear* treatment, values for *both* sustainability and quality increased linearly, as reflected by the information provided in panels A and B. 2. In the *sustainability convex* treatment, values of the sustainability attribute increased significantly only for the top-tier of the sustainability rating, such that the mid-tier of sustainability had a similar value to the bottom tier (panel C). Quality outcomes increased linearly, as described in panel B. 3. Analogously, the third condition, the *quality convex* treatment, displayed a linear value increase for sustainability (panel A) and a convex value increase for quality (panel D) that is equivalent to the convex sustainability increase in panel C.

After the completion of the second block of decisions, we elicited participants' beliefs about the ratings once again. This assessment is a manipulation check confirming whether participants processed the rating scale values provided to them after the first block and whether they remember this information after making additional decisions in block two. Following the belief elicitation, we presented participants with three graphs for each rating, a linear, a convex, and a concave

[2]See Appendix D for more details about the belief elicitation method.

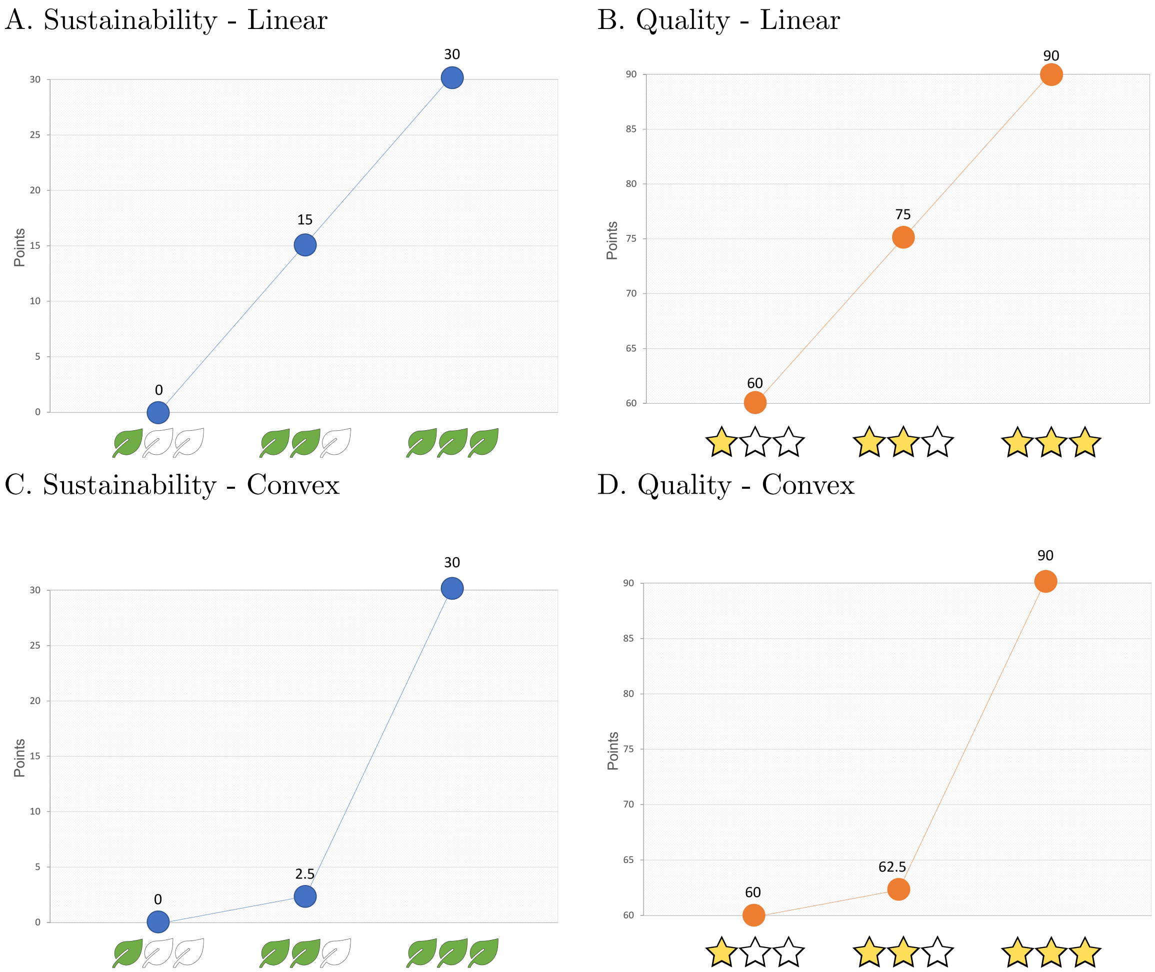


Figure 2

This figure shows values underlying each tier of the sustainability and quality rating scales. Participants were shown different combinations of these rating scales depending on their treatment assignment: Participants in the *linear treatment* condition were shown panels A and B, participants in the *sustainability convex* treatment were shown panels C and A, and participants in the *quality convex* treatment were shown panels A and D. This information was provided after the first block of decisions, so at the halfway point of the experiment. The left column shows the graphs for sustainability, while the right column shows the graphs for quality; top panels show linear values, while bottom panels show convex values.

graph. We asked participants to choose the type of graph that they saw after the completion of block one. Across all treatments, only four participants (0.013 percent of all participants) failed to remember the correct graph for either sustainability or quality. Next, participants proceeded to fill out additional questionnaires (which ones).

We conducted a previous study with equivalent experimental procedures (N = 459), with the exception that we used different information treatment conditions. Specifically, the treatment ratings scales were closer to a linear scale and therefore differed from the linear baseline condition to a lesser extent compared to the current study, and ambiguity was added to the exact values of the rating scale as values were surrounded by confidence bounds within which final values could fall, instead of the specific point values used in the current study. Under these conditions, our manipulation checks showed that more than two-thirds of the participants did not perceive or remember any differences across treatments by the end of the experiment. The design of the previous study can be seen in Appendix E. Of note, in the pilot study, we ran an additional treatment condition, in which no additional information was provided after block 1. Given that the results showed no differences in behavior between the linear and no-information conditions, we decided to omit that condition in the current study.

4 Theoretical Framework

In this section, we describe the empirical methods used in our analysis and state our hypotheses. First, we present the baseline model for representing the participants' choices. Then, we analyze the impact of the information treatments on the baseline behavior. Finally, we incorporate the method from Hirmas et al. (2023) to capture heterogeneous behavior via the participants' attention patterns.

4.1 Decision process

We model the choice between two products using a random utility model (RUM; McFadden, 1973). The RUM assumes that agents assess the different available options and estimate their subjective value (or utility) imprecisely due to distractions, time pressure, impulsiveness, attentional biases or misperceptions. Hence, the decision process becomes stochastic.

To describe the decision model, consider an agent i belonging to a population J, who makes a series of purchasing decisions (indexed by $t \in \{1, ..., T\}$) between two products. The agent assigns or calculates subjective value to each option, ($V^o_{i,j,t}$ for $o \in \{1, 2\}$). The subjective value is specified as a linear combination of the option's attributes ($x_{k,i,t}$ for $k \in K$). The difference in subjective value for both options, $\Delta V_{i,t} = V^1_{i,j,t} - V^2_{i,j,t}$, is described in equation 1:

$$\Delta V_{i,t} \quad = \quad \alpha_{0,i,t} + \sum_{k \in K} \omega_{k,i,t} \Delta x_{k,t} + \epsilon_{i,t} \tag{1}$$

Where $\omega_{k,i,t}$ represents the weight that agent i allocates to attribute k in the decision trial t, $\alpha_{0,i,t}$ is an ex-ante predisposition for option 1 over 2; and $\epsilon_{i,t}$ is the error term, which follows an independent Gumbel distribution.

In our experiment, each product has three attributes, price, quality, and sustainability. Since the attribute values of quality and sustainability are categorical variables (bottom, middle, and top tier), we allow the increase between tiers to be non-linear. For $k \in \{Q, S\}$, we define the attribute values as follows:

$$\omega_{k,i,t} \Delta x_{k,t} \quad := \quad \begin{cases} \omega^{a,b}_{k,i,t} & \text{if} \quad x^1_{k,t} = a \text{ and } x^2_{k,t} = b \\ -\omega^{a,b}_{k,i,t} & \text{if} \quad x^1_{k,t} = b \text{ and } x^2_{k,t} = a \end{cases} \tag{2}$$

Where $(a, b) \in \{(2, 1), (3, 2)\}$ represent the rating tiers for the different products. Based on our previous experiment (see Appendix E), we predict that in the absence of any additional information, participants expect a linear increase in the underlying values behind the attributes' ratings. Nonetheless, we expect that participants will not value the increase in the ratings linearly (i.e., marginal decreasing returns). Which lead us to our two first pre-registered hypotheses:

Hypothesis 1. *Participant's belief's about label values increase linearly for attribute $k \in \{Q, S\}$.*

Hypothesis 2. *The marginal value of choosing a product with a higher rating in attribute $k \in \{Q, S\}$ is decreasing.*

$$\omega^{2,1}_{k,t} > \omega^{3,2}_{k,t} \quad \forall k \in \{Q, S\}$$

Following the common practice in economics, we use as a benchmark a simpler representation of our model, random-effects logistic regression, which can be represented in our model by imposing the following constraints:

$$\omega_{k,i,t} := \omega_k \qquad \text{(common weights for all agents and periods)}$$
$$\alpha_{0,i,t} := \alpha_i \qquad \text{(random-intercepts for each participant)}$$

4.2 Information treatments and changes in preferences

The additional information, provided in the middle of the experiment, precisely explains the underlying values driving the quality- and sustainability ratings. To assess the impact of the information on the decision process, we estimate the changes in all decision weights after the new information, conditional on the treatments. We operationalize the effect of the information treatments as follows. For every attribute $k \in K$, the decision weight is:

$$\omega_{k,i,t} := \pi_{k,\tau} + \pi_{k,after}\mathbb{1}\{t > T/2\} + \pi_{k,DiD,\tau}\mathbb{1}\{t > T/2\} \tag{3}$$

Where the $\pi_{k,\tau}$ captures the treatment group effects, $\pi_{k,after}$ captures the before vs after effects, and $\pi_{k,DiD,\tau}$ is the differences-in-differences effect of treatment τ on the decision weight for attribute k.

When comparing our baseline linear condition (L) with our two information treatments, Sustainability Convex (SC) and Quality Convex (QC), we expect the following results. First, in the Sustainability Convex condition, the middle tier of sustainability rating is decreased almost to the level of the bottom tier. Therefore, if participants incorporate this information, they will decrease their willingness to pay for switching from the bottom to the middle tier of sustainability (2 vs 1), but will increase their willingness to pay to switch from the middle to the highest (3 vs 2). This leads us to our next hypotheses:

Hypothesis 3a. *The willingness to pay for the middle tier of the sustainability rating decreases after the information treatment in the sustainability convex condition (compared to the linear condition)*

$$\pi^{2,1}_{S,DiD,SC} < 0 \quad \pi^{3,2}_{S,DiD,SC} > 0$$

Similarly, in the Quality convex treatment, we expect participants to reduce their willingness to pay for the second tier of quality.

Hypothesis 3b. *The willingness to pay for the middle tier of the quality rating decreases after the information treatment in the sustainability convex condition (compared to the linear condition)*

$$\pi^{2,1}_{Q,DiD,QC} < 0 \quad \pi^{3,2}_{Q,DiD,QC} > 0$$

In the next section, we enhance our decision model by incorporating differences in the decision weights based on attention (Hirmas et al., 2023). We allow the decision weights, $\omega_{k,i,t}$, and the intercepts, $\alpha_{0,i,t}$, to be contingent on the individual making the decision (i.e., individual differences), but also the context in which the decision is made (i.e., contextual differences). The next subsection elaborates on how we use attentional measures to capture these individual- and contextual-differences in the decision model.

4.3 Decision weights and attention

We refer to attention as the cognitive mechanism by which available information is processed and filtered during decision-making. Attention supports decision-making in important ways, as effective decision-making relies on efficiently acquiring choice-relevant information. Therefore, examining how individuals seek information provides insights into the cognitive processes underlying decisions. This notion is supported by prior theoretical and empirical work. Theories such as rational inattention theory or salience theory, suggest that information that appears more often or is more salient gain greater relevance in the decision process (e.g., Bordalo et al., 2013; Matějka and McKay, 2015). Overall, these theories predict a greater weighting of those attributes that receive more attention in the decision process. These predictions are supported by recent empirical work that has shown that information that is more relevant for the choice is sampled more frequently and for longer (e.g., Orquin and Mueller Loose, 2013; Hirmas et al., 2023). Conversely, when information is salient (e.g., visually striking), one is also more likely to fixate on that information, which in turn is weighted more heavily in the decision (e.g., Alós-Ferrer and Ritschel, 2022; Li and Camerer, 2022).

Given the positive link between attention and decisions, we can expect attentional patterns to vary across participants in the presence of heterogeneous preferences for product attributes, and across choice contexts. Our approach makes use of these heterogeneities (Hirmas et al., 2023). Specifically, by analyzing systematic differences in attention, we can capture differences in the relative importance of the available information during the decision. Differences in attention can arise due to (1) individual specific factors, such as preferences, personality traits, or individual-specific information (e.g., between-subject treatments), as well as (2) context-specific factors that are not constant across the whole experiment, such as the relative value of the options' attributes. To capture variations in attention due to individual and contextual factors we construct two independent indexes of attention for each attribute.

4.3.1 Individual-average attention

We denote the attention allocated to attribute k by agent i in trial t as $a_{k,i,t}$. We define, individual average of attention, $\bar{a}_{k,i}$, in equation (4). This index represents *how much more participant i attends to attribute k compared to the other participants (measured in standard deviations).*

$$\bar{a}_{k,i} \quad := \quad \frac{\frac{1}{T}\left(\sum_{t=1}^{T} a_{k,i,t}\right) - \bar{a}_k}{sd(a_k)}. \tag{4}$$

The individual-average attention index captures idiosyncratic effects that remain relatively constant for the participant across the experiment. These constant effects reflect individual preferences, personality traits, but are also influenced by between-subject treatment effects. Based on our and others prior results (Hirmas et al., 2023), we expect these factors to influence both the attention and decision process. Hence, variations in the individual-average attention should be correlated with changes in the decision weights. Using these indexes as moderators for the attribute value on the choice allows us to capture the correlation between decision weights and individual-average attention.

Hypothesis 4. *The individual-average attention index ($\bar{a}_{k,i}$)for attribute k correlates positively with the decision weight of the attribute in the choice.*

$$\rho(\bar{a}_{x,i}, \omega_{k,i,t}) > 0$$

4.3.2 Trial-wise deviations of attention

The previous index captures stable effects about the individual that affect both attention and the decision at a low frequency (i.e., with relatively little variation throughout the experiment).

Now, we turn into contextual effects that change across the experiment and can have additional impacts on both attention and the decision, but at a higher frequency. The trial-wise deviations of attention, $\tilde{a}_{x,i,t}$, in equation (5) represents *how much more participant i attends to attribute k in trial t compared to the participant's average behavior (measured in standard deviations).*

$$\tilde{a}_{x,i,t} \quad := \quad \frac{a_{x,i,t} - \frac{1}{T}\sum_{t=1}^{T} a_{x,i,t}}{sd(a_x)}. \tag{5}$$

This index captures any context-specific factor that can change throughout the experiment and affects both the decision and attention. Factors such as experience on the task or variation in attribute values would be captured by this index. If these contextual factors affect both the decision and the attention process, then this index can be used as a proxy to estimate the effect of the contextual factors on the decision. Our hypothesis is that this index will be correlated with the decision weights:

Hypothesis 5. *The index of trial-wise deviations in attention for attribute k correlates positively with the decision weight of the attribute in the choice.*

$$\rho(\tilde{a}_{k,i}, \omega_{k,i,t}) > 0$$

4.4 Incorporating the attention indexes to the decision process

We further develop the decision model, defined by equations (1) and (3), by allowing the decision weights to depend on our attention proxies. Namely, for every attribute $k \in K$, the decision weight will be:

$$\omega_{k,i,t} \quad := \quad \pi_{k,\tau} + \pi_{k,after}\mathbb{1}\{t > T/2\} + \pi_{k,DiD,\tau}\mathbb{1}\{t > T/2\} + \pi_{k,\bar{a}}\bar{a}_{k,i} + \pi_{k,\tilde{a}}\tilde{a}_{k,i,t} \tag{6}$$

In practical terms, for each attribute we incorporate an interaction effect of the attention indexes with the attribute's value[3]. We can contrast this model with our benchmark with constant slopes, where $\pi_{k,\bar{a}} = \pi_{k,\tilde{a}} = 0$. Note that Hypothesis 4, stating that the individual-average attention

[3] We also incorporate the attention indexes without the interaction. Thus, the attention indexes can also affect the intercept. For simplicity, we do not describe these equations in this section.

positively correlates with the decision weights, implies that $\pi_{k,\bar{a}} > 0$. Similarly, Hypothesis 5, stating that the trial-wise deviations are positively correlated with the decision weights, is represented by $\pi_{k,\tilde{a}} > 0$.

Now that we have established our decision model, we proceed to use our estimations to calculate the willingness to pay for the different attributes, depending on the treatments, the rating comparison and the attention allocated to the attributes by the participants.

4.5 Empirical estimation and Willingness to Pay

In the following question we show our estimations of the model based on equations (1) and (6). For better readability, we repeat the relevant equations below. As equation (1, revisited) shows, price enters linearly into our decision process. The attributes presented in ratings, quality, and sustainability, are introduced discretely (i.e., signed dummy variable depending on the combination c).

$$\Delta V_{i,t} = \alpha_{0,i,t} + \omega_{P,i,t}\Delta P_{k,t} + \sum_{k\in\{Q,S\}} \sum_{c\in\{(2,1),(3,2)\}} \omega^c_{k,i,t}\Delta x^c_{k,t} + \epsilon_{i,t} \tag{1, revisited}$$

$$\omega_{k,i,t} = \pi_{k,\tau} + \pi_{k,after}\mathbb{1}\{t > T/2\} + \pi_{k,DiD,\tau}\mathbb{1}\{t > T/2\} + \pi_{k,\bar{a}}\bar{a}_{k,i} + \pi_{k,\tilde{a}}\tilde{a}_{k,i,t} \tag{6}$$

Using the estimates of the decision weights, we construct the willingness to pay of participants for the different attributes. Namely, we estimate the ratio between the weight of a given attribute and the weight of the price.

$$WTP^c_{i,t} = \frac{\omega^c_{k,i,t}}{\omega_{P,i,t}} \qquad \begin{array}{c} \forall k \in \{Q, S\} \\ \forall c \in \{(2,1),(3,2)\} \end{array} \tag{7}$$

The ratio in equation (7) represents the value in pounds that participants are willing to pay to increase the attribute k of the chosen product from the low to the middle tier (2 vs 1) or from the middle to high tiers (3 vs 2). We use the WTP estimations to calculate the monetary impact of our treatments and attention on the decisions.

5 Results

In this section, we describe the results of our analysis concerning the participants' sustainable decisions. We use a random-effects logistic regression to estimate the model represented by equations (1, revisited) and (6). For a more comprehensive presentation of the results, we separate the analysis based on our hypotheses. The analysis is structured as follows. First, we analyze the overall consumer behavior and their willingness to pay for quality and sustainability conditional on the attribute's tier in the rating. Second, we analyze the impact of the different information treatments and explore whether attention plays an additional role in capturing the heterogeneous effects of these treatments. Finally, we investigate the role of our attention measures in the decision process and their impact on the willingness to pay.

5.1 Participants' choices and their Willingness to pay (WTP) for Quality and Sustainability

We first analyze the participants' purchasing choices before the information treatment to assess their sensitivity to each of the product attributes, specifically the price of the products and their quality- and sustainability ratings. Table 1 summarizes the purchasing decisions of participants based on these three attributes before the information treatments. Panel A shows the percentage of choices favoring the most sustainable product depending on the sustainability rating of the compared products. Panel B shows the percentage of choices where the chosen product had the highest quality rating, contingent on the quality ratings comparison. Finally, the third panel presents the percentage of decisions leading to the lowest price product conditional on the price difference of both products.

Overall the results in Table 1 show that participants are sensitive to each attribute. If the decisions were made by chance, we would expect these proportions to be around 50%. Specifically, we find that participants are more likely to choose the higher quality product when the product difference is higher (3 vs 1) and they are more likely to choose the cheapest product when the price difference is larger than 1. Finally, participants are more likely to make sustainable decisions when the difference between the products' sustainability is large (3 vs 1).

Now, we proceed to analyze the beliefs of participants regarding the underlying values behind both quality and sustainability ratings. We test whether participants expect that the ratings increase linearly. Namely, we test whether the expected underlying value increases equally from

Table 1: Percentage of choices given attribute differences

Panel A:		Difference in Sustainability			
		2vs1	3vs2	3vs1	Total
Highest Sustainability chosen		49.7%	45.7%*	65.4%***	53.6%***

Panel B:		Difference in Quality			
		2vs1	3vs2	3vs1	Total
Highest Quality chosen		65.7%***	54.6%*	82.7%***	67.8%***

Panel C:	Difference in Price				
	0.5	1.0	1.5	2.0	Total
Lowest Price chosen	40.9%***	51.8%	60.1%***	63.1%***	51.2%

The estimated percentages above are calculated based on the decisions before the information treatments. For each panel, observations where both products have the same level of the relevant attribute are omitted. Significance level for rejecting null-hypothesis that decisions are made by chance (i.e. proportion equal to 50%) with Bonferroni correction for multiple hypotheses ($\alpha/3$).
* $p < 0.05$; ** $p < 0.01$, *** $p < 0.001$

the bottom to the middle tier and from the middle to the top tier. The results of a signed-rank test (Wilcoxon et al., 1970) show that participants do not expect non-linear increases in Quality ($[B(Q(3)) - B(Q(2))] - [B(Q(2)) - B(Q(1))] = 0.64$ points, $p = 0.128$).

Result 1. *Participants believe that the underlying value driving the quality ratings increases linearly.*

On the other hand, participants expect a slightly convex increase in the sustainability ratings ($[B(S(3)) - B(S(2))] - [B(S(2)) - B(S(1))] = 0.497$ points, $p < 0.001$). It must be noted that the underlying values for sustainability range from 0 to 30 sustainability points. Hence, a difference of about half a point is quite small. These results partially support our hypothesis 1, that the beliefs before the information treatments are linear[4].

Result 2. *Participants believe that the underlying value driving the sustainability ratings increases convexly.*

So far, we have established that the three attributes influence choice and that beliefs regarding the ratings are close to linear. To further disentangle the relevance of the three attributes on the

[4]See the results presented in appendix section F

decision process, we estimate our baseline random-utility model (1, revisited), with the constraint of equal weights for all participants (i.e., $\omega_{k,i,t} = \omega_k$). We focus on the data collected before the information treatments to estimate the pre-information willingness to pay and decision weights for each attribute[5]. Our decision models use two assumptions, (1) there are no significant differences in the treatment groups' behavior before the additional information, and (2) the participants' decisions are transitive. We refer to transitive decisions when the willingness to pay to switch from the first to the third tier for any attribute is equal to the willingness to pay for increasing from the first to the second, plus increasing from the second to the third (i.e., $\omega_k^{2,1} + \omega_k^{3,2} = \omega_k^{3,1}$). We find evidence supporting both assumptions in an unrestricted model (See Appendix section G for further details).

Table 2 shows the estimated decision weights for the different attributes, where we find that all attributes significantly influence choices. Additionally, we find that the marginal value of increasing the attributes from the bottom to the middle tier is larger than the increase from the middle to the top. Both, the difference for quality ($\omega_Q^{32} - \omega_Q^{21} = -.519$, p$<$ 0.001) and sustainability ($\omega_S^{32} - \omega_S^{21} = -.232$, p= 0.001) are significant. These results support our hypothesis 2 which states that the marginal value of choosing a product with a higher rating is decreasing.

Result 3. *Participants' willingness to pay for increasing the quality and sustainability of the products is concave with respect to the attribute's tier.*

Table 2: Decision weights before information treatment

ΔP	-1.093***	(0.072)
ΔQ^{21}	1.754***	(0.096)
ΔQ^{32}	1.235***	(0.094)
ΔS^{21}	1.233***	(0.070)
ΔS^{32}	1.001***	(0.068)
Constant	0.0236	(0.034)
Observations	4929	
AIC	4904.0	
BIC	4943.0	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

We proceed to estimate the participants' willingness to pay (WTP) for improving a specific attribute depending on the rating comparison. We calculate the willingness to pay, defined in

[5]Section 5.2 shows that these results are similar once the information after the treatments is incorporated.

equation 7, as the ratio between the weight for a specific attribute k given the tier combination a, b, $\omega_k^{a,b}$, and the weight allocated to the price difference, ω_P. This ratio represents the amount in pounds that participants are willing to pay to increase the rating of attribute k from tier b to tier a. Figure 3 shows the estimated willingness to pay for both Quality (orange) and Sustainability (Green) and for each type of comparison (2 vs 1 and 3 vs 2). The participants' willingness to pay to increase the quality of a product from the bottom to the highest tier was 2.74 pounds. Since the value of a product ranged from 3 to 4.5 pounds, participants overpaid in average 1.24 pounds (2.74 - 1.5) for the product's quality. The WTP for increasing the sustainability rating from the bottom to the top tiers was 2.04 pounds. The value of planting a tree was 1 USD (0.8115 GBP / USD based on the current exchange rate) and depending on the participants' choices, zero to three trees would be planted on their behalf. Therefore, participants underpaid, on average, 0.39 pounds (2.04 - 2.43) for the product's sustainability. It must be noted, that participants were not aware of the cost of planting trees.

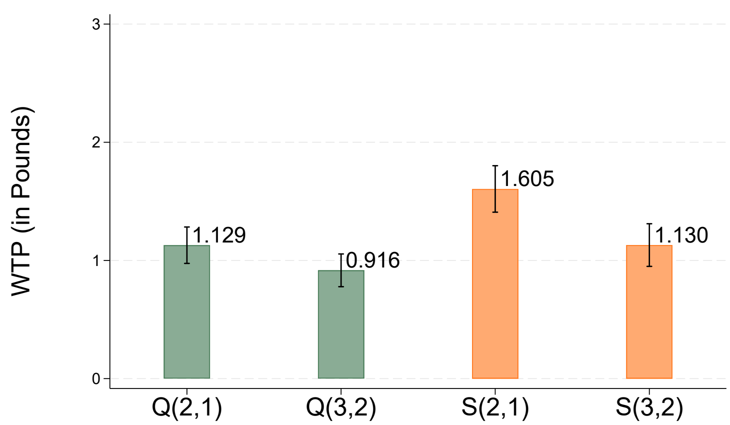


Figure 3: Willingness to pay for the attributes depending on the tier comparison

5.2 The effect of new information

So far, we have determined how participants use the quality and sustainability ratings in the absence of further information regarding what is behind these labels. In this section, we investigate how the decision process changes when participants are presented with new information regarding the labels. To this end, we first analyze the raw data regarding the purchasing choices and compare the different treatments with the average behavior before the information.

Table 3 provides an overview of the changes in behavior after the information treatments. In

Panel A, we examine the shift in the proportion of sustainable choices after the different information treatments are provided (compared with the behavior before). The proportions are conditional on the comparison of sustainability levels between the two products (columns). In the Sustainability convex (SC) treatment, following the expected direction, participants chose the sustainable option less frequently when comparing between the lowest and the middle tier (p=0.031). Conversely, they chose more the sustainable option when comparing between the middle and the highest tier (p=0.014). As expected, there are no large differences when comparing the bottom to the highest tier (p=0.969).

A. Sustainable choices				B. Highest quality choices			C. Lowest price choices			
	2vs1	3vs2	3vs1	2vs1	3vs2	3vs1	0.5	1	1.5	2
Before	0.497	0.457	0.654	0.658	0.546	0.827	0.409	0.518	0.601	0.631
Linear	0.52	0.468	0.639	0.603	0.565	0.826	0.437	0.509	0.581	0.559
SC	0.442	0.521*	0.655	0.722*	0.574	0.765*	0.357	0.479	0.601	0.616
QC	0.535	0.489	0.68	0.592*	0.618*	0.808	0.321**	0.481	0.575	0.627

Table 3: Proportion of choices before and after treatments depending on attribute values.

The tables above show the proportion of sustainable (Panel A), highest quality (Panel B) and lowest price choices (Panel C) for each treatment condition (Linear, SC and QC) after the information appears. As a reference, the first row of each table presents the proportion of choices before all condition treatments. The columns describe the relevant attribute's comparison (Sustainability for A, Quality for B and Price for C). Significance level for rejecting null-hypothesis that proportion of choices is equal to the proportion before the information (p values are adjusted using a Bonferroni correction for multiple hypotheses).

* $p < 0.05/3$; ** $p < 0.01/3$, *** $p < 0.001/3$

SC: Sustainability convex, QC: Quality convex

In the sustainability convex condition (SC), the marginal benefit between choosing a product from the bottom versus the middle tier of sustainability is close to zero. Hence, we expected even a stronger reaction from the treatment. On the other hand, We find no significant differences in the proportion of sustainable choices between the linear and quality convex treatment (QC). This result was expected since the information regarding the sustainability ratings is equivalent in both treatment conditions.

Panel B shows the proportion of choices, where the highest quality product was chosen, conditional on the treatments and levels of quality. We find an analogous effect regarding quality-driven choices. When comparing products from the lowest- and middle-quality tiers in the QC treatment, participants' choices for the highest-quality product were less than before the information (p=0.016). When comparing middle to high tier, participants chose more the highest quality option than before (p=0.01).

Additionally, we find a somewhat striking result. Participants are more likely to choose the highest quality option in the SC treatment when comparing both low- to middle-tier products (p=0.011) and low-to-high (p=0.004). This effect is most likely driven by the fact that the sustainable options become less appealing due to the SC condition.

In Panel C, we can see the proportion of choices where the lowest price was chosen depending on the price difference. We find a decrease in the choices of the lowest price when the price difference is 0.5 (SC: p=0.044; QC: p=0.001). These effects suggest that participants become more sensitive to the labels (relative to the price) after the information treatments.

To disentangle the treatment effects on the decision weights for the different attributes, we estimate the model represented by equations (1, revisited) and (3). Table 4 shows the estimated treatment effects of the information treatments on the decision weights. The first column shows the estimates of the decision weights using only the data before the information treatments (same results as in Table 2). The second column presents the treatment effects (and baseline decision weights) based on the whole dataset (For the complete regression table see Appendix Table H).

Table 4: Differences-in-Differences estimates of information effects on decision weights

	(1) Before		(2) After	
ΔP	-1.093***	(0.072)	-0.979***	(0.123)
$\delta^{SC}(P)$			0.159	(0.136)
$\delta^{QC}(P)$			0.082	(0.138)
ΔQ^{21}	1.754***	(0.096)	1.690***	(0.175)
$\delta^{SC}(Q,21)$			0.005	(0.218)
$\delta^{QC}(Q,21)$			-0.218	(0.244)
ΔQ^{32}	1.235***	(0.094)	1.254***	(0.165)
$\delta^{SC}(Q,32)$			-0.096	(0.190)
$\delta^{QC}(Q,32)$			0.696**	(0.249)
ΔS^{21}	1.233***	(0.070)	1.114***	(0.124)
$\delta^{SC}(S,21)$			-0.447**	(0.165)
$\delta^{QC}(S,21)$			0.043	(0.162)
ΔS^{32}	1.001***	(0.068)	0.903***	(0.123)
$\delta^{SC}(S,32)$			0.369*	(0.184)
$\delta^{QC}(S,32)$			0.080	(0.175)
N	4929		9851	
AIC	4903.967		9950.416	
BIC	4942.984		10216.643	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Based on the results of column (2), we find that neither the Quality convex (QC) nor Sustainability convex (SC) treatments have a significant effect on the decision weights for the price ($\pi_{P,DiD,SC} = 0.159, p = 0.242$; $\pi_{P,DiD,QC} = 0.082, p = 0.554$). Hence, any effect on the willingness to pay for quality and sustainability will come through changes in the decision weights for said attributes and not the price.

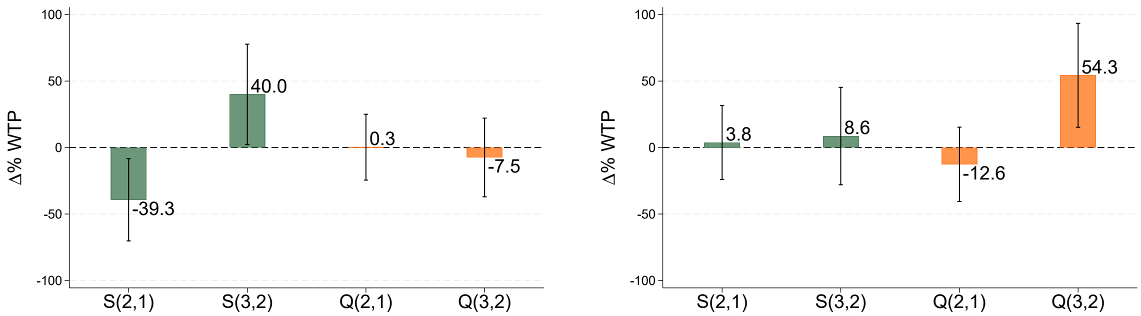
When we consider the SC condition, we find no significant effect on the decision weights for quality ($\pi^{2,1}_{Q,DiD,SC} = 0.005, p = 0.982$; $\pi^{3,2}_{Q,DiD,SC} = -0.0957, p = 0.614$). On the other hand, we find a significant decrease in the decision weights for S(2,1) ($\pi^{2,1}_{S,DiD,SC} = -0.447, p = 0.007$) and an increase for S(3,2) ($\pi^{3,2}_{S,DiD,QC} = 0.369, p = 0.045$). These results are in line with our hypothesis 3a, which predicts that the participants' willingness to pay for the mid-tier will decrease in the SC condition.

Result 4. *In the sustainability convex condition (SC), participants shift from choosing the middle sustainability products to both low and top sustainability products.*

In the QC condition, we find a large and significant increase in the decision weight on Q(3,2) ($\pi^{3,2}_{Q,DiD,QC} = 0.696, p = 0.005$), but no significant decrease in the weights for Q(2,1) ($\pi^{2,1}_{Q,DiD,QC} = -0.218, p = 0.372$). These results partially confirm our hypothesis 3b, stating that participants decrease their willingness to pay for the middle-tier quality in the QC treatment. We find no significant effects on the decision weights for sustainability from the QC treatment ($\pi^{2,1}_{S,DiD,QC} = 0.0432, p = 0.789$; $\pi^{3,2}_{S,DiD,QC} = 0.0797, p = 0.649$).

Result 5. *In the quality convex condition (QC), participants shift from choosing middle quality products to top quality, but not to lower quality products.*

In both, the sustainability and quality convex conditions, the middle tier of the affected attribute has a similar value to the bottom lowest tier. In theory, this means that participants should be willing to pay an amount close to zero to increase the attribute from the bottom to the middle tier (2 vs 1). In Figure 4, we can see the difference in difference effects relative to the WTP before the information. As we can see in the left panel, the WTP for S(2,1) decreases by 39.29% (p=0.013) and the WTP for S(3,2) increases by 39.99% (p=0.038). These results suggest that participants underreact to the new information in the SC condition, lowering the WTP for the middle tier less than expected. When we analyze the effect of the Quality convex condition, we observe that participants do not significantly decrease the WTP for Q(2,1) ($\Delta = 12.6\%, p = 0.377$), while they increase their WTP for Q(3,2) in 54.33% (p=0.006). These results show not only an underreaction to the information but also an asymmetric shift in their preferences. Participants do not shift down, but only up in response to negative information about the mid-quality products.



Sustainability Convex

Quality Convex

Figure 4: Treatment effects relative to WTP before information

5.3 The role of attention in the decision process

So far, we have established how participants use the quality and sustainability ratings. We have also determined how they react to clear information regarding the underlying attributes driving these ratings. In this section, we analyze their attention patterns to further understand the participants' behavior. To this end, we perform the following analyses. First, we analyze what are the drivers of attention in our experimental setting. Secondly, we analyze how variations in attention can help us further explain the purchasing decisions.

First, we analyze whether attention is driven by individual and contextual factors; and whether the information treatments have an impact on the attention to the attributes. In Appendix section I we show that the attention to the three attributes is partially explained by both individual and contextual factors. When it comes to the information treatments, we find that across conditions, participants attend less to the price after the information treatments. This suggests that the ratings become more relevant after the information treatments since the information provided by the ratings is richer now. Additionally, participants attend more to the quality ratings and even less to the price after the quality convex condition. We find no effects on attention after the sustainability convex treatment.

Now that we have established that both individual and contextual factors affect the attention paid to the different attributes, we proceed to analyze if the differences in attention driven by these factors predict differences in the decision process as well. To do so, we construct the indexes described in section 4.3 and incorporate them into our decision models. Table 5 presents the moderating effect of the attention indexes on the decision weights from the model defined by equations (1, revisited) and (6). In this table, we only present the baseline decision weights and the moderating effects of attention (see Appendix table J for the complete estimations). Column (1) presents the model with no attention, which is identical to the decision model in the previous section (Table 4, column 2). The second and third columns present the models which sequentially introduce the effect of individual-average and the trial-wise deviations of attention.

Table 5: Effects of attention indexes on decision weights

	(1)		(2)		(3)	
	No Attention		Individual Effects		Individual + Contextual Effects	
ΔP	-0.979***	(0.123)	-1.141***	(0.128)	-1.143***	(0.129)
$\Delta P \times \bar{a}(P)$			-0.324***	(0.057)	-0.324***	(0.058)
$\Delta P \times \tilde{a}(P)$					-0.041	(0.027)
ΔQ^{21}	1.690***	(0.175)	1.766***	(0.180)	1.769***	(0.182)
$\Delta Q^{21} \times \bar{a}(Q)$			-0.043	(0.079)	-0.041	(0.079)
$\Delta Q^{21} \times \tilde{a}(Q)$					0.120**	(0.046)
ΔQ^{32}	1.254***	(0.165)	1.391***	(0.166)	1.401***	(0.167)
$\Delta Q^{32} \times \bar{a}(Q)$			0.182*	(0.082)	0.181*	(0.082)
$\Delta Q^{32} \times \tilde{a}(Q)$					0.010	(0.046)
ΔS^{21}	1.114***	(0.124)	1.166***	(0.120)	1.180***	(0.119)
$\Delta S^{21} \times \bar{a}(S)$			0.373***	(0.057)	0.373***	(0.057)
$\Delta S^{21} \times \tilde{a}(S)$					0.018	(0.042)
ΔS^{32}	0.903***	(0.123)	0.951***	(0.123)	0.954***	(0.124)
$\Delta S^{32} \times \bar{a}(S)$			0.356***	(0.055)	0.362***	(0.055)
$\Delta S^{32} \times \tilde{a}(S)$					0.089	(0.047)
Observations	9851		9851		9851	
AIC	9950.416		9399.544		9381.839	
BIC	10216.643		9716.138		9748.801	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

To test the descriptive effect of the attention indices, we use the model in column 3 to test our hypotheses 4 and 5, which state that individual-average and trial-wise deviations of attention positively correlate with the decision weights. The joint tests show that the individual average has a significant effect on describing choice (H0: $\pi_{k,\bar{a}} = 0 \forall k$, $\chi^2(5) = 102.333, p < 0.0001$), supporting our hypothesis 4, which states that individual-average attention is positively correlated with the decision weights. We also find that all the moderator effects of the individual attention on the choice are significant (except for ΔQ^{21}), suggesting that this effect is independent of the attribute.

Result 6. *Individual-average attention to an attribute is positively correlated with the weight of said attribute in the decision.*

When analyzing the impact of the trial-wise deviations in attention over the decision weights, we find a significant joint effect (H0: $\pi_{k,\tilde{a}} = 0 \forall k$, $\chi^2(5) = 24.63, p = 0.0002$), although most of the individual parameters for the trial-wise deviations in attention are not significant (except for ΔQ^{21}). When we compare the BIC of the different models, we see that although the model including both indexes of attention describes the data better than a model with no attention, the marginal contribution of the trial-wise deviations does not compensate for the cost of more parameters. Thus, we conclude that if there is an effect of trial-wise deviations of attention on choice, this effect is weak and specific to certain attributes. Thus, our results only partially confirm our hypothesis 5. Based on these results and the fact that the best-fitting model (according to BIC) includes only the individual effects, we continue the rest of our analysis based on the model described in column (2).

Result 7. *Trial-wise deviations in attention to an attribute have a weak impact on the decision weights, and it is specific to some attributes only.*

To further assess the economic significance of the captured individual differences in the decision weights, we estimate the participants' willingness to pay (WTP) for quality and sustainability conditional on their attention to the attributes (compared to the rest of the sample). To do so, we measure the average attention for the different attributes for participants that are on the lowest 10th percentile of the individual average attention, participants around the median, and participants above the 90th percentile. It is important to note, that the WTP of an attribute is the ratio between the weight of the attribute and the weight of the price. Hence, if for example participants, that allocate low levels of attention to sustainability, focus mostly on the price, the effects of attention on the willingness to pay will be enhanced (compared to the case where the focus shifts to quality).

Figure 5 shows the willingness to pay (WTP) for Sustainability (in green) and Quality (in orange) across the 10th, 50th, and 90th percentiles of attention distribution toward the respective attributes. When comparing the WTP for elevating the sustainability rating from low to middle tier, participants with low attention to sustainability exhibit a 64.66% decrease in their WTP compared to the median participant. Conversely, those with high attention levels to sustainability demonstrate a 54% increase in WTP for the same upgrade. Similar patterns emerge when assessing the WTP for increasing the sustainability rating from middle to top tier, with participants paying 71.56% less at the low attention end and 88.48% more at the high attention end.

We find similar, but smaller effects for the quality ratings. When comparing low-to-middle tier decisions, participants at the low end of attention towards quality are willing to pay 11.88% percent less, while participants at the high end are willing to pay 25% more. When comparing middle-to-top-tier decisions, participants are willing to pay 31.7% less and 55.8% more for the low- and

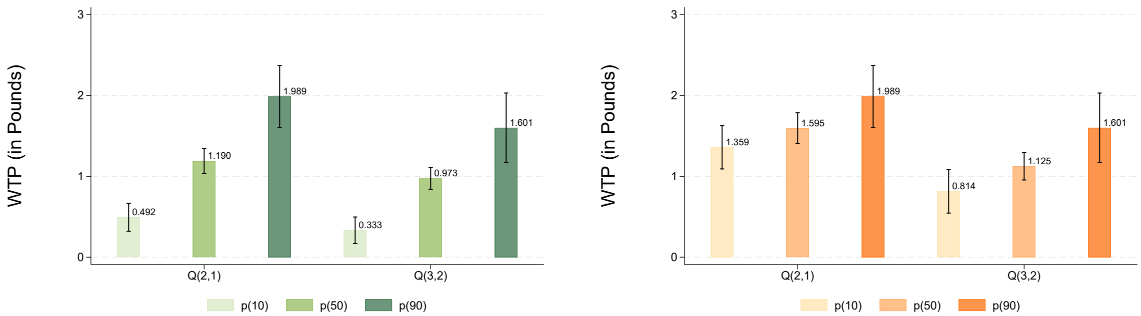


Figure 5: Willingness to pay for attributes depending on level of attributes and levels of attention

high-end participants. The lower differences compared to sustainability suggest that participants that are inattentive to quality, are usually also inattentive to price. Thus, the attentional effects due to lower attention to quality get counteracted by the lower attention to price.

6 Discussion

In this study, we analyze the decision-making process of purchasing products in the presence of product ratings regarding quality and sustainability. Our approach involves the creation of an incentivized paradigm that mirrors the online shopping experience. In our experiment, we study the information-gathering process of participants while they make their choices. Our experimental design tests whether participants use sustainability and quality ratings differently and whether they fully integrate any additional information regarding the ratings' underlying attributes when using these ratings. We also analyze the role of attention in this decision process and study if different attentional patterns are linked with different behavior towards these ratings.

Our results show that participants consider both the level of quality and sustainability when making a decision, displaying a larger willingness to pay (WTP) for quality than sustainability. The estimated marginal value that participants assign to purchasing products with higher ratings is decreasing (i.e., concave WTP with respect to the attribute's rating), although their beliefs about the underlying attributes driving the ratings is fairly linear.

We also find that if participants receive additional and clear information regarding the ratings, they react to the information and adapt their WTP for the different tiers of the rating. Still, participants do not fully adapt to the new information. These results are consistent with anchoring behavior (Tversky and Kahneman, 1974), which lead to sub-optimal updating in beliefs. We cannot attribute these results to participants forgetting the information, since most participants perfectly recall the information by the end of the experiment.

We implement the methods used in (Hirmas et al., 2023) to use individual- and contextual differences in attention to predict heterogeneous patterns in behavior. Our results show that participants are quite heterogeneous in how much attention they allocate to the different attributes, and in turn, these differences are correlated with the weight the attribute plays in the decision. These individual differences in attention are not correlated with any of the demographics we measured (i.e., gender, age, attitudes towards sustainability and connectedness to nature). We do find a position effect on the attention of the attributes. Namely, if either quality or sustainability are presented in the middle instead of in the bottom, participants will allocate more attention to that attribute. In appendix section L, we show that even when controlling for other moderating effects, such as the position of the attribute, the individual-average index of attention still has a strong and significant descriptive power on the participants decision weights.

We also find that the participants' attention is driven by contextual factors such as the attribute values presented on the specific trial. Our tests, show that these effects also significantly predict differences in the decision weights. Namely, if a specific participant allocated more attention to an attribute in a specific trial, this attribute will be weighted more in that specific trial. It is important to note that these effects are milder in scale and significance. Hence, in our experiment, we find stronger individual compared to contextual effects of attention.

Finally, we found that the information treatments do not have significant changes on attention. In our pre-registration, we aimed to look for alternative ways that attention can help predicting heterogeneous effects of the information. In appendix section K, we show alternative specifications that allow attention to moderate the effect of the information treatments. We find that incorporating the changes in attention from before and after do not improve the model fit of our estimations. Moreover, we control whether the individual average attention also moderates the treatment effects (e.g., participants that attend sustainability more, also react more to the new information). Our results show no significant moderating effects on the treatments either. Further research is needed to test whether within-subject treatments that significantly and heterogeneously affect choices can be captured by variations in attention.

Following prior work on process tracing, we use the proportion of time spent looking at an attribute as our proxy for attention. The proportion of time spent looking at an attribute is a recommended measure for capturing relative differences in the importance of the attributes Rahal and Fiedler (2019). Other measures commonly used are the absolute dwell-time (i.e., time spent looking at an attribute) or number of fixations on an attribute (i.e., how many times an attribute was looked at). In appendix section M, we estimate our decision model using these different attention measures, finding similar results. Thus, our results are robust to the measure of attention used.

7 Conclusion

In this study, we explored consumer decision-making regarding product purchases in the context of quality and sustainability ratings. Our findings show that participants consider both quality and sustainability in their decision process. We find that even though participants are unaware of how the ratings reflect on the underlying attributes, they expect it to be linear, but assign a decreasing value to getting products with higher labels. Using the attention data, we find strong heterogeneity in the participants preferences for sustainability (relative to quality).

When we provide additional information regarding the ratings, participants change their preferences accordingly, though they are still under-adjusting with respect to the expected behavior. This means that given the information that they get, they could act differently and obtain higher benefits (based on their decisions before this information). This evidence suggests that any amendments or news about a new sustainability rating will not be as effective as the initial implementation of the rating itself. Therefore, if a new sustainability rating is created, we suggest to consider that (1) consumers anchor to their previous behavior, and (2) the demand has decreasing marginal returns on purchasing products with higher rating. Based on the two previous recommendations, additional studies on the supply side, that use our results as a benchmark for the demand, can provide interesting insights on how to lead firms into making their products more sustainable.

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Appendix

A Exclusion Criteria

We recruited 330 participants from the online platform Prolific. As preregistered, we excluded from analysis, any participant that did not pass the attention checks. The attention checks were three questions within the questionnaire, where we prompted participants to give a specific answer. Participants with two or more mistakes were excluded from the analysis and exempt from payment. Additionally, we check how long participants spent on each page during the instructions. We also excluded participants that skipped the instructions and tried to force the answers for the comprehension questions. When participants signed the informed consent, we told them that they needed to keep the experiment on fullscreen and that they should not change tabs to go to other pages during the length of the experiment. We excluded from the analysis all participants that spent more than 30 seconds on other pages or that would change tabs more than three times. Since we cannot verify that participants are actually paying attention to the task (e.g., they could still check their phones), we excluded any participant that had an average response three standard deviations above the sample average. In total, 13 participants were excluded due to the aforementioned criteria.

In our experiment, participants were asked to state their beliefs about the underlying values behind the quality and sustainability ratings. In the instructions, we explicitly explained to them that a higher rating meant higher underlying values for the represented attribute. We excluded any participant that showed decreasing beliefs about any of the ratings (i.e. beliefs that a higher rating yields lower values). Additionally, for some participants the system did not constrain the range of values that participants could state for the beliefs. This was due to software compability (problems with the browser). We excluded all participants that had beliefs out of range. In total, 26 participants were excluded due decreasing or out-of-range beliefs.

The final sample consists on 291 participants. In order to see that our results were not driven due to the exclusion of these participants, we ran the analysis with the whole sample. We do not report these results, as they yield very similar results. All our scripts and databases for the analysis are available here.

B Locations of planted trees

Location of planted trees

The map above shows the amount of trees planted in different locations. Participants could either choose to plant the trees on a specific location, or they could choose the default option of planting them anywhere. the organisation 'One Tree planted' offers an option to plant trees where they are needed the most at the moment. We used this option for all participants that chose the default of planting the trees "anywhere". The amount of trees planted in our two studies adds up to 1.153 trees across the world. We thank Diana Garcia for providing us with this graph.

C Pseudo-randomization of attribute values

We ensure that participants observe sufficient trials for every relevant combination of sustainability ratings. Specifically, every product pair will offer choice options that differ in sustainability ratings (i.e., 1 vs. 3 leaves, 2 vs. 3 leaves and 1 vs. 2 leaves) across multiple trials. Sustainability pairs will be offered with varying combinations of price and quality. Across the three sustainability pairs, however, the presented price-quality combinations will be the same for each participant. We show which type of combinations below. To describe these price-quality combinations, we refer to the products as the sustainable option (one with higher sustainability rating) and the competing option. Each sustainability pair will be presented in combination with the following sets of prices and quality ratings:

1. The price and quality of the competing product are higher.
2. The price of the sustainable product is higher and the quality of the competing product is higher.
3. The sustainable product has higher price and quality
4. Both products have the same price, but the competing product has higher quality
5. Both products have the same quality, but the competing product is more expensive.

For comparing quality and sustainability ratings, we also add two trials where both products have equal levels of sustainability and the price and quality of one of the products is higher. These trials will be shown to participants in randomized order and the values of price and quality are randomized within the aforementioned restrictions.

D Belief elicitation

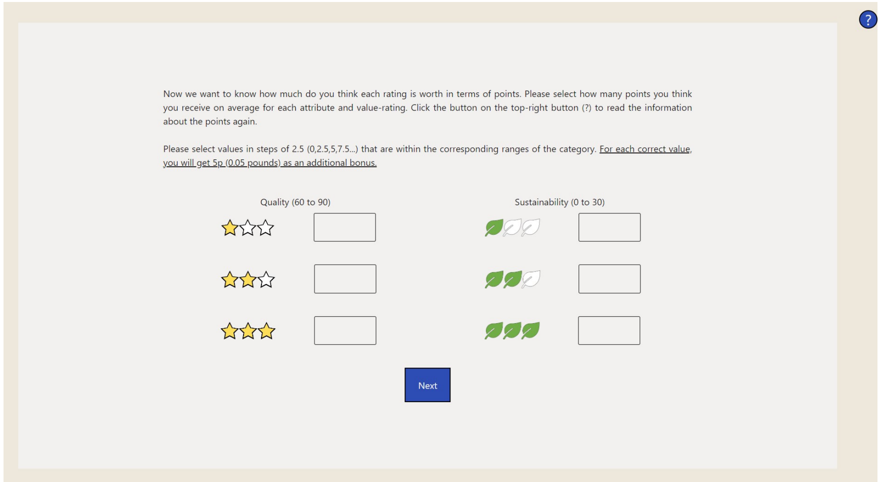


Figure A1: Belief elicitation screen

The Figure shows the decision screen for eliciting beliefs about the ratings. After each block of decisions, participants were asked to state their beliefs about the underlying values for each rating level. Participants were reminded of the ranges for each attribute, but also could revisit the general information about each attribute by pressing the '?' button on the top-right of the screen. They were informed that they would receive 0.1 pounds per correct belief. To make participants' decision easier and increase the chance that the beliefs were correct, we restricted the participants responses in steps of 2.5 points (e.g., 0, 2.5, 5,...). The attribute presented on the left is the attribute that is presented above in the purchasing decisions screen.

E Design of previous study

In a previous version of this study, we ran a similar experiment analyzing the role of ratings on the decision process. In that experiment, we aimed to see whether different underlying information regarding sustainability ratings will influence choice. In that study, we had four between-subject treatments pertaining the information regarding sustainability. This experiment is identical to the one presented in section 3.2, with the exception of the information presented in the middle of the experiment.

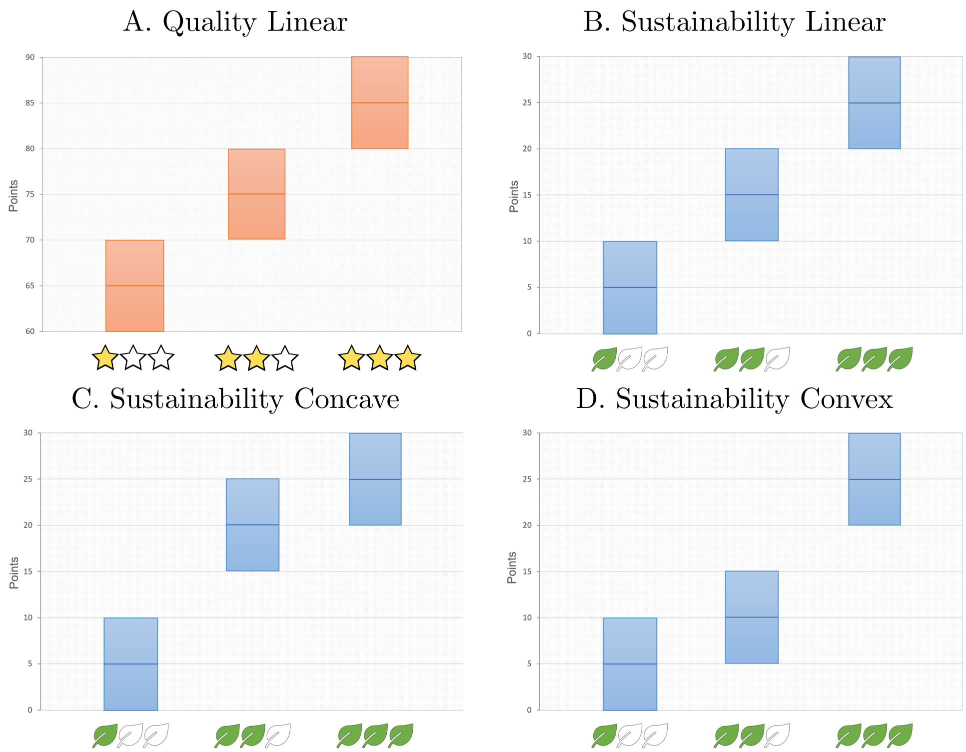


Figure A2: Information treatments for previous study

The figure above describes the possible information provided to participants. The different treatments were (1) a no-information treatment, where no information was provided in the middle of the experiment, (2) a linear treatment, where participants observed the information presented in panels A and B, and then (3) and (4) where instead of panel B, participants observed panels C and D respectively.

Another relevant difference of the information provided here compared to the experiment in our main task is that the underlying values driving the ratings had a range of possible values instead of being just one specific value. Moreover, if we compare the information contained in panels, B, C and D, we can see that the difference across treatments is much more nuanced compared to our treatments in section 3.2.

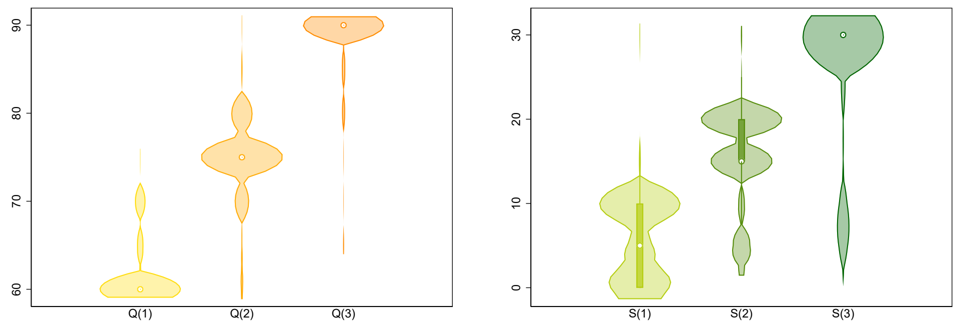
When analyzing our confirmation checks, we found that 21.6% of participants could not identify the treatment they were in (compared to 98.6% in our current experiment). Thus, we concluded that the information treatments in that experiment were too mild for people to internalize.

F Beliefs about ratings

The figures below show the distribution of the participants' beliefs about the quality and sustainability ratings before the information treatments (panels A and B), and the beliefs at the end of the experiment for each information treatment (panels C and D). The violin plots in panel A show the distribution of beliefs for sustainability for each tier of the rating. Panel B displays the beliefs about each tier of the quality ratings.

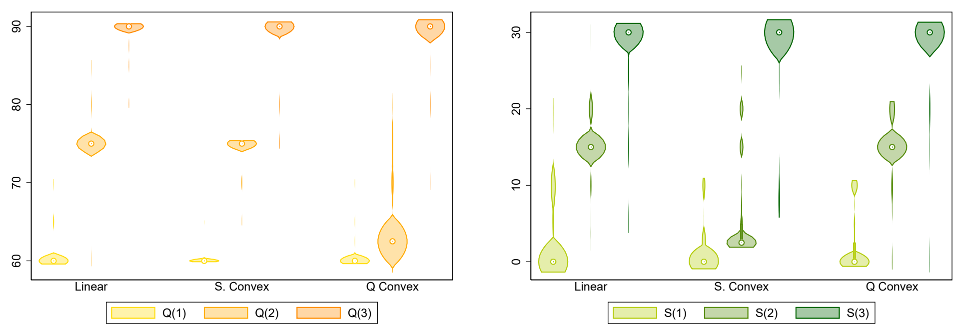
Before information treatment

A. Quality B. Sustainability



In the end of experiment

C. Quality D. Sustainability



As we can see, the participants' beliefs about the underlying values driving both ratings are fairly linear. In the case of sustainability, the beliefs seem to be bi-modal, where some participants expected the ratings to cover the whole range (0 to 30 points), while others expected it to start from 10 sustainability points.

It is clear from panels C and D, that participants understand the treatments quite clearly. This can be seen by comparing the beliefs regarding the middle tier (Q(2) and S(2)) for the different treatments. Most participants perfectly recall the values of the information treatments at the end of the experiment.

G Transitivity of decisions

The table below present three representations of the decision model using the data before the information treatment. In column (1), we use the difference in ratings as a linear function. Column (2) allows for all possible non-linear combinations of parameters. Finally, column (3) incorporates non-linearities on the ratings, but assumes that the preferences are transitives (i.e. value of going from bottom to top is equal to the sum of the values going from bottom to middle and from middle to top).

	(1) Linear		(2) Unconstrained		(3) Constrained	
ΔQ	1.485***	(0.069)				
ΔQ^{21}			1.732***	(0.106)	1.754***	(0.096)
ΔQ^{32}			1.218***	(0.100)	1.235***	(0.094)
ΔQ^{31}			3.031***	(0.166)		
ΔS	1.116***	(0.059)				
ΔS^{21}			1.266***	(0.087)	1.233***	(0.070)
ΔS^{32}			1.033***	(0.086)	1.001***	(0.068)
ΔS^{31}			2.204***	(0.111)		
ΔP	-1.083***	(0.072)	-1.097***	(0.072)	-1.093***	(0.072)
Constant	0.027	(0.034)	0.023	(0.034)	0.024	(0.034)
var(_cons[id])	0.000	(0.000)	0.000	(0.000)	0.000*	(0.000)
Observations	4929		4929		4929	
AIC	4936.629		4906.754		4903.967	
BIC	4962.641		4958.777		4942.984	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

When comparing the models by their Bayesian information criteria (BIC), the best fitting model is the constrained non-linear model presented in column (3). Moreover, we use the models in column (2) and (3) to test our assumptions. The results of the different linear tests are provided below:

Hypothesis	Model	Test	χ^2	p-value
Transitiveness (Q)	(2)	$\Delta Q^{21} + \Delta Q^{32} = \Delta Q^{31}$	0.22	0.6399
Transitiveness (S)	(2)	$\Delta S^{21} + \Delta S^{32} = \Delta S^{31}$	0.81	0.3692
Non-linearity (Q)	(3)	$\Delta Q^{21} = \Delta Q^{32}$	16.25	0.0001
Non-linearity (S)	(3)	$\Delta S^{21} = \Delta S^{32}$	10.24	0.0014

H Estimation tables of decision model

	(1) Before Treatment		(2) All Data		(3) All Data + Ind. Attention	
idec						
ΔP	-1.093***	(-15.14)	-0.979***	(-7.95)	-1.141***	(-8.91)
After $\times$ ΔP			0.0963	(1.24)	0.106	(1.26)
SC $\times$ ΔP			-0.282	(-1.54)	-0.168	(-0.87)
QC $\times$ ΔP			-0.125	(-0.72)	-0.0468	(-0.25)
After $\times$ SC $\times$ ΔP			0.159	(1.17)	0.166	(1.14)
After $\times$ QC $\times$ ΔP			0.0815	(0.59)	0.0867	(0.58)
$\Delta P \times \bar{a}(P)$					-0.324***	(-5.65)
ΔQ^{21}	1.754***	(18.33)	1.690***	(9.67)	1.766***	(9.82)
After $\times$ ΔQ^{21}			-0.209	(-1.43)	-0.228	(-1.45)
SC $\times$ ΔQ^{21}			0.298	(1.20)	0.361	(1.42)
QC $\times$ ΔQ^{21}			-0.0189	(-0.08)	0.0367	(0.15)
After $\times$ SC $\times$ ΔQ^{21}			0.00482	(0.02)	0.0222	(0.10)
After $\times$ QC $\times$ ΔQ^{21}			-0.218	(-0.89)	-0.227	(-0.87)
$\Delta Q^{21} \times \bar{a}(Q)$					-0.0429	(-0.54)
ΔQ^{32}	1.235***	(13.20)	1.254***	(7.58)	1.391***	(8.38)
After $\times$ ΔQ^{32}			-0.115	(-0.92)	-0.123	(-0.93)
SC $\times$ ΔQ^{32}			0.108	(0.47)	-0.0260	(-0.11)
QC $\times$ ΔQ^{32}			-0.0872	(-0.37)	-0.129	(-0.54)
After $\times$ SC $\times$ ΔQ^{32}			-0.0957	(-0.50)	-0.103	(-0.51)
After $\times$ QC $\times$ ΔQ^{32}			0.696**	(2.79)	0.749**	(2.80)
$\Delta Q^{32} \times \bar{a}(Q)$					0.182*	(2.23)
ΔS^{21}	1.233***	(17.65)	1.114***	(9.00)	1.166***	(9.73)
After $\times$ ΔS^{21}			-0.00613	(-0.06)	-0.00658	(-0.06)
SC $\times$ ΔS^{21}			0.220	(1.29)	0.307	(1.82)
QC $\times$ ΔS^{21}			0.224	(1.27)	0.231	(1.31)
After $\times$ SC $\times$ ΔS^{21}			-0.447**	(-2.71)	-0.464**	(-2.69)
After $\times$ QC $\times$ ΔS^{21}			0.0432	(0.27)	0.0442	(0.26)
$\Delta S^{21} \times \bar{a}(S)$					0.373***	(6.58)
ΔS^{32}	1.001***	(14.64)	0.903***	(7.36)	0.951***	(7.72)
After $\times$ ΔS^{32}			-0.0873	(-0.79)	-0.0920	(-0.79)
SC $\times$ ΔS^{32}			0.161	(0.94)	0.235	(1.38)
QC $\times$ ΔS^{32}			0.195	(1.15)	0.188	(1.09)
After $\times$ SC $\times$ ΔS^{32}			0.369*	(2.01)	0.392*	(2.03)
After $\times$ QC $\times$ ΔS^{32}			0.0797	(0.46)	0.0819	(0.44)
$\Delta S^{32} \times \bar{a}(S)$					0.356***	(6.51)
After			-0.0377	(-0.62)	-0.0402	(-0.62)
SC			-0.0140	(-0.17)	0.00803	(0.09)
QC			0.0236	(0.28)	0.0488	(0.57)
After $\times$ SC			-0.0246	(-0.27)	-0.0248	(-0.25)
After $\times$ QC			0.129	(1.39)	0.140	(1.41)
$\bar{a}(P)$					-0.0334	(-0.95)
$\bar{a}(Q)$					-0.0603	(-1.95)
$\bar{a}(S)$					0	(.)
Constant	0.0236	(0.69)	0.0233	(0.41)	0.0284	(0.48)
Ind. Random Effects	2.33e-34*	(2.28)	0.0822***	(3.64)	0.0721**	(3.26)
Observations	4929		9851		9851	
AIC	4904.0		9950.4		9399.5	
BIC	4943.0		10216.6		9716.1	

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

I Treatment effects on attention

In order to estimate which factors affect attention, we estimate a linear regression with random effects for the attention variables of each attribute. The results are presented in appendix table I. We separate the factors into three categories: (1) individual factors, which represent characteristics that are fixed throughout the experiment, (2) contextual factors, which include any element that changes over the different trials and (3) treatment effects. The dependent variable is the standardized measure of attention.

The results show that there is high variability in attention at an individual level, captured by the random effects, but these differences are not correlated with any of the individual measures we elicited from participants, such as gender, age, sustainability attitudes and connectedness to nature. The position of the attributes Quality and Sustainability was randomized at an individual level. Here we see that there is a significant effect of the position on the attention for quality and sustainability.

	(1)		(2)		(3)	
	Price		Quality		Sustainability	
Individual Factors						
Sustainability First	0.008	(0.062)	-0.657***	(0.056)	0.653***	(0.059)
Female	0.017	(0.062)	0.019	(0.057)	-0.000	(0.060)
Age	-0.001	(0.031)	-0.000	(0.028)	0.011	(0.030)
Sust. Attitude.	-0.023	(0.034)	-0.028	(0.031)	0.046	(0.033)
CNS	-0.016	(0.035)	-0.009	(0.032)	0.030	(0.033)
Contextual Factors						
S(2vs1)	-0.141***	(0.034)	-0.029	(0.033)		
S(3vs2)	-0.096**	(0.034)	-0.070*	(0.033)	-0.021	(0.022)
S(3vs1)	-0.085*	(0.034)	-0.058	(0.033)	-0.043*	(0.022)
Q(2vs1)	-0.145***	(0.029)			-0.099***	(0.027)
Q(3vs2)	-0.090**	(0.029)	-0.018	(0.026)	-0.142***	(0.027)
Q(3vs1)	-0.058*	(0.029)	-0.015	(0.027)	-0.157***	(0.027)
$\|\Delta P\|$	-0.002	(0.021)	-0.095***	(0.015)	-0.096***	(0.015)
Treatment Effects						
After	-0.082*	(0.034)	0.006	(0.033)	0.015	(0.030)
SC	0.107	(0.078)	0.046	(0.072)	-0.181*	(0.075)
QC	0.102	(0.081)	-0.087	(0.074)	-0.038	(0.077)
After × SC	-0.005	(0.047)	0.010	(0.046)	0.035	(0.043)
After × QC	-0.103*	(0.049)	0.115*	(0.047)	0.047	(0.044)
Constant	0.222*	(0.113)	1.131***	(0.103)	-0.673***	(0.106)
Random Effects						
Individual	-0.707***	(0.046)	-0.802***	(0.047)	-0.737***	(0.046)
Constant	-0.141***	(0.008)	-0.173***	(0.008)	-0.199***	(0.008)
Observations	7848		7843		8694	
AIC	20750.426		20205.350		21952.843	
BIC	20889.786		20337.730		22087.181	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

We find that the attention to price and sustainability are affected by the attribute values presented in the trial. For quality, the attention is mostly correlated with the differences in price between products. When comparing by treatment effects, we find that quality is attended more after the Quality convex information treatment.

J Models with attention

	(1)		(2)		(3)	
idec						
ΔP	-0.979***	(-7.95)	-1.141***	(-8.91)	-1.143***	(-8.88)
After × ΔP	0.0963	(1.24)	0.106	(1.26)	0.0958	(1.15)
SC × ΔP	-0.282	(-1.54)	-0.168	(-0.87)	-0.165	(-0.85)
QC × ΔP	-0.125	(-0.72)	-0.0468	(-0.25)	-0.0353	(-0.19)
After × SC × ΔP	0.159	(1.17)	0.166	(1.14)	0.178	(1.24)
After × QC × ΔP	0.0815	(0.59)	0.0867	(0.58)	0.0815	(0.54)
ΔP × $\bar{a}(P)$			-0.324***	(-5.65)	-0.324***	(-5.58)
ΔP × $\tilde{a}(P)$					-0.0409	(-1.50)
ΔQ^{21}	1.690***	(9.67)	1.766***	(9.82)	1.769***	(9.72)
After × ΔQ^{21}	-0.209	(-1.43)	-0.228	(-1.45)	-0.229	(-1.45)
SC × ΔQ^{21}	0.298	(1.20)	0.361	(1.42)	0.354	(1.39)
QC × ΔQ^{21}	-0.0189	(-0.08)	0.0367	(0.15)	0.0352	(0.15)
After × SC × ΔQ^{21}	0.00482	(0.02)	0.0222	(0.10)	0.0163	(0.07)
After × QC × ΔQ^{21}	-0.218	(-0.89)	-0.227	(-0.87)	-0.248	(-0.96)
ΔQ^{21} × $\bar{a}(Q)$			-0.0429	(-0.54)	-0.0411	(-0.52)
ΔQ^{21} × $\tilde{a}(Q)$					0.120**	(2.59)
ΔQ^{32}	1.254***	(7.58)	1.391***	(8.38)	1.401***	(8.40)
After × ΔQ^{32}	-0.115	(-0.92)	-0.123	(-0.93)	-0.121	(-0.92)
SC × ΔQ^{32}	0.108	(0.47)	-0.0260	(-0.11)	-0.0214	(-0.09)
QC × ΔQ^{32}	-0.0872	(-0.37)	-0.129	(-0.54)	-0.146	(-0.60)
After × SC × ΔQ^{32}	-0.0957	(-0.50)	-0.103	(-0.51)	-0.114	(-0.58)
After × QC × ΔQ^{32}	0.696**	(2.79)	0.749**	(2.80)	0.755**	(2.82)
ΔQ^{32} × $\bar{a}(Q)$			0.182*	(2.23)	0.181*	(2.20)
ΔQ^{32} × $\tilde{a}(Q)$					0.0101	(0.22)
ΔS^{21}	1.114***	(9.00)	1.166***	(9.73)	1.180***	(9.92)
After × ΔS^{21}	-0.00613	(-0.06)	-0.00658	(-0.06)	-0.00506	(-0.05)
SC × ΔS^{21}	0.220	(1.29)	0.307	(1.82)	0.306	(1.83)
QC × ΔS^{21}	0.224	(1.27)	0.231	(1.31)	0.221	(1.26)
After × SC × ΔS^{21}	-0.447**	(-2.71)	-0.464**	(-2.69)	-0.471**	(-2.75)
After × QC × ΔS^{21}	0.0432	(0.27)	0.0442	(0.26)	0.0400	(0.23)
ΔS^{21} × $\bar{a}(S)$			0.373***	(6.58)	0.373***	(6.55)
ΔS^{21} × $\tilde{a}(S)$					0.0184	(0.43)
ΔS^{32}	0.903***	(7.36)	0.951***	(7.72)	0.954***	(7.71)
After × ΔS^{32}	-0.0873	(-0.79)	-0.0920	(-0.79)	-0.0867	(-0.73)
SC × ΔS^{32}	0.161	(0.94)	0.235	(1.38)	0.239	(1.39)
QC × ΔS^{32}	0.195	(1.15)	0.188	(1.09)	0.180	(1.05)
After × SC × ΔS^{32}	0.369*	(2.01)	0.392*	(2.03)	0.384*	(1.97)
After × QC × ΔS^{32}	0.0797	(0.46)	0.0819	(0.44)	0.0787	(0.42)
ΔS^{32} × $\bar{a}(S)$			0.356***	(6.51)	0.362***	(6.60)
ΔS^{32} × $\tilde{a}(S)$					0.0892	(1.91)
After	-0.0377	(-0.62)	-0.0402	(-0.62)	-0.0450	(-0.68)
SC	-0.0140	(-0.17)	0.00803	(0.09)	0.00712	(0.08)
QC	0.0236	(0.28)	0.0488	(0.57)	0.0464	(0.54)
After × SC	-0.0246	(-0.27)	-0.0248	(-0.25)	-0.0172	(-0.17)
After × QC	0.129	(1.39)	0.140	(1.41)	0.149	(1.48)
$\bar{a}(P)$			-0.0334	(-0.95)	-0.0346	(-1.01)
$\bar{a}(Q)$			-0.0603	(-1.95)	-0.0565	(-1.80)
$\bar{a}(S)$			0	(.)	0	(.)
$\tilde{a}(P)$					0.0536	(1.64)
$\tilde{a}(Q)$					0.0515	(1.58)
$\tilde{a}(S)$					0	(.)
Constant	0.0233	(0.41)	0.0284	(0.48)	0.0305	(0.51)
/						
var(Constant[id])	0.0822***	(3.64)	0.0721**	(3.26)	0.0708**	(3.16)
Observations	9851		9851		9851	
AIC	9950.4		9399.5		9381.8	
BIC	10216.6		9716.1		9748.8	

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

K Alternative models with attention

	(1)		(2)		(3)	
idec						
ΔP	-0.979***	(-7.95)	-1.141***	(-8.91)	-1.146***	(-8.44)
After × ΔP	0.0963	(1.24)	0.106	(1.26)	0.0640	(0.64)
SC × ΔP	-0.282	(-1.54)	-0.168	(-0.87)	-0.150	(-0.77)
QC × ΔP	-0.125	(-0.72)	-0.0468	(-0.25)	-0.0564	(-0.30)
After × SC × ΔP	0.159	(1.17)	0.166	(1.14)	0.209	(1.33)
After × QC × ΔP	0.0815	(0.59)	0.0867	(0.58)	0.123	(0.74)
ΔP × $\bar{a}(P)$			-0.324***	(-5.65)	-0.304*	(-2.18)
After × SC × ΔP × $\bar{a}(P)$					0.0814	(0.46)
After × QC × ΔP × $\bar{a}(P)$					-0.154	(-0.96)
ΔQ^{21}	1.690***	(9.67)	1.766***	(9.82)	1.779***	(10.15)
After × ΔQ^{21}	-0.209	(-1.43)	-0.228	(-1.45)	-0.211	(-1.32)
SC × ΔQ^{21}	0.298	(1.20)	0.361	(1.42)	0.343	(1.38)
QC × ΔQ^{21}	-0.0189	(-0.08)	0.0367	(0.15)	0.0891	(0.38)
After × SC × ΔQ^{21}	0.00482	(0.02)	0.0222	(0.10)	-0.00734	(-0.03)
After × QC × ΔQ^{21}	-0.218	(-0.89)	-0.227	(-0.87)	-0.308	(-1.13)
ΔQ^{21} × $\bar{a}(Q)$			-0.0429	(-0.54)	0.238	(1.44)
After × SC × ΔQ^{21} × $\bar{a}(Q)$					-0.428	(-1.73)
After × QC × ΔQ^{21} × $\bar{a}(Q)$					-0.435	(-1.83)
ΔQ^{32}	1.254***	(7.58)	1.391***	(8.38)	1.411***	(8.36)
After × ΔQ^{32}	-0.115	(-0.92)	-0.123	(-0.93)	-0.118	(-0.88)
SC × ΔQ^{32}	0.108	(0.47)	-0.0260	(-0.11)	-0.0450	(-0.19)
QC × ΔQ^{32}	-0.0872	(-0.37)	-0.129	(-0.54)	-0.127	(-0.52)
After × SC × ΔQ^{32}	-0.0957	(-0.50)	-0.103	(-0.51)	-0.121	(-0.60)
After × QC × ΔQ^{32}	0.696**	(2.79)	0.749**	(2.80)	0.775**	(2.78)
ΔQ^{32} × $\bar{a}(Q)$			0.182*	(2.23)	0.0825	(0.46)
After × SC × ΔQ^{32} × $\bar{a}(Q)$					0.0444	(0.19)
After × QC × ΔQ^{32} × $\bar{a}(Q)$					0.233	(1.00)
ΔS^{21}	1.114***	(9.00)	1.166***	(9.73)	1.167***	(9.48)
After × ΔS^{21}	-0.00613	(-0.06)	-0.00658	(-0.06)	0.00865	(0.08)
SC × ΔS^{21}	0.220	(1.29)	0.307	(1.82)	0.299	(1.74)
QC × ΔS^{21}	0.224	(1.27)	0.231	(1.31)	0.260	(1.46)
After × SC × ΔS^{21}	-0.447**	(-2.71)	-0.464**	(-2.69)	-0.506**	(-2.83)
After × QC × ΔS^{21}	0.0432	(0.27)	0.0442	(0.26)	0.0232	(0.13)
ΔS^{21} × $\bar{a}(S)$			0.373***	(6.58)	0.451***	(4.04)
After × SC × ΔS^{21} × $\bar{a}(S)$					-0.205	(-1.30)
After × QC × ΔS^{21} × $\bar{a}(S)$					-0.0693	(-0.46)
ΔS^{32}	0.903***	(7.36)	0.951***	(7.72)	0.977***	(7.92)
After × ΔS^{32}	-0.0873	(-0.79)	-0.0920	(-0.79)	-0.0908	(-0.78)
SC × ΔS^{32}	0.161	(0.94)	0.235	(1.38)	0.207	(1.20)
QC × ΔS^{32}	0.195	(1.15)	0.188	(1.09)	0.164	(0.94)
After × SC × ΔS^{32}	0.369*	(2.01)	0.392*	(2.03)	0.389	(1.90)
After × QC × ΔS^{32}	0.0797	(0.46)	0.0819	(0.44)	0.106	(0.56)
ΔS^{32} × $\bar{a}(S)$			0.356***	(6.51)	0.229	(1.94)
After × SC × ΔS^{32} × $\bar{a}(S)$					0.221	(1.23)
After × QC × ΔS^{32} × $\bar{a}(S)$					0.0818	(0.51)
After	-0.0377	(-0.62)	-0.0402	(-0.62)	-0.0417	(-0.64)
SC	-0.0140	(-0.17)	0.00803	(0.09)	0.00912	(0.10)
QC	0.0236	(0.28)	0.0488	(0.57)	0.0478	(0.55)
After × SC	-0.0246	(-0.27)	-0.0248	(-0.25)	-0.0231	(-0.24)
After × QC	0.129	(1.39)	0.140	(1.41)	0.150	(1.49)
$\bar{a}(P)$			-0.0334	(-0.95)	-0.0346	(-0.97)
$\bar{a}(Q)$			-0.0603	(-1.95)	-0.0627*	(-1.96)
$\bar{a}(S)$			0	(.)	0	(.)
Constant	0.0233	(0.41)	0.0284	(0.48)	0.0294	(0.49)
/						
var(Constant[id])	0.0822***	(3.64)	0.0721**	(3.26)	0.0714***	(3.31)
Observations	9851		9851		9851	
AIC	9950.4		9399.5		9405.6	
BIC	10216.6		9716.1		9902.1	

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

L Effects of attention after controlling for other moderators

The table below presents the moderating effects of attention on the decision weights after controlling for other individual factors that could be measured. In this table we only present the moderating effect of the individual factors on the decision weights. Column (1) presents the full decision model presented in column (3) from appendix table H. The other columns present the introduction of the position of attributes, demographics and the sustainability scales. Although some of these factors predict differences in the decision weights, the correlation between the individual-average index of attention and the decision weights remains fairly similar.

	(1)		(2)		(3)		(4)		(5)	
ΔP	-1.141***	(0.128)	-1.239***	(0.143)	-1.378***	(0.154)	-1.266***	(0.146)	-1.230***	(0.146)
$\Delta P \times \bar{a}(P)$	-0.324***	(0.057)	-0.285***	(0.060)	-0.292***	(0.062)	-0.285***	(0.063)	-0.289***	(0.060)
S. First $\times \Delta P$			0.198	(0.129)	0.176	(0.126)	0.205	(0.130)	0.197	(0.131)
$\Delta P \times$ Female					0.339**	(0.128)				
$\Delta P \times$ Age					0.019	(0.066)				
$\Delta P \times$ CNS							0.170*	(0.066)		
$\Delta P \times$ Sust. Attitude.									0.139*	(0.064)
ΔQ^{21}	1.766***	(0.180)	1.632***	(0.194)	1.713***	(0.199)	1.628***	(0.192)	1.615***	(0.192)
$\Delta Q^{21} \times \bar{a}(Q)$	-0.043	(0.079)	0.157	(0.098)	0.164	(0.099)	0.169	(0.094)	0.158	(0.095)
S. First $\times \Delta Q^{21}$			0.335	(0.203)	0.347	(0.205)	0.341	(0.200)	0.324	(0.197)
$\Delta Q^{21} \times$ Female					-0.150	(0.173)				
$\Delta Q^{21} \times$ Age					-0.027	(0.074)				
$\Delta Q^{21} \times$ CNS							-0.204*	(0.090)		
$\Delta Q^{21} \times$ Sust. Attitude.									-0.235**	(0.079)
ΔQ^{32}	1.391***	(0.166)	1.309***	(0.178)	1.351***	(0.209)	1.334***	(0.181)	1.309***	(0.174)
$\Delta Q^{32} \times \bar{a}(Q)$	0.182*	(0.082)	0.317**	(0.098)	0.326**	(0.101)	0.306**	(0.098)	0.302**	(0.094)
S. First $\times \Delta Q^{32}$			0.173	(0.192)	0.209	(0.196)	0.140	(0.193)	0.157	(0.191)
$\Delta Q^{32} \times$ Female					-0.147	(0.170)				
$\Delta Q^{32} \times$ Age					-0.086	(0.082)				
$\Delta Q^{32} \times$ CNS							-0.037	(0.083)		
$\Delta Q^{32} \times$ Sust. Attitude.									-0.055	(0.077)
ΔS^{21}	1.166***	(0.120)	1.421***	(0.135)	1.393***	(0.143)	1.433***	(0.135)	1.426***	(0.136)
$\Delta S^{21} \times \bar{a}(S)$	0.373***	(0.057)	0.528***	(0.066)	0.535***	(0.066)	0.515***	(0.068)	0.516***	(0.067)
S. First $\times \Delta S^{21}$			-0.572***	(0.138)	-0.581***	(0.137)	-0.558***	(0.139)	-0.553***	(0.137)
$\Delta S^{21} \times$ Female					0.078	(0.124)				
$\Delta S^{21} \times$ Age					-0.046	(0.051)				
$\Delta S^{21} \times$ CNS							0.095	(0.061)		
$\Delta S^{21} \times$ Sust. Attitude.									0.084	(0.056)
ΔS^{32}	0.951***	(0.123)	1.185***	(0.132)	1.206***	(0.149)	1.194***	(0.131)	1.187***	(0.132)
$\Delta S^{32} \times \bar{a}(S)$	0.356***	(0.055)	0.498***	(0.063)	0.501***	(0.063)	0.491***	(0.064)	0.490***	(0.063)
S. First $\times \Delta S^{32}$			-0.532***	(0.137)	-0.529***	(0.138)	-0.521***	(0.139)	-0.515***	(0.138)
$\Delta S^{32} \times$ Female					-0.040	(0.120)				
$\Delta S^{32} \times$ Age					-0.030	(0.048)				
$\Delta S^{32} \times$ CNS							0.057	(0.061)		
$\Delta S^{32} \times$ Sust. Attitude.									0.039	(0.052)
N	9851.000		9851.000		9851.000		9851.000		9851.000	
aic	9399.544		9237.835		9208.354		9155.646		9161.426	
bic	9716.138		9597.601		9654.464		9558.584		9564.365	
Position	No		Yes		Yes		Yes		Yes	
Demographics	No		No		Yes		No		No	
CNS	No		No		No		Yes		No	
Attitudes	No		No		No		No		Yes	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

M Analysis with other attention measures

The table below shows our estimated models when using alternative attention measures. Column (1) and (2) display the decision models presented in column (2) and (3) from appendix table H respectively. The first column corresponds to the full model with no attention, while the second uses the proportion of time spent looking at the attribute as the attention measure. The columns (3) and (4) show the attention model when using the absolute dwell time and number of fixations as attention measures. As we can see, the effects of attention are still significant and quite similar. Moreover, all the attention models display more descriptive power compared to the model with no attention.

	(1) No Attention		(2) Prop(DT)		(3) DT		(4) N	
ΔP	-0.979***	(0.123)	-1.141***	(0.128)	-1.110***	(0.122)	-1.016***	(0.116)
After × ΔP	0.096	(0.078)	0.106	(0.084)	0.100	(0.080)	0.097	(0.079)
SC × ΔP	-0.282	(0.183)	-0.168	(0.193)	-0.206	(0.180)	-0.277	(0.176)
QC × ΔP	-0.125	(0.175)	-0.047	(0.184)	-0.025	(0.172)	-0.108	(0.170)
After × SC × ΔP	0.159	(0.136)	0.166	(0.146)	0.159	(0.139)	0.160	(0.138)
After × QC × ΔP	0.082	(0.138)	0.087	(0.150)	0.080	(0.142)	0.083	(0.141)
$\Delta P \times \bar{a}(P)$			-0.324***	(0.057)	-0.359***	(0.075)	-0.264***	(0.062)
ΔQ^{21}	1.690***	(0.175)	1.766***	(0.180)	1.751***	(0.175)	1.703***	(0.175)
After × ΔQ^{21}	-0.209	(0.146)	-0.228	(0.157)	-0.218	(0.151)	-0.211	(0.147)
SC × ΔQ^{21}	0.298	(0.249)	0.361	(0.253)	0.298	(0.248)	0.303	(0.250)
QC × ΔQ^{21}	-0.019	(0.230)	0.037	(0.240)	-0.024	(0.231)	-0.003	(0.229)
After × SC × ΔQ^{21}	0.005	(0.218)	0.022	(0.229)	0.019	(0.222)	0.006	(0.220)
After × QC × ΔQ^{21}	-0.218	(0.244)	-0.227	(0.262)	-0.217	(0.252)	-0.217	(0.246)
$\Delta Q^{21} \times \bar{a}(Q)$			-0.043	(0.079)	0.150	(0.098)	0.022	(0.083)
ΔQ^{32}	1.254***	(0.165)	1.391***	(0.166)	1.336***	(0.164)	1.283***	(0.169)
After × ΔQ^{32}	-0.115	(0.125)	-0.123	(0.133)	-0.119	(0.130)	-0.117	(0.127)
SC × ΔQ^{32}	0.108	(0.228)	-0.026	(0.229)	0.060	(0.226)	0.115	(0.230)
QC × ΔQ^{32}	-0.087	(0.239)	-0.129	(0.241)	-0.147	(0.237)	-0.120	(0.241)
After × SC × ΔQ^{32}	-0.096	(0.190)	-0.103	(0.200)	-0.100	(0.196)	-0.097	(0.192)
After × QC × ΔQ^{32}	0.696**	(0.249)	0.749**	(0.268)	0.717**	(0.257)	0.707**	(0.254)
$\Delta Q^{32} \times \bar{a}(Q)$			0.182*	(0.082)	0.127	(0.086)	0.001	(0.074)
ΔS^{21}	1.114***	(0.124)	1.166***	(0.120)	1.197***	(0.121)	1.140***	(0.123)
After × ΔS^{21}	-0.006	(0.096)	-0.007	(0.102)	-0.006	(0.099)	-0.006	(0.098)
SC × ΔS^{21}	0.220	(0.170)	0.307	(0.168)	0.217	(0.165)	0.215	(0.171)
QC × ΔS^{21}	0.224	(0.176)	0.231	(0.176)	0.137	(0.172)	0.215	(0.174)
After × SC × ΔS^{21}	-0.447**	(0.165)	-0.464**	(0.173)	-0.452**	(0.168)	-0.450**	(0.167)
After × QC × ΔS^{21}	0.043	(0.162)	0.044	(0.172)	0.046	(0.165)	0.046	(0.163)
$\Delta S^{21} \times \bar{a}(S)$			0.373***	(0.057)	0.322***	(0.071)	0.149*	(0.061)
ΔS^{32}	0.903***	(0.123)	0.951***	(0.123)	0.982***	(0.121)	0.930***	(0.123)
After × ΔS^{32}	-0.087	(0.111)	-0.092	(0.117)	-0.090	(0.114)	-0.089	(0.112)
SC × ΔS^{32}	0.161	(0.171)	0.235	(0.171)	0.152	(0.169)	0.157	(0.173)
QC × ΔS^{32}	0.195	(0.170)	0.188	(0.172)	0.116	(0.169)	0.185	(0.171)
After × SC × ΔS^{32}	0.369*	(0.184)	0.392*	(0.193)	0.383*	(0.188)	0.374*	(0.186)
After × QC × ΔS^{32}	0.080	(0.175)	0.082	(0.187)	0.085	(0.180)	0.082	(0.178)
$\Delta S^{32} \times \bar{a}(S)$			0.356***	(0.055)	0.281***	(0.066)	0.100	(0.058)
After	-0.038	(0.060)	-0.040	(0.064)	-0.039	(0.062)	-0.038	(0.061)
SC	-0.014	(0.084)	0.008	(0.091)	0.010	(0.087)	-0.004	(0.087)
QC	0.024	(0.085)	0.049	(0.086)	0.037	(0.084)	0.033	(0.084)
After × SC	-0.025	(0.092)	-0.025	(0.098)	-0.026	(0.095)	-0.027	(0.093)
After × QC	0.129	(0.093)	0.140	(0.099)	0.134	(0.095)	0.130	(0.094)
$\bar{a}(P)$			-0.033	(0.035)	-0.028	(0.033)	-0.030	(0.034)
$\bar{a}(Q)$			-0.060	(0.031)	-0.098**	(0.034)	-0.072*	(0.028)
$\bar{a}(S)$			0.000	(.)	0.066*	(0.034)	-0.002	(0.034)
Constant	0.023	(0.056)	0.028	(0.060)	0.019	(0.057)	0.017	(0.057)
Var(random effects)	0.082***	(0.023)	0.072**	(0.022)	0.072***	(0.022)	0.081***	(0.023)
Observations	9851		9851		9851		9851	
AIC	9950.416		9399.544		9706.908		9851.018	
BIC	10216.643		9716.138		10030.697		10174.807	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

N Informed consent and instructions

Introduction

Welcome!

- You are participating in a study conducted by: UNIVERSITY OF AMSTERDAM
- Your decisions and information provided will be recorded **anonymously** (Your response in this experiment cannot be traced back to you.).
- Your data will only be used for **academic research**.
- You can choose at any point during the experiment to stop your participation and your data will be discarded.
- If you choose to participate, you will have to make multiple decisions that can lead to **additional payments and donations to charity**.
- The study will last about **15-20 minutes**.

Informed Consent

To participate in this experiment you need to:

- Be **18 or older**
- Be fluent in **English**.
- Focus only on the experiment (It will take around 15-20 minutes).
- Use your **computer** . The experiment does not work on phones or tablets.
- Set this window into **Fullscreen** mode (if you do not know how to do it, we will explain)

We reserve the right to exclude you from payment if we detect that you are not paying attention (jumping between other windows or setting off the Fullscreen too many times) or you do not comply with any of the above mentioned requirements.

☐ I agree to the Terms and Conditions above and to participate in this experiment.

Next

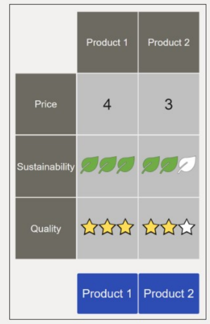
The Experiment

- In this study you will make purchasing decisions.
- The products that you will observe are **not real**.
- There is no physical product, but your decisions will have **real consequences.**
- Depending on your decisions you can obtain an additional **bonus payment of up to £3** and help the environment by **planting trees in a location of your choosing.**
- The trees will be planted by: ONETREEPLANTED
- There are many locations where the trees could be planted.
- Would you like to choose where to plant the trees? Anywhere

Your Decisions

In this experiment you will:

- Make multiple purchasing decisions (**37 rounds**).
- In each round, you will see **2 products** and their characteristics.
- These products are not real, but their benefits are.
- The next slide explains the benefits and characteristics of the products.



The product characteristics

- **Price:** This is the cost you need to pay for the product. The price is in **£**.
  Higher Price → lower bonus payments.
- **Quality:** 1-3 star ( ) rating. Products with more stars ( ) are more likely to have higher quality.
  Higher quality → higher bonus payments.
- **Eco-Label:** 1-3 leaf ( ) rating. Products with more leaves ( ) are more likely to be more sustainable.
  Higher sustainability → more trees planted.

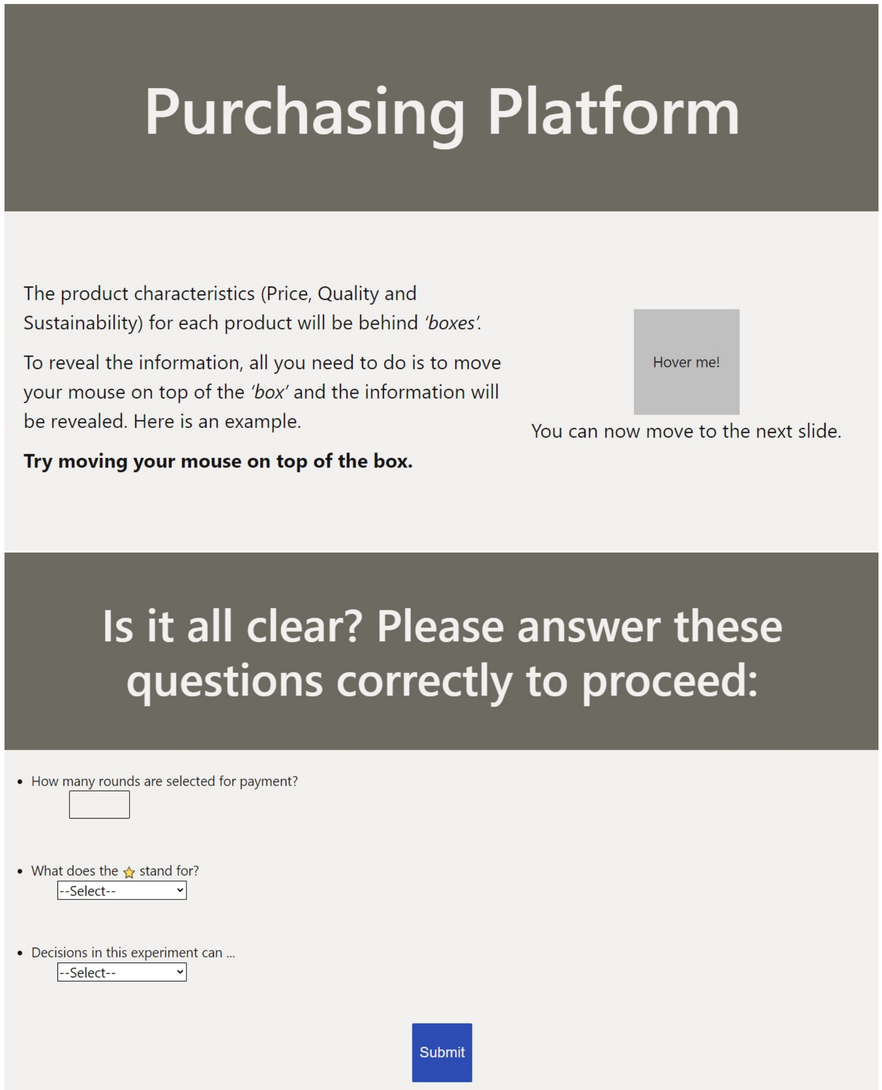
Value of Labels

Quality:

- Quality is measured in Quality points (10 points = 0.5 pound).
- Quality points go from 60 to 90. This means that the worst possible product (in terms of quality) is worth 3 pounds and the best one is worth 4.5.
- If a product has more stars , it means that you get more Quality points on average

Sustainability:

- Sustainability is measured in Sustainability points (10 points = 1 tree planted).
- Sustainability points go from 0 to 30. This means that the worst possible product (in terms of sustainability) will plant 0 trees and the best will plant 3 trees.
- If a product has more leaves , it means that you get more Sustainability points on average
- The total amount of points donated to the area you selected will be rounded up, so no point will be lost. For example, 102 points will mean 11 trees planted (instead of 10).


Purchasing Platform
The product characteristics (Price, Quality and Sustainability) for each product will be behind 'boxes'.
To reveal the information, all you need to do is to move your mouse on top of the 'box' and the information will be revealed. Here is an example.
Try moving your mouse on top of the box.
Hover me!
You can now move to the next slide.
Is it all clear? Please answer these questions correctly to proceed:
How many rounds are selected for payment?
What does the stand for?
--Select--
Decisions in this experiment can ...
--Select--
Submit