Coarse and Precise Information in Food Labeling

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Abstract

Public authorities and companies often adopt simple categorical labels to convey information and promote healthy, ethical, or energy-friendly behavior. These labels often provide coarse information: for example, food front-of-package labels might report *low-fat* but not the exact fat content. In this paper I study how labels with different precision affect choices: can precision become "too much" and impair choices?
In a preregistered online study conducted on a representative US sample, I manipulate the precision of front-of-package labels about foods' calorie content. Coarse labels generate healthier choices compared to more detailed ones despite providing less information (-2% calories, -3% high-calorie products chosen). Participants also declare they prefer coarse labels.
Choices are at odds with the predictions of a Bayesian updating model, showing that participants are less sensitive to detailed information. A bounded rationality model with precision overload can capture the main experimental results. When detailed labels are more complex and harder to understand, consumers face a tradeoff between simplicity and precision. Some information helps, but too much detail can be confusing, and lead to less healthy food choices.

Keywords: Consumer Behavior, Nutrition, Food Labels, Experiment, Attention.

JEL codes: C91, D83, D91, Q28.

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1 Introduction

Coarse labels - i.e. labels that indicate that a product's attribute falls within a range of values, without specifying the exact number - are everywhere. You might have started your day by opening an energy-efficient refrigerator (how many kilowatt-hours?) to grab a low-fat yogurt (how many grams of fat?) while you drink a fair-trade coffee (how much was the farmer paid?). Public authorities and private companies often adopt these simple categorical labels to convey information and promote healthy, energy-friendly, or ethical behavior.[1] Food labels across the world provide examples of coarse messages, some of which are shown in Figure 1: warning labels in Chile (binary messages), traffic lights in Ecuador (three colors), and Nutri-Score in France (five grades) among others. We have evidence that coarse food labels can have a significant impact on consumer behavior. For example, Barahona et al. (2020) estimate that the introduction of warning labels in Chile in 2016 led to a 6.5% calorie reduction. We also know that the effectiveness of these labels can depend on their visual features such as color and shape (Schuldt, 2013; Khandpur et al., 2019) but there is no clear evidence of how the coarseness of the message determines its effectiveness, and whether more detailed labels would be even more effective.

Figure 1: Examples of coarse nutrient labels used in different countries. From the left: Warning label (Chile), Traffic light (Ecuador), Nutri-Score (France), Guiding Stars (US), Health Star Rating (Australia). The first two labels refer to the amount of specific nutrients (e.g. calories and sugar), the other three provide a summary based on multiple nutrients.

In this paper I study the role of coarse and precise labels in food choice. I investigate the effect of different calorie labels on consumer behavior and the underlying mechanisms that lead to such effect. This will help understanding why these labels are frequently used and whether they can help consumers choose what they themselves want. In principle, labels could provide the same information *and more* by refining the message. For example, a

[1] The effect of labels on consumer behavior has been studied in various contexts, including food choice (Ikonen et al., 2020; Crosetto, Muller and Ruffieux, 2016), energy efficiency (Davis and Metcalf, 2016; Andor, Gerster and Götte, 2019), and fair trade (Hainmueller, Hiscox and Sequeira, 2015; Rousseau, 2015). Studies in these areas typically compare the effectiveness of labels that differ in multiple dimensions, including coarseness.

nutrient label with five grades, from A to E,[2] could become more informative[3] by adopting a richer scheme that partitions the A grade into three sub-grades (A+, A, and A-). In standard information models, higher precision should allow consumers to make weakly better choices. This observation opens a question on whether coarse labels achieve their goal from the perspective of the regulator. Is coarseness an attempt by regulators to manipulate the choices of consumers in the manner of Bayesian persuasion?[4] Or is it an optimal response to some form of bounded rationality, and detailed labels are harder to understand? I call this hypothesis *precision overload*: providing a precise message could be confusing and lead to systematically worse choices with respect to a coarse message.

I conduct an experiment with incentivized food choices and vary the precision of the labels to answer three questions. First, how do coarse and precise labels on calorie content affect food choices? Increasing labels' precision has a U-shaped effect on calories: coarse labels reduce the number of calories by up to 3% less, but detailed labels have a weaker effect, only 1% less; the weaker effect is driven by lower sensitivity to the information provided by detailed labels. Second, are results consistent with the standard approach in decision theory, the Bayesian updating model? I estimate the effect of labels on choices in a simple demand model and I reject the standard Bayesian updating model; detailed labels have systematically lower weights in the decision process compared with coarse ones, suggesting that subjects learn less from them. Third, how can I generalize the updating model to capture the results? I show that the experimental results cannot be captured by standard approaches of limited rationality, such as salience and rational inattention, but are consistent with a limited attention model that introduce precision overload. Consumers with limited cognitive resources face an explicit tradeoff between simplicity and accuracy: detailed messages are more complex than coarse ones and are associated with larger noise in the evaluation process.

I focus on food as an application of this framework because several countries recently discussed which guidelines to adopt in terms of food labeling. Obesity and diet-related chronic diseases are widespread concerns (Flegal et al., 2010; Popkin et al., 2001) and most consumers are not fully aware of how to understand nutrient information (Chandon and Wansink, 2007). In Section 2 I provide more background on the various types of nutrient

[2] The Nutri-Score is an example of a coarse label with five grades from A to E used to rate the healthiness of food products. The grade is obtained through an algorithm that takes into account multiple nutrients and generates a raw score between -15 (healthiest) and +40. This raw score is coarsen into five grades, from A (-15 to -1 points) to E (19 to 40 points). The Nutri-Score has been officially recommended by health authorities in France, Germany, Switzerland, and other European countries.

[3] A finer partition of the signal space is more informative in the Blackwell sense (Blackwell, 1953).

[4] In the Bayesian persuasion literature (e.g. (Kamenica and Gentzkow, 2011; Bloedel and Segal, 2018)) principal and agent have misaligned incentives, and the principal can design a signal structure that induces the agent to make choices more aligned with the principal's goal.

labels and how countries across the world recently introduced coarse nutrient labels to inform consumers.

Section 3 contains details on the experimental design, the hypotheses, and the implementation. Subjects are randomly assigned to treatments that differ in the level of granularity of the nutrient labels. I focus on one single nutrient, calories, that is already available on the Back-Of-Package (BOP) as an exact amount and I manipulate the Front-Of-Package (FOP) label only. There is no universal definition of healthy food, but nutritionists and policy makers agree on the importance of monitoring the number of calories (Chandon and Wansink, 2007; Wartella et al., 2012; Kraus et al., 2019).[5] I collect data on food choice, preference for information, and consumer characteristics. In the main part of the study participants make choices between small choice sets of cereals and snacks in an interface similar to the one typically used for online grocery. Participants can observe the package and consult the nutrition facts panel on the back before making a choice. I conduct the study online on a representative US sample (n=856), and I use products that are largely available in US stores. I preregistered experimental design, hypotheses, and sample size before conducting the study.

The primary hypothesis of the experimental investigation is that an increase in the precision of calorie labels generates a nonmonotonic change in choices. If we interpret healthy (low-calorie) choices as good choices the implication would be that coarse messages can lead to systematically better choices with respect to more precise messages. This hypothesis is motivated by existing evidence on information overload (Roetzel, 2019), and cognitive limits in perception and memory (Pollack, 1952; Miller, 1956; Cowan, 2001).[6] Following closely the definition introduced by Roetzel (2019) for information overload, I define *precision overload* as a state in which the precision of the information inhibits the decision maker's ability to optimally determine the best possible decision. In lay terms, decision makers could find the detailed information so confusing that they make worse use of it with respect to the case in which they were receiving a coarser message.

Conducting an experiment to study the effect of labels' precision has three major advantages. First, the experimental manipulation provides a clean randomization of the treatment. I use a between-subject design, with each participant observing only one of the four treatments. Empirical studies that consider policy implementations are limited by the labels

[5] Brinkley et al. (2021) conducted a randomize controlled trial and observe that a reduction of 200 calories per day (10% of the recommended daily value) has significant effects on weight loss (-18 lb.) and heart strength (-8% pulse velocity), reducing the risk of obesity and chronic cardiovascular disease.

[6] In a series of studies on the ability to classify auditory stimuli Pollack (1952) reports that subjects can discriminate up to five tones with perfect accuracy, but accuracy decreases when the number of tones gets higher. The interpretation the author offers is that decision makers have limited processing capacity, for example facing a constraint in the Shannon's entropy reduction of the signal (Shannon, 1948; Norwich, 1993).

that were successfully implemented, and can compare only across time (before and after the reform) or countries (with and without a label). Second, the experimental setup provides additional control with respect to field data. Participants in the study need to read the instructions and answer correctly the comprehension questions before proceeding with the main task. I provide contextual information about what is the typical range of calories and how to interpret the calorie labels. This will allow to rule out possible concerns about the nature of the information conveyed through the labels. Third, I collect choices and process data, plus additional participants' characteristics (demographics, food literacy, calorie preferences). Having access to process data is valuable to study how participants acquire information, in particular if they consult the panel by flipping the packages.

The main experimental result is that increasing labels' precision has a U-shaped effect on the calorie content of the selected products. From the policy maker perspective, the most desirable outcome (low calories) is achieved using coarse labels. The coarse label with four messages (ranging from *very low* to *very high* calories) generates healthier choices compared to treatments with more or fewer messages. Section 4 contains the descriptive results of the experiment, including analysis of the process data and decomposition of the effect across trials and groups of participants. When I decompose the effect, I observe that the subjects are less sensitive to information provided through detailed labels. The magnitude of the effect is heterogeneous across demographic groups, with larger effect across low-income and low-education groups. Participants also indicate that they prefer coarse labels to detailed ones. They rank the labels used in the treatments; the coarse label is the most popular first choice as well as the Condorcet winner in the pairwise comparisons.

These descriptive results are not sufficient to rule out that participants' behavior is consistent with the Bayesian updating model, which represent the standard approach in decision theory. In section 5 I consider an updating model in which consumers are uncertain about calorie content and learn about it through labels. This framework provides testable predictions on the relation between calories' beliefs across treatments; values in coarse treatments should be convex combinations of values in more detailed treatments. I test the model by comparing the estimated label fixed effects for different treatments in a simple demand model. The estimates are not consistent with the predictions of the Bayesian updating model, with coarse labels having systematically larger weights in the evaluation of products.

In order to capture the main results of the experiment I extend the updating model by introducing limited attention. In Section 6 I discuss how other behavioral models like salience (Bordalo, Gennaioli and Shleifer (2012); Bordalo, Gennaioli and Shleifer (2016)) and rational inattention (Sims (2003); Caplin and Dean (2015)) are not able to capture the nonmonotonic effect of precision. I explicitly model precision overload by using a stochastic mapping between the correct label and the mental representation that the agent uses to make a choice. I assume agents face a tradeoff between *simplicity* and *accuracy* of the information. They have limited cognitive resources that can be used to process the new information: when labels are more precise, agents recall them with lower accuracy. This leads to lower sensitivity to the message and might impair choices if sufficiently large. I assume that agents face two types of attention costs: a retrieval and a recognition cost. The first cost depends on the accuracy of retrieval from memory; as in the rational inattention literature, more accurate signals are more costly. The novel feature of the model is the introduction of a second type of cost: the recognition cost depends on the complexity of the messages, regardless of how they are used later in the decision process. The introduction of an explicit recognition cost endogenizes precision overload; complex labels reduce the cognitive resources used to recall the message accurately and lead to larger mistakes. I interpret the inaccuracy in the retrieval process as noisy recall from memory; for example, a B-grade label could be recalled as an A or a C. I discuss in the Appendix alternative interpretations of the role of labels: consumers might not be sure about the meaning of the label (how many calories correspond to a B-grade label) or about how to interpret the calorie information (how healthy is a snack with 200 calories) and infer this information with different level of uncertainty based on the precision of the label.

A vast and interdisciplinary literature has been studying the effect of food labels on consumer behavior using laboratory experiments (Bix et al., 2015; Ono and Ono, 2015; Crosetto et al., 2020), field experiments (Dubois et al., 2020; Shangguan et al., 2019), and after reforms (Barahona et al., 2020; Sandoval, Carpio and Sanchez-Plata, 2019). This is the first paper that focuses on the role of precision of the food labels, tests whether more detailed messages lead to healthier choices, and shows that excessive precision can backfire by controlling for other factors (contextual information, process data). The results are connected to the empirical literature on limited consumer attention. We have evidence that consumers do not use all the information available and make costly mistakes (Chetty, Looney and Kroft, 2009; Brown and Jeon, 2019); my study highlights that mistakes can be associated with excessive granularity of information, similarly to what has been discussed for choice overload (Iyengar and Lepper, 2000) and information overload (Roetzel, 2019). The adoption of coarse messages as optimal strategy in communication relates to a broad theoretical literature. Coarsening can emerge in principal-agent settings in which incentives are not aligned (Crawford and Sobel, 1982; Kamenica and Gentzkow, 2011); I show that another possible explanation is that agents face larger noise when they process detailed information and are not able to fully absorb the content of the message. This frameworks follows the rational inattention approach (Sims, 2003; Caplin and Dean, 2015) with the addition of an explicit recognition cost that depends on the complexity of the message and not on how it will be used in the decision process. Section 8 contains a more extensive overview of the relevant literature, the contribution of this paper, and the open questions related to this topic.

To summarize, the results of the experiment highlight that coarsening can be desirable both for consumers and regulators, and coarse labels can be more effective than detailed ones in generating publicly desirable behavior, such as promoting a healthier diet with fewer calories. Precision overload provides a compelling mechanism to capture the effect: even a benevolent information designer, whose interests are aligned with the consumer, might want to simplify the labels' information by reducing their granularity to make them less confusing. The experimental results refer to food choices and calories information, but precision overload might be relevant in many other decisions that involve imperfect attention to information. I observe that the precision effect is stronger for consumers from a low socioeconomic status, suggesting that regulators should take into account how different consumers respond to information. Some information helps, but too much detail can be confusing and lead to less healthy food choices.

2 Nutrition Labels: Institutional Background

Food choices provide a natural setting to study the effect of label precision. The shelves of the supermarkets are filled with products like low-fat yogurts, high-fiber cereals, reduced-calorie chocolate, and sugar-free snacks, all examples of coarse messages. In this section I provide some background about nutrition labels and their role in food choice, and I discuss the relevance of studying this topic in light of the recent discussion about this topic in many countries, including United States and Chile. Readers who want to jump to the experimental design can simply skip this section. I am confident that their personal experience as consumers is sufficient to understand the role of nutrition labels. Coarse labels are used in different domains but food labels are of particular interest for two reasons: a policy and an information one. First, many countries have recently discussed the adoption of different kinds of labels as part of the effort to reduce obesity (more on this in Section 2.2) and as an alternative to other policy tools like sugar tax or soda tax. Second, coarse labels provide information on product characteristics that are already described on the package. Packaged foods typically indicate exact information on nutritions and ingredients in a Nutrition Facts panel, and front-of-package labels are not revealing information that was previously missing, but present it in a way that is simpler or more salient for the consumer. This leads to a natural null hypothesis: coarse labels should not affect consumer behavior at all since the information is already provided. Consumers might not be sufficiently motivated to consult the nutrition fact, and in that case the coarse labels might be providing relevant information. Marketing studies indicate that grocery shoppers spend on average 12 seconds purchasing from a category when in store (Hoyer, 1984; Dickson and Sawyer, 1990) and 10 seconds for online grocery (Anesbury et al., 2016), and they rarely pay attention to the nutrients,[7] and what is written on the front is more prominent for consumers' choices. With consumers making fast choices, understanding how they respond to package messages is important to design effective policies.

In the rest of this section I provide more background about nutrition labels. First, I discuss the different types of labels that are commonly used. After, I provide a brief overview of the current regulation in the United States. Finally, I discuss some mandatory and voluntary nutrition labels recently introduced in Latin American and European countries.

2.1 Typologies of Nutrition Labels

Nutrition labels can have different content and purposes, and it might be confusing to refer to the entire universe of labels without clarifying what I am focusing on in the study and which other relevant features are not part of this investigation. In the experiment I will focus on a very specific type of labels: interpretive, nutrient-specific, mandatory, front-of-package labels, and I am about to clarify what this means. A possible multidimensional classification of labels can consider four features: interpretation (simplification of the numerical value), synthesis (summary of multiple nutrient), obligatoriness (mandatory to display), and position (on the front of the package).[8]

Interpretation: Reductive vs. Interpretive. Reductive labels contain the same numerical information as in the Nutrient Facts panel (NFP), and interpretive labels provide an evaluation using for example colors, stars, or health symbols. Typical examples include Facts Up Front as reductive label (show few nutrient information on the FOP) and warning messages as interpretive label (indicate that the calorie content is above a recommended threshold).

Synthesis: Nutrient-specific vs. Summary. Nutrient-specific labels refer to one or more individual nutrient, and summary labels aggregate multiple nutrients in a single scale. Typical examples include multiple traffic lights as nutrient-specific labels (indicate for each

[7] In a survey conducted in France, Mannell et al. (2006) report that only 45% of the consumers read the nutrition labels, with the majority of them reading labels only occasionally. Derby and Levy (2001) use the data of the US Diet and Health Survey and highlight that one third of respondents declare they had changed their decision to by a product because of nutrition label information.

[8] Ikonen et al. (2020) provide a classification of reductive, interpretive, and summary labels and compare their effectiveness in a meta-analysis.

nutrient if it is high or low) and Nutri-score as summary label (combine calories, sugar, fat, and other nutrients into a single value).

Obligatoriness: Voluntary vs. Mandatory. Public authorities regulate what the product package must, must not, and can contain. Many countries, including the United States, require information about the main nutrition facts in a detailed numerical format and let the manufacturers free to add claims as long as they are not confusing for the consumers. This regulation is called "truth in advertising" and gives the manufacturer large flexibility on how to emphasize positive properties of the product. When standard claims are regulated by public authorities, some terms or combinations of terms could not be used freely. For example, FDA regulates the use of "low calorie" but terms like "low sugar" are not allowed on product packages.

Position: Front-Of-Package vs. Back-Of-Package. Regulators rarely indicate where the label should be displayed. One notable exception is the warning label introduced in Chile, that is mandatory and must be shows on the front of the package to guarantee higher visibility.

2.2 Nutrition Labels in the United States

In the United States the Food and Drug Administration regulates food labeling with a combination of mandatory information (nutrition facts panel) and truth-in-advertising regulation of nutrition claims.[9] The nutrition facts panel located on the back-of-package is mandatory since the introduction of the Nutrition Labeling and Education Act (NLEA) in 1990 (Moorman, 1996; Balasubramanian and Cole, 2002; Abaluck, 2011), that became fully effective in 1994. The NLEA also introduced other tools to simplify the comparison across products, including the food ingredient panel, standard serving sizes, and definitions for claims such as *low-fat* and *light*. The objective of this regulation is to prevent ambiguous claims that could confuse consumers (Mayer, Scammon and Golodner, 1993; Hoadley and Rowlands, 2014). Requirements and standard terms faced minor adjustments since the NLEA; FDA required additional information in the nutrition labels since 2003, and redesigned the label in 2016. In 2010 the Institute of Medicine and FDA created a commission to collect and analyze evidence related to the impact of food Front-Of-Package labels on consumer behavior (Boon et al., 2010; Wartella et al., 2012). The initial motivation was to provide guidelines for a new standardized FOP label for US consumers, but the project was prematurely terminated in 2012 without providing a final answer. In the same year various US manufacturers vol-

[9] FDA regulation of food labeling is part of the Code of Federal Regulations, Title 21, Chapter 1, subchapter B, Part 101, available on FDA website.

untarily adopted the Facts Up Front label, that displays some key nutrition information on the front of the package. The FDA commission wrote two reports that discuss the plurality of functions of front-of-package rating systems and symbols and support the goal to target the "general population," with emphasis on fighting obesity. But they also highlight that given the current knowledge they recommend a system equivalent to the EnergyStar (voluntary and binary) used by the Environmental Protection Agency to encourage consumer to purchase energy-efficient products. According to the report, the system should use "*one simple, standard symbol translating information from the Nutrition Facts panel (NFP) on each product into a quickly and easily grasped health meaning, making healthier options unmistakable*" (Wartella et al., 2012). It appears that the need for simplicity and coarseness is justified by the concern that consumers would be confused, and make mistakes, by adopting more complex rating systems.

2.3 Coarse Food Labels in the World

Despite the attempt of the FDA commission, the United States have not reached a standardized front-of-package label. Other countries started from the very same premises and recently introduced labels that aim to guide consumers towards healthier options. Some interesting insights come from Chile, Ecuador and France, that between 2013 and 2017 introduced standardized labels. In all three cases the labels are coarse, with a number of possible messages between two and five.

Chile: Warning labels. Chile's food labeling and advertising law was approved in 2012 and enacted in 2016. It requires food and beverage packages to display warning labels if products exceed the thresholds for calories, sugars, saturated fat, or sodium.[10] It is the manufacturers' responsibility to implement the requirement and display the label on the front of the package, and products can display up to four warning labels (if they exceed the thresholds for all the four nutrients), but the message is binary: for each nutrient the product can either display or not display the label. The law also prohibited the sale of products with labels in schools and restricted the advertising to children under fourteen. Early studies on the effect of this reform show large and persistent effect (Pachali et al., 2020; Barahona et al., 2020; Alé-Chilet and Moshary, 2020), with an overall 6.5 reduction in calories consumed.

Ecuador: Traffic lights. Ecuador's traffic lights labeling was approved in 2013 and enacted in 2014. Traffic light labels indicate the amount of sugar, fat, and salt and can take four values (high, medium, low, none) expressed through a combination of color and text.

[10]Chilean warning labels thresholds are expressed with respect to 100 grams servings for food, and 100 milliliters for beverages. The thresholds were gradually reduced in 2018 and in 2019.

Sandoval, Carpio and Sanchez-Plata (2019) show that the reform did not have a significant effect on soft drink purchases. The difference with the successful Chilean reform might be due to the position of the label; many Ecuadorean manufacturers placed the labels on the side or back of the products, making them less visible than the Chilean one. Another possible concern, more related to this study, is that Ecuadorean labels might be more complex to process; consumers might be unsure about the meaning of a medium-label whereas in the case of Chilean labels there are only two possible outcomes (label or no label).

France: Nutri-score. In 2017 the French government recommended a voluntary nutritional rating system. The scoring takes into account calories, fat, sugar, and other nutrients per 100 grams of product and generates a letter/color combination between A/green and E/red. The Nutri-score rating system has also been recommended by the European Commission, WHO, and public authorities in Belgium, Germany, Netherlands, Spain, and Switzerland. The score is determined as a coarsening of a numerical value, calculated according to the UK Food Standards Agency nutrient profiling system. The labels are voluntary but laboratory and field studies have shown that Nutri-score outperformed other labeling systems in driving consumers towards healthier food options (Dubois et al., 2020; Julia et al., 2018).

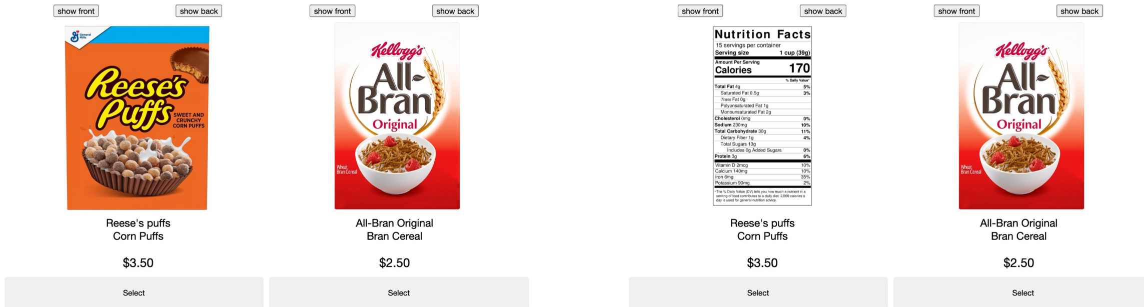
3 Experimental Design

I use a field-framed online study with incentivized choices between food items. The experiment is implemented in a way that is similar to other label manipulation studies in the literature (see e.g. Ikonen et al. 2020; Crosetto et al. 2020). In the first part of the session, subjects choose a product (cereals or snacks) from each choice set, with an interface that mimics online grocery stores. Figure 2 show an example of choice between two cereals. Products display front-of-package labels that indicate the calorie content of the product. Subjects are assigned to treatments that differ in the precision of the label, up to ten different calorie levels. In the second part of the session, subjects answer additional questions about label preferences, calorie preferences, and food habits.

3.1 Experiment

3.1.1 Choice Task

The first part of the study is a choice task in which subjects choose one food items among those presented on the screen. The task is incentive compatible, as subjects have a chance of receiving one of the selected products directly at home (details in the Recruitment section).



(a) Default interface (front package). (b) Back-of-package information.

Figure 2: Experimental interface for the choice task (control treatment, Absent label). Examples of information displayed on the front and back of the package. Subjects can freely consult the nutrition facts by clicking the buttons above each product.

Subjects complete 80 trials of the task at their own pace. The interface contains the same elements that customers would see in an online platform: an image of the package, a brief description, and the price of the product. By clicking on the buttons "front" and "back," subjects can flip the package and read the nutrition facts. Subjects are not required to consult the nutrition facts in the task to make a choice.[11]

3.1.2 Treatments

Each subject is assigned to one out of four experimental treatments, that differ in the precision of front-package labels used to convey information on the calories per serving. The products used in the study have a number of calories per serving that range between 60 and 240 Calories. The four treatments have different number of labels and therefore different partitions of the calorie range. The four treatments are displayed in Figure 3 and are:

- Absent (A): no label.
- Binary (B): 2 categorical labels (Low calorie, High calorie).
- Coarse (C): 4 categorical labels (Very low calorie, Low c., High c., Very high c.).
- Detailed (D): 10 numerical labels (3% recommended c. Daily Value, 4% DV, ...).

The message on the label is presented on a colored background, ranging from yellow

[11] All the subjects are made aware of the "flip the package" feature in the instructions. In a practice trial, with a slightly different interface, they are not allowed to proceed until they have consulted the information on the back of the package.

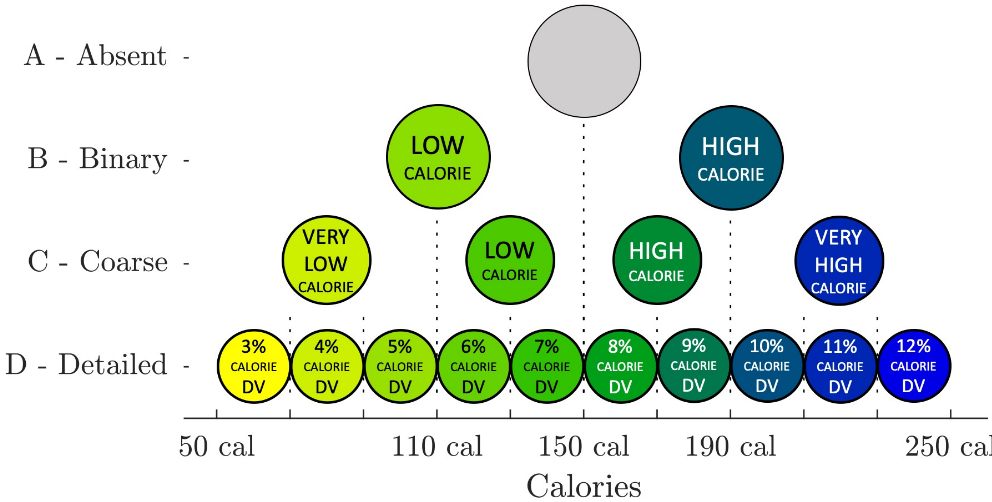


Figure 3: Treatments. Labels used in the four treatments and corresponding range of calories values. Labels are expressed as a combination of color (yellow to blue) and message (categorical for treatments B and C, numerical for treatment D.

(for low calories) to blue (for high calories). I avoid the classic *traffic light* color palette,[12] and red in particular, to minimize the framing of high-calorie products as dangerous or undesirable. We know from other studies Schuldt (2013); Shen, Shi and Gao (2018) that labels' colors affect their effectiveness, with red and black being typically associated with warning messages.

Instructions and general explanation of the meaning of labels are unchanged across treatments, control treatment included. The instruction include the explanation of what are the recommended daily values, the relation between DV percentages and number of calories, and other resources available to understand nutrition facts.

Packaged food often display information about nutrient fact on the front of the package, in the form of claims (e.g. low-fat) and exact value (e.g. facts up front). In order to minimize concerns about interaction between labels and existing information, I manually remove all of them from the front of the package. Figure 4 shows an example of how the original package is edited by removing the existing nutrient claims and adding a calorie label according to the treatment and the true calorie content of the product.

3.1.3 Instructions and interpretation of the label

The instructions of the experiment contain information about the context and the meaning of the labels. The general instructions show the distribution of calories across products

[12]Traffic lights colors (green/red) are commonly used to express recommendations in the form of go/no go binary messages. Yellow and intermediate shades of green and red are also used to indicate intermediate levels. Nutri-score labels, for example, have five labels ranging from A/green to E/red.

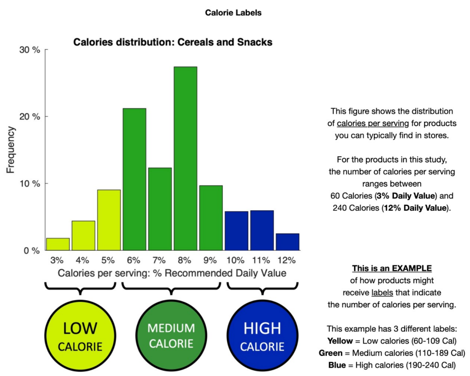
Figure 4: Product front package manipulation. The original pictures of the packages (left) are edited to remove existing nutrient claims and obtain a clean version of the package (center). The calorie label, if any, is added to the package according to the treatment and the true calorie content of the product (right).

according to the USDA National Nutrient Database for Standard References. For cereals and snacks over 95% of the products fall between 60 and 240 calories per serving, as displayed in Figure 5.a.[13] The general instructions show the probability distribution of calories, explain how to interpret the calories amount in terms of recommended daily values, and introduce the concept of calorie labels to provide information about the range of values for the product. The comprehension questions test whether the subjects remember and test this information. In order to proceed with the study, they need to answer the questions correctly and indicate the range of calories for the products in the study, both as numerical value (60 to 240 calories) and percentage of recommended daily value (3 to 12%). After the random assignment to one of the treatments, the same distribution is shown again with the label mapping that is implemented in the rest of the study. Figure 5.b shows the information for the Detailed treatment. Subjects can consult again this information at any time during the experiment, as it is available in the choice task page.

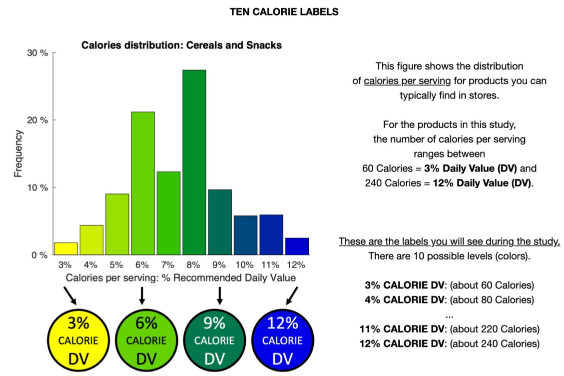
3.1.4 Features of the experimental design

The experimental design has two features that are worth discussing before proceeding further: subjects have the possibility to consult back-of-package information, and detailed labels contain numerical messages. I want to clarify why I chose these features and what are the

[13]The products used in the study provide an approximation of the empirical distribution, with more products in the medium-calorie range.



(a) Calorie distribution (general instructions).



(b) Calorie distribution (Treatment D)

Figure 5: Explanation of the label meaning in the general instructions (left, example with three labels) and Detailed treatments (right).

advantages compared to different choices.

Subject can consult the back-of-package, but an alternative approach would have been forcing them to choose based on front-package information only. This feature is motivated by a stronger test of the precision overload effect. Suppose the effect exists but consumers can overcome the confusion that arises from the precise labels by consulting the back-of-package: then consumers might not be worse off under precise labels, as they are just substituting front-package with back-package information. As a consequence, I would be able to find precision overload as a result of the experiment but this would not be a real concern in the real world. Instead, the fact that I observe the effect in an experiment in which subjects have the possibility to search further is a stronger evidence that consumers might be more confused, but not take further actions to address this issue. The free search feature has two additional advantages. First, it allows to collect process data (what do consumers consult before making the choice) and test secondary hypotheses (how do labels affect the search behavior). Second, this provides a more natural choice environment; online and in-store grocery experience allows to collect information about the product before making choices.

Detailed labels in the experiment contain numerical messages (e.g., 3% calorie Daily Value) whereas coarser labels display categorical messages without numbers (e.g., low calorie). A possible concern is that any effect of precision from this comparison is due to the type of message and not to the granularity by itself. A limitation of the current design is that it does not aim to separate whether the effect of precision is uniquely due to one of these two aspects. The experiment allows to test the joint hypothesis that detailed-numerical labels lead to worse (calorie-wise) choices compared to coarse-categorical labels: in everyday experience precise information is in fact typically associated with numerical values. An alternative experimental design could use only labels with the same type of messages: for example, coarse-numerical label that indicates the calorie range (3-7% calorie DV) or detailed-textual labels with higher precision (very-very-very-low calorie). Both these approaches rise a different type of concerns because they are dissimilar to labels we can encounter in the real world, and can lead subjects to behave differently because of lack of familiarity. The experimental design addresses the more general concern that subjects would not be able to interpret or compare the numerical information. Numbers are integers in the 3-12 range, instructions contain information about the calorie range (also tested in the comprehension questions), and the color of the label indicates its meaning in all the treatments.

3.1.5 Implementation

Instructions and Comprehension Questions. After signing the consent form, subjects are walked through the general instructions for the study (types of tasks, length of the study, incentives) and detailed instructions for the choice task. The detailed instructions include practice rounds to familiarize with the interface, details on the type of products, explanations of the labels that might be presented in the study,[14] and of the meaning of the recommended daily value of calories according to FDA guidelines.[15] At the end of the instructions, subjects are presented with three comprehension questions on the nature of the task (choose between food items), the incentives (receive one of the chosen products), and the range of calories for the products used in the study (between 3% DV [60 Calories] and 12% DV [240 Calories]). Subjects cannot start the task until they answer correctly all the questions.[16] The latter question tests whether subjects remember what is the lowest and highest amount of calories they can expect to find among the products in the study. A summary of the instructions is also available during the main task by clicking on the instructions button.

Products and Calories Distributions. The study contains choice sets comprised of two or four items. The products used are cereals and salty snacks that can be typically purchased in grocery stores. Within each trials, all the product belong to the same category. These product categories have the advantages of being largely popular food (Hamrick, 2016; Rhodes et al., 2017) and displaying a large heterogeneity in the nutrient characteristics.

[14] Subjects in all the treatments are presented a trinary label scheme as example (low, medium, and high calorie). They would not be presented that specific label scheme, but whatever they will see has similar properties (e.g. yellow-blue palette).

[15] The instructions include information on the 2,000 daily calorie guideline (and how the exact recommendation varies based on personal characteristics and behavior), the use of daily value percentages (e.g. 5% to indicate 100 calories), and an explanation that all the nutrition information in the study are expressed in calories per serving. Subjects can also use the links provided to visit the FDA website and learn more.

[16] The main results of the study are qualitatively and quantitatively robust if I restrict the analysis to the subjects that pass the comprehension questions at the first attempt.

Using publicly available data of the US Department of Agriculture, I extract the nutritional information on calories per serving and I include that in the study as part of the instructions (to explain calorie heterogeneity across products) and task (to explain how each label is associated with a particular range of calorie values). I truncate the distribution at 60 and 240 Calories per serving (a range that includes more than 95% of the observations for each category).[17]

Randomization. Randomization is operated at the subject level and at the trial level. Subjects are randomly assigned a treatment and an order of the blocks of choice trials. Trials are grouped into blocks to avoid that the same item appears several times at short distance, and to maintain the same choice set size for several rounds in a row.[18] For each trial, I randomize the position of the products on the screen to remove position concerns. All subjects face the same choice sets, and the choice sets are designed with desirable properties for the subsequent analysis. First, the marginal calorie distribution approximates the empirical one shown in Figure 5, with mid-calorie levels being more frequent than extreme ones. Second, choice sets are heterogeneous in the combinations of calories of the products: calorie content is similar in some cases and very different in others.[19] Each choice set is presented twice to each subject with different prices, once with the higher price for the high-calorie products, and once with the higher price for the low-calorie products.

Programming. The study is conducted using the online platform Qualtrics and custom JavaScript code. Qualtrics does not have specific features for mousetracking, and other features, for example the ranking questions, have limited flexibility. I developed various JavaScript tools that facilitate product visualization and data collection and can be used for a variety of online studies.

3.1.6 Additional Data

After the choice task, the subjects complete other two short tasks and a questionnaire.

Preference over Labels. Subjects are asked to indicate which type of mandatory front-package label they would prefer. They rank the four types of labels used in the treatments:[20]

[17] The USDA National Nutrient Database for Standard References can be found on the USDA website.

[18] There is no significant interaction between order of appearance and healthy choices. Subjects are equally likely to choose a healthy product in early and late trials of the study.

[19] For choice sets with two products I group the products in four quartile levels according to the coarse labels, and I generate ten combinations with replacement of two levels out of four. For choice sets with four products I generate choice sets that are balanced or skewed towards low or high calories.

[20] Note that at the moment of the question subjects had experienced only one of the four labels in the choice task. The results show a small and significant familiarity effect (the familiar label is chosen on average more than in the other treatments), but the overall ranking of the four options is the same across all the treatments.

no labels, two types, four types, or daily value percentage (with an image displaying ten types). After the first choice (most preferred option), the selected type disappears and the subject is asked to repeat the choice among the remaining options, until there is only one option left.[21]

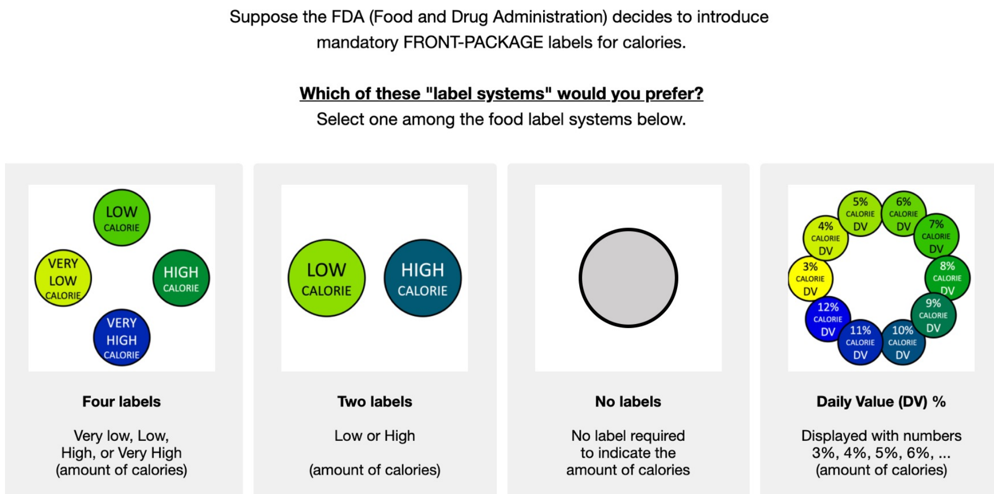


Figure 6: Preference over types of labels.

Preference over Calories. The study contains two categories of products (cereals and salty snacks). For each category, I use an incentivized task to elicit subjects' preferences over calories amounts - whether they prefer low-calorie products, high-calorie, or anything in between.

First, I remind the subjects that similar products can have very different calories amount, and that most of the products are typically between 50 and 250 Calories per serving. Then, I ask them to rank the products based on calories (in ten bins of 20 Calories each), from the most to the least preferred.

Food Literacy Questionnaire. I use eight items from the food literacy questionnaire validated in Poelman et al. (2018). These questions focus on the subject's habitual behavior when it comes to consult and compare products' information (e.g. Do you check the nutritional labels of products for calories, fat, sugar, or salt content?) and reflect about own food choice (e.g. If you have something to each, do you reflect on what you have eaten earlier that day?). I collect answers using a Likert 7 scale, with values ranging from 1 (no, never) to 7 (yes, always). To facilitate comparison of answers, in the analysis I refer to the FLI (food literacy index) that is a score that ranges between 0 (if all the answers are no) to 100 (if all the answers are yes).

[21]The label ranking question is not incentivized and does not affect any subsequent question in the study.

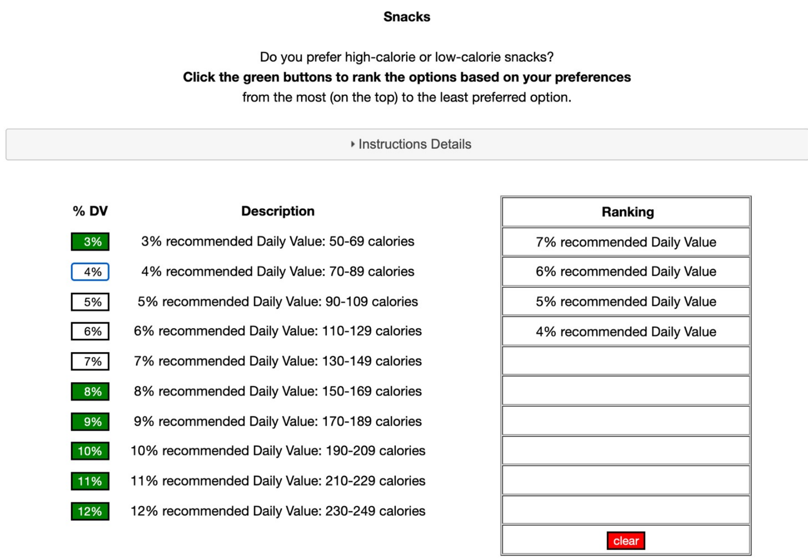


Figure 7: Preference over calorie amounts.

Final Questionnaire. At the end of the study I collect additional information about subjects' food habits (allergies, food intolerance, and dietary restrictions), body weight (whether they are underweight, healthy weight, overweight, or obese), and drivers of purchase (importance of price, brand, and healthiness of food). Sociodemographic data (e.g. gender, age, household income) are collected by the panel at the beginning of the study and used to screen the subjects according to the target quotas (details in the Recruitment section).

3.2 Hypotheses

The experimental design, hypotheses, and sample size were preregistered on the American Economic Review Social Science Registry under the name "Coarse and Granular Nutritional Labels," trial AEARCTR-0007856.

The primary hypothesis refer to the effect of labels on healthy choices. My hypothesis is that coarse labels generate healthier and better choices with respect to the control treatment, but most detailed labels are less effective than coarse ones. Healthier choices are defined in accordance with the number of calories per serving of the selected products. The variables of interest are the average amount of calories and the probability of choosing a low-calorie food option. Better choices are defined in accordance with self-reported preferences. Subjects are asked to rank products based only on the calorie amount. This allows to separate subjects that prefer high-calorie products, low-calorie, or intermediate values. Results are consistent with the hypothesis, as reported in Figure 8 and Table 2.

Secondary hypotheses refer to the effect of labels on the search process. My hypotheses are that more detailed labels lead to lower information collection (fewer consultations of the back-of-package information) and faster responses. The results show that the introduction of a label reduces search, but more detailed labels do not affect the search process (Figure 9.a). Responses are not faster under detailed labels; the opposite is true, with detailed labels being associated with longer response time (Figure 9.b).

The hypotheses are nested in the conjecture that providing more precise information might not help consumers in their decision process. I discussed in the introduction that the experiment aims to test precision overload; if decision makers find detailed information more confusing than coarse one, then precise labels can lead to worse choices.

3.3 Experimental procedure

CloudResearch Prime Panels. Subjects are recruited online through the CloudResearch Prime Panels platform, an aggregation of double opt-in subject panels.[22] To increase the representativeness of the sample CloudResearch applied demographic quotas (purposive sampling) for gender, age, race, and ethnicity that are matched to the U.S. Census.[23]

Sentry Screening. All subjects who enter a survey on Prime Panels are first run through CloudResearch's Sentry data validation system. Sentry is a short (1 minute) pre-study screening that ensures subjects are attentive, engaged, and ready to participate. People who fail Sentry are routed away from the survey. Research shows that these sorts of short, pre-study validation measures are an effective way to increase data quality obtained from market research panels like Prime Panels (Chandler et al., 2019; Litman et al., 2020).

Compensation. The study took on average 23 minutes to complete.[24] The cost per complete for this study is $5.25, that is divided between CloudResearch, the panel, and the subject. Subjects also have the chance to receive one of the products selected during the study.[25] Subjects on Prime Panels are compensated in a variety of ways. Some receive direct

[22]CloudResearch is the platform used to recruit participant from online panels. The subject panels are samples of volunteers who have agreed to complete online surveys and receive some form of compensation in exchange. Subjects are recruited by navigating to a website and signing up to take surveys. For this study, I required subjects to use a computer (not a mobile device) to make sure all the choice interface was visible in a single page.

[23]Demographic quotas. Age: 24% 18-29, 24% 30-44, 24% 45-59, 28% 60-99. Gender: 50% Female, 50% Male.Hispanic: 16% Hispanic, Latino, or Spanish origin. Race: 4% Asian, 12% Black, 82% White. Region: 21% MidWest, 17% NorthEast, 38% South, 24% West. One limitation of the sampling design is that the survey is only offered in English.

[24]Average completion time for each section of the study: instructions and comprehension questions (4 minutes), choice task (11 minutes), preferences over labels (1 minute), preferences over calories (2 minutes), final questionnaire (5 minutes).

[25]The cost per complete ($5.25) corresponds to how much the experimenter paid to CloudResearch for

monetary compensation. Others participate in studies for a donation to charity or for points that they can redeem for prizes. Compensation is determined at the panel level, meaning that each individual panel decides how much and in what form subject compensation is administered (panels do not share compensation information with CloudResearch).

Subjects. 856 subjects completed the study. Table 1 contains the distribution of the subjects according to the main demographic characteristics and shows that the four treatments are demographically balanced according to gender, age, race, ethnicity, and region.

	US Population	All Treatments	A	B	C	D
N. subjects		856	216	213	214	213
Female	0.51	0.51	0.56	0.46	0.50	0.49
Age 18-29	0.18	0.21	0.21	0.22	0.21	0.22
Age 30-44	0.18	0.26	0.27	0.29	0.28	0.22
Age 45-59	0.19	0.23	0.22	0.22	0.21	0.27
Age 60+	0.21	0.30	0.31	0.27	0.31	0.30
Asian	0.06	0.06	0.05	0.05	0.07	0.06
Black	0.13	0.13	0.12	0.15	0.14	0.13
White	0.76	0.74	0.77	0.75	0.71	0.75
Hispanic	0.19	0.17	0.18	0.17	0.17	0.15
MidWest	0.21	0.20	0.19	0.20	0.18	0.23
NorthEast	0.17	0.17	0.14	0.19	0.20	0.15
South	0.38	0.38	0.41	0.39	0.39	0.33
West	0.24	0.24	0.26	0.21	0.22	0.28

Table 1: Distribution of respondents based on target demographic characteristics: all subjects (column *All Treatments*) and separately by treatment (columns A, B, C, and D).

4 Results

The main results of the experiment highlight how label precision affects choices and the search process. Consistent with the primary hypothesis, I show that coarse labels are more effective than detailed labels in reducing the number of calories of the selected product.

a complete response to the study. At the end of the study, subjects can leave their email address in order to have the chance to receive a product from the study as bonus. The bonus can be from the choice task (each subject had one chance out of ten to receive one product they selected, plus the remaining part of the $5 endowment after paying the price displayed by the product in the study) or the calorie preference task (one subject from the study received a product based on the preferences expressed). The products used in the study have prices typically between $4 and $6 and were presented in the study with displayed values between $2.50 and $3.50 to increase their attractiveness.

Secondary hypotheses on the search process are only partially validated: the introduction of front-of-package labels reduces the probability of consulting the back of the package, but the probability is not different across labels with different precision. We see the opposite effect for response time, with slower responses for detailed labels, suggesting that precise information might be more difficult to process. When asked explicitly, subjects report that they would prefer to receive coarse labels. Towards the end of the section I look at the results into more details, by analyzing effect in different choice sets (small and large differences between products' calories) and across groups of subjects (e.g., participants with high and low food literacy).

4.1 Treatment Effect on Choice

How does label precision affect food choices? Figure 8 shows that all the label treatments (Binary, Coarse, and Detailed) generate a small but statistically significant shift towards low-calorie products. We observe a U-shaped effect of label precision on calories per serving (left) and probability of selecting a high-calorie product (right).[26] The average amount of calories per serving decreases from 143.1 (47% high-calorie products chosen in the control treatment in which the label is Absent) to 141.4 (45%, Binary label) and 139 (42%, Coarse). The effect of precision on choice is not monotonic, with higher calories in the Detailed treatment (141.6 calories per serving, 45% high-calorie products chosen.)[27]

A 3% decrease in calories is similar in magnitude to results observed in the empirical literature.[28] The reader should keep in mind that choices are made between similar products (cereals vs. cereals, snacks vs. snacks) and that the ranges of calories differ across trials.[30] The feasible amount of calories given these constraints lies between 106 and 186 calories.[31]. The U-shaped effect contains three separate - and statistically significant - effects when we consider pairs of adjacent treatments and study how choices change when we introduce

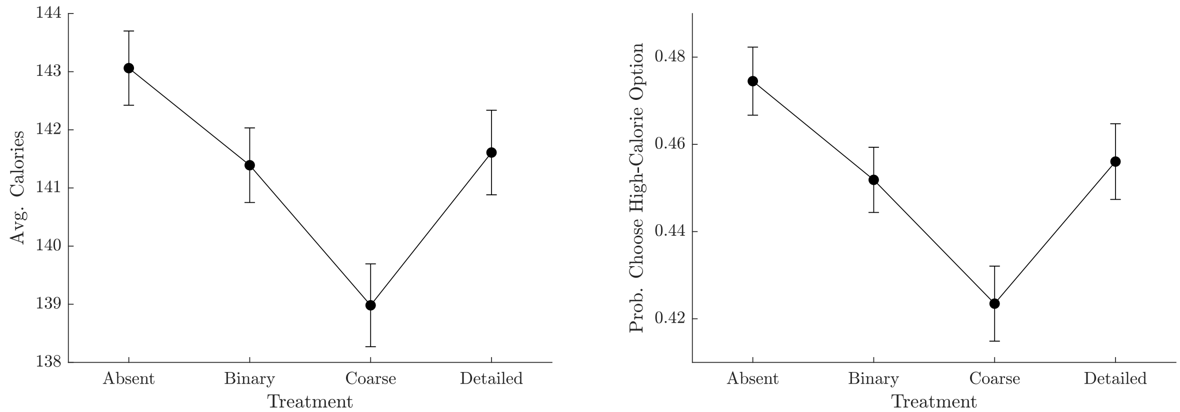
[26]High-calorie products are defined in relative terms with respect to the current choice set; these products have a number of calories per serving above the median value in the current choice set. Results are robust to different definitions of high-calorie products based on absolute amount of calories per serving (100, 150, or 200 calories per serving).

[27]All the differences between treatments A and B, B and C, and between C and D are statistically significant at the 5% level.

[28]Abaluck (2011) estimates a 50-90 calories decrease in the US after the introduction of mandatory BOP labels[29], and Barahona et al. (2020) estimate a 6.5% decrease in calories in Chile after the introduction of mandatory warning labels.

[30]Low-variance choice sets have products with similar characteristics (e.g. 60 vs. 100 calories per serving), high-variance choice sets have larger differences (e.g. 100 vs. 200 calories.

[31]A respondent who chooses the lowest-calorie product in every trial would show an average amount of calories per serving equal to 106 calories. A random respondent who chooses randomly in every trial would reach 146.



(a) Average calories per serving. (b) Probability of selecting a high-calorie product

Figure 8: Treatment effect on food choices. SE clustered at the subject-category level. Left: average number of calories per serving. Right: probability of choosing high-calorie product (number of calories below the median in the current choice set).

labels and refine their granularity. I will mostly focus on the effect of precise labels in the Coarse-Detailed comparison, as this is a striking results at odds with the predictions of the standard updating models. The comparison Binary-Coarse treatments highlight that increasing granularity can sometime be beneficial, and in fact results are not statistically different between Binary and Detailed treatment.

Tables 2 and 3 show that the results are robust to several specifications. Model 1 shows the differences across treatments. Model 2 introduces endogenous search by controlling for collection of information on the back of the package (discussed in more details in the next section). Model 3 adds choice set controls: the minimum and maximum number of calories among the products available, product category (cereals or snacks) and choice set size. Model 4 introduces demographic controls, with categorical variables for gender, age bracket, race, ethnicity, income, and education. Model 5 controls for preferences by restricting the analysis to monotonic preferences for low-calorie products. Observations that respect the monotonic preferences constraints are defined using subject-category level data on preferences over calories. Model 5 restriction provides a stronger test that address concerns about heterogeneous preferences. A possible explanation for the U-shaped effect is that subjects do not always prefer fewer calories; instead, they might find a product more appealing exactly because it has more calories than expected. I take this concern seriously by considering only observations in which, according to their own responses, subjects would prefer to move towards products with lower calories.[32] In lay terms, a monotonic observation is a trial in

[32]Here is a formal definition of how I restrict the analysis to monotonic observations. Each label is associated to a range of feasible calorie values. For each product in the choice set, I consider what would

which the subject prefers low-calories over high-calories over the whole range of values that the products can take.

OLS Regression. DV: Calories per serving of the selected product.

	(1)	(2)	(3)	(4)	(5)
Constant	143.06***	146.12***	144.93***	145.40***	141.18***
	(0.64)	(0.53)	(0.67)	(1.09)	(1.83)
Treatment B	−1.67*	−2.56***	−2.56***	−2.85***	−3.22**
	(0.90)	(0.79)	(0.79)	(0.82)	(1.30)
Treatment C	−4.08***	−5.17***	−5.16***	−5.04***	−5.82***
	(0.96)	(0.83)	(0.82)	(0.85)	(1.42)
Treatment D	−1.45	−2.42***	−2.41***	−2.14**	−2.89**
	(0.97)	(0.88)	(0.87)	(0.88)	(1.39)
Flip Package		−14.22***	−14.10***	−13.55***	−13.01***
		(0.95)	(0.92)	(0.96)	(1.27)
Treatment $B \to C$	−2.41**	−2.61***	−2.60***	−2.18**	−2.61*
	(0.96)	(0.87)	(0.85)	(0.88)	(1.35)
Treatment $C \to D$	2.63***	2.75***	2.75***	2.89***	2.94**
	(1.02)	(0.94)	(0.93)	(0.94)	(1.45)
Treatment $B \to D$	0.22	0.14	0.15	0.71	0.33
	(0.97)	(0.91)	(0.90)	(0.91)	(1.34)
Choice set Controls			✓	✓	✓
Demographic Controls				✓	✓
Restrictions					Monotonic
Observations	68451	68451	68451	64851	22792
Adjusted R^2	.001	.014	.428	.427	.505

Table 2: Treatment effect on calories per serving (OLS regression). SE clustered at the subject-category level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.2 Treatment Effect on Search

How does label precision affect information acquisition? Figure 9 shows the difference in search and response time across treatments. During the study subjects can consult the nutrient facts in the BOP by flipping the package. The left panel shows that subjects check the nutrient facts sporadically, and even less when the FOP contains a label. In the Absent treatment they flip the package 21% of the times, whereas in the three label treatments they flip it only 14% of the times. The difference is large and statistically significant when

be the intervals if participants were in the coarse treatment and I consider the preferences over calories in that interval. An observation fulfill the monotonicity requirement if, for all the intervals, the subject declares monotonic preferences with low-calorie products preferred to high-calorie products. This means that I always include observations of subjects that declare monotonic preferences low-to-high calories for the whole range of possible values, I always exclude the opposite pattern (high-to-low calories) and, for single-peaked preferences, I consider only observations that are on the right-hand side of the peak.

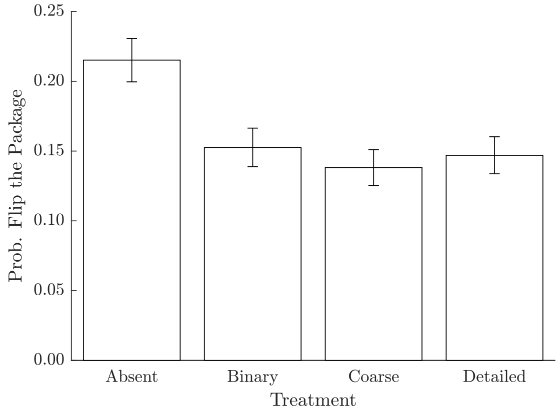
OLS Regression. DV: Probability of choosing a high-calorie product.					
	(1)	(2)	(3)	(4)	(5)
Constant	0.474***	0.509***	0.508***	0.513***	0.465***
	(0.008)	(0.006)	(0.008)	(0.013)	(0.023)
Treatment B	−0.023**	−0.033***	−0.033***	−0.035***	−0.035**
	(0.011)	(0.010)	(0.010)	(0.010)	(0.017)
Treatment C	−0.051***	−0.063***	−0.064***	−0.062***	−0.071***
	(0.012)	(0.010)	(0.010)	(0.010)	(0.019)
Treatment D	−0.018	−0.029***	−0.030***	−0.024**	−0.038**
	(0.012)	(0.011)	(0.011)	(0.011)	(0.018)
Flip Package		−0.160***	−0.165***	−0.157***	−0.162***
		(0.012)	(0.012)	(0.012)	(0.017)
Treatment $B \to C$	−0.028**	−0.031***	−0.031***	−0.027**	−0.036**
	(0.011)	(0.010)	(0.010)	(0.011)	(0.017)
Treatment C → D	0.033***	0.034***	0.034***	0.038***	0.032*
	(0.012)	(0.011)	(0.011)	(0.011)	(0.018)
Treatment $B \to D$	0.004	0.003	0.003	0.011	−0.003
	(0.011)	(0.011)	(0.011)	(0.011)	(0.017)
Choice set Controls			✓	✓	✓
Demographic Controls				✓	✓
Restrictions					Monotonic
Observations	68454	68451	68451	64851	22792
Adjusted R^2	.001	.015	.025	.024	.033

Table 3: Treatment effect on probability of selecting a high-calorie product (OLS regression). SE clustered at the subject-category level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. High-calorie products have a number of calories per serving above median in the current choice set.

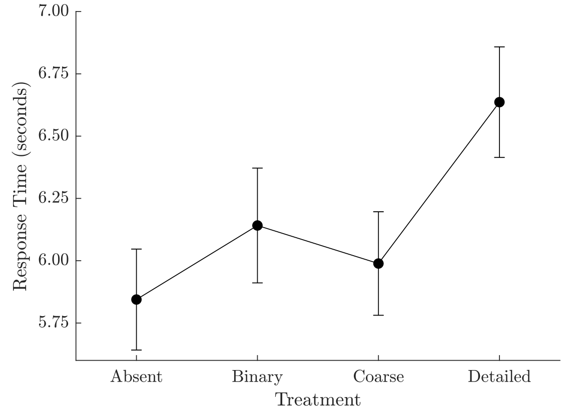
I compare treatment A against each of the other three (all $p < 0.01$) but not when we compare the label treatments with each other (all $p > 0.82$). Table 5 show that this pattern is robust to different specifications that introduce controls for the choice set and demographic characteristics of the respondents.

The right panel shows that the response time for each choice is on average 6 seconds, and is 0.6 seconds higher in the Detailed treatment. The difference is statistically significant when I compare treatment D against each of the other three (all $p < 0.01$) but not when we compare the first three treatments with each other (all $p > 0.57$). The longer response time associated with the detailed treatments suggests that the most precise labels could be confusing or difficult to understand for the subjects, and provides a suggestive evidence in favor of precision overload.

How does information acquisition interact with choices? Figure 10 separates choices based on the search behavior. The figures show the effect of two types of information: the exogenous FOP label manipulation and the endogenous information acquisition. Flipping



(a) Search probability.



(b) Average response time.

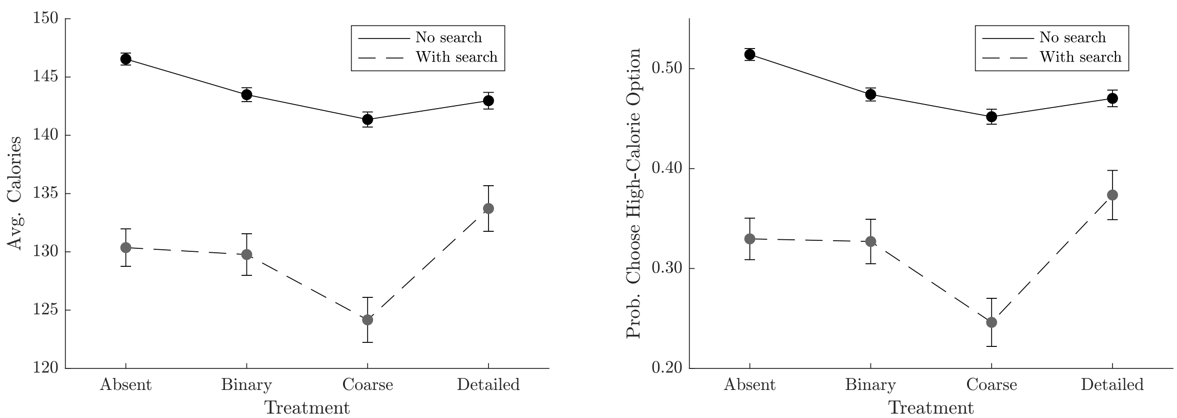
Figure 9: Process data across treatments. SE clustered at the subject-category level. Left: the probability of consulting back-of-package information decreases when any front-of-package label is introduced. Right: the average response time is significantly longer only in the Detailed treatment.

the package is associated with low-calorie choices; the calories per serving in the Absent treatment are 130 and 147 ($p < 0.001$), with and without search respectively, and high-calorie choices probabilities are 33% and 51% ($p < 0.001$).[33] Differences remain large and significant across treatments. This is not surprising if we consider that the few subjects who consult the nutrient facts might be those who care the most about the calorie content.

This conjecture is confirmed by comparing the search behavior across groups; Table 7 shows that search is more frequent among high-income, high-education, and high-food literacy subjects, and in general among subjects who display healthier choices in the study. Another striking feature is that search behavior appears highly concentrated, with three patterns. First, search is concentrated across subjects; only few participants flip the package, but they do it consistently. 14% of the subjects flip the package in 40 trials or more (out of 80), and 66% of the subjects flip the package in less than 5 trial. Second, search is concentrated across products; once one product in the choice set is flipped, typically all the other products available are also flipped. The conditional probabilities of flipping all the remaining packages are 97% and 75% in trials with two and four products respectively. Third, search is concentrated across time; when multiple products are flipped, they are flipped early and almost simultaneously. Trials in which all products are flipped have an average response time of 14.2 seconds; on average the first product is opened after 2.1 seconds and the last product after 4.4 seconds.

[33] A trial is classified as "with search" if the subject checked the BOP for the selected product. The results are robust to different specifications (search for at least one product, search for all the products).

The U-shaped treatment effect is robust to the search behavior. When we consider the effect of different labels conditional on information acquisition we see the familiar pattern, with fewer calories when we move towards Coarse labels and higher calories when we introduce Detailed labels. Suppose that having access to BOP information was sufficient to make an informed choice; in that case we would expect choices not to differ across treatments, conditional on observing the endogenous information acquisition. Instead, the pattern persists even in the observations in which search occurs. A possible interpretation is that subjects do not fully absorb the information on the BOP and make use of the front label. This would be consistent with the behavioral models I discuss in Section 6, in which consumers have noisy mental representations of the information acquired.

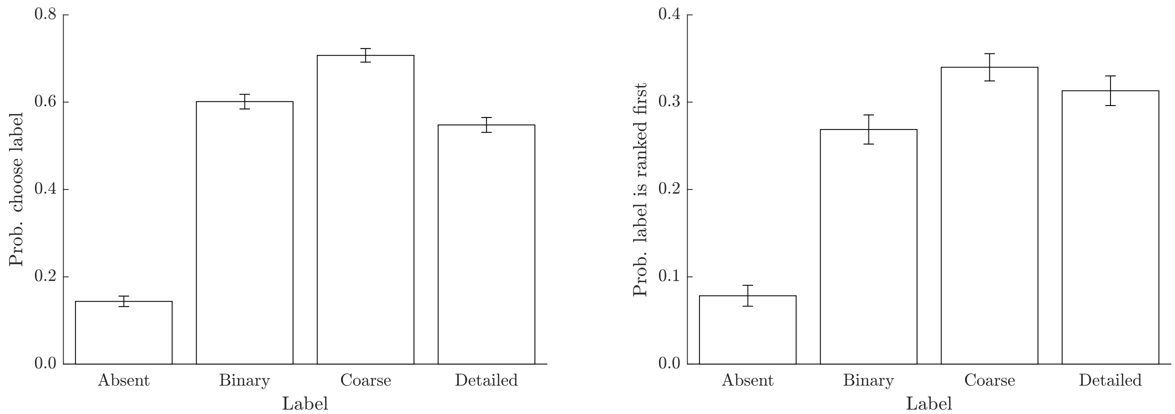


(a) Average calories per serving. (b) Probability of selecting a high-calorie product.

Figure 10: Treatment effect on food choices, conditional on search behavior. SE clustered at the subject-category level. Left: Average number of calories per serving. Right: probability of choosing high-calorie products. Observations are divided based on whether the subject had consulted the back-of-package information for the product they selected.

4.3 Preferences over Types of Labels

What kind of labels do subjects prefer? After the choice task, I present a scenario in which FDA is evaluating the implementation of mandatory FOP calorie labels. I ask the subjects to rank the four possible types of labels (absent, binary, coarse, and detailed) based on their preferences as consumers. Figure 11 shows that choice probability for each label. Standard information models would predict that the most detailed label should always be preferred. Instead subject responses show that not only binary and coarse labels are selected by a large fraction of the respondents, but coarse labels are the overall preferred option. Coarse labels have the highest probability of being ranked above other ones (71%, $p < 0.001$, followed by the binary labels with 60%) and the highest probability of being ranked first (34%, $p = 0.20$, followed by the detailed labels with 31%). Table 4 considers the whole ranking and contains the choice probability for each pairwise comparison. Coarse labels are the Condorcet winner, receiving more than 60% of the preferences in each pairwise comparison. The Condorcet winner of a voting problem is the option that would win the two-options election against each of the other candidates in a plurality vote. Coarse and Detailed labels are selected as first option by a similar fraction of subjects, but coarse labels are much more likely to be ranked second (47% of the times).



(a) Label choice probability (overall). (b) Label choice probability (pairwise).

Figure 11: Preferences over types of labels. Left: overall probability of ranking a label above other ones (including all the pairwise comparisons). Right: probability of ranking a label as first among the four options.

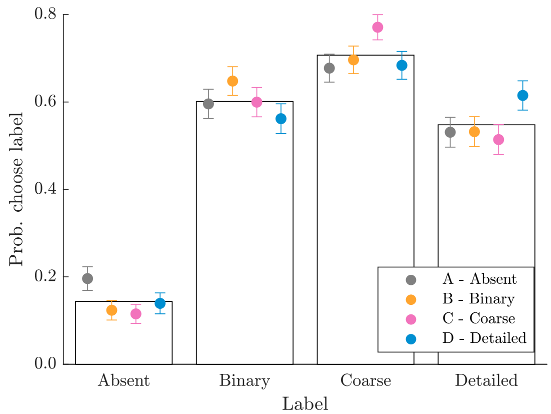
Probability that label X...	...is preferred to label Y.			
	Absent	Binary	Coarse	Detailed
Absent		0.12	0.11	0.20
Binary	0.88		0.37	0.55
Coarse	0.89	0.63		0.61
Detailed	0.80	0.45	0.39	

Table 4: Choice probability for each pair of labels determined from the ranking distribution.

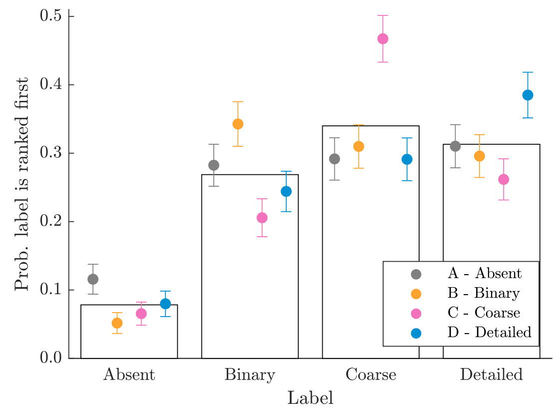
Are preferences over labels affected by the treatment? I elicit the preferences after the choice task, and subjects in different treatments are exposed to one label more than the other three. Figure 12 shows that familiarity[34] improves the ranking of all types of labels

[34]The effect of familiarity observed in the data is consistent with what is discussed in the literature, see e.g. Hansen and Wänke (2009).

and in particular it boosts the likelihood of the same label being ranked first, but the coarse label remains the Condorcet winner in all the treatments.[35] The label observed in the choice task is ranked first in 33% of the cases, while we would observe just one quarter if there was no such effect ($p < 0.001$).



(a) Label choice probability (overall).



(b) Label choice probability (pairwise).

Figure 12: Preferences over types of labels across treatments. The colors indicate the treatments that the subjects completed, the x-axis indicate the type of label. Left: overall probability of ranking a label above other ones (including all the pairwise comparisons). Right: probability of ranking a label as first among the four options.

Table 5 shows that the result is robust to specifications that take into account treatments and demographic controls. Later in the section, Table 7 highlights the heterogeneous label preferences across groups; more detailed labels are preferred by subjects with high food literacy index, high education, high income, and preference for low-calorie products.

Subjects prefer coarse labels over detailed ones and also over not receiving any additional information. The result is not driven by two separate groups with opposite preferences (all or nothing); instead there is a significant number of people who place it as first option, plus other subjects (on both extremes) that are satisfied by coarse labels. This result is related but deeply different from what we know about information avoidance (see e.g. Golman, Hagmann and Loewenstein 2017 and Reisch, Sunstein and Kaiser 2021). Value of information is commonly defined through a combination of instrumental and hedonic effects. The first one is directly linked to the ability of making better choices thanks to the additional knowledge, while the second refers to the utility, or disutility, generated by receiving the information. For example, receiving good news can lead to immediate utility (or anticipation of future

[35] The coarse label is the most selected in all the treatments and the Condorcet winner, but it is not always the most frequently ranked first. In treatments B, C, and D, the familiar label is ranked first with the highest probability.

	Prob. Search		Label Preference	
	(1)	(2)	(3)	(4)
Constant	0.22***	0.16***	0.60***	0.55***
	(0.02)	(0.03)	(0.02)	(0.03)
Treatment B	−0.07**	−0.07**	0.02	0.01
	(0.03)	(0.03)	(0.03)	(0.03)
Treatment C	−0.08***	−0.08***	0.04	0.04
	(0.03)	(0.03)	(0.03)	(0.03)
Treatment D	−0.07**	−0.07**	0.06*	0.06*
	(0.03)	(0.03)	(0.03)	(0.03)
Demographic Controls		✓		✓
Observations	68451	68451	856	856
Adjusted R^2	.011	.046	.006	.035

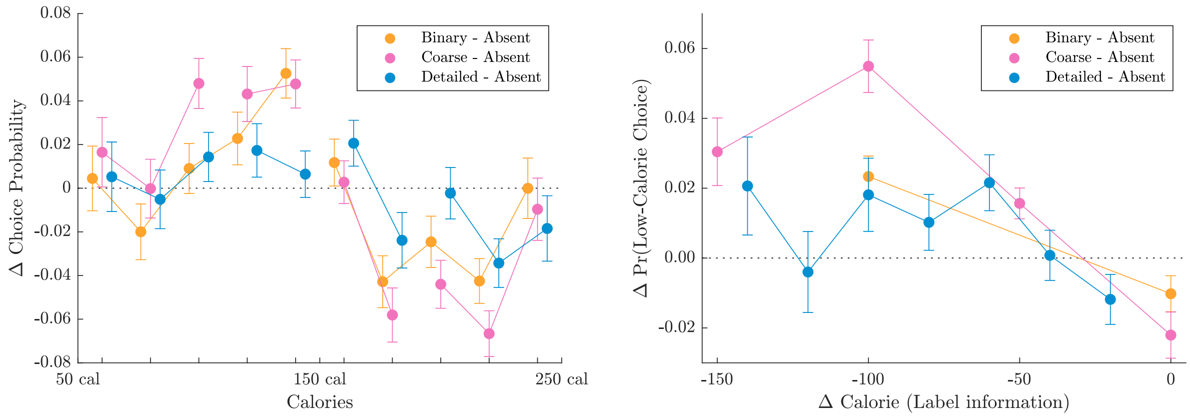
Table 5: Treatment effect on search and label preference. SE clustered at the subject-category level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Search probability: probability of consulting the back-of-package information. Label preference: preferred calorie label (explicit elicitation) normalized between 0 (prefer Absent label) and 1 (prefer Detailed label).

utility as in Loewenstein 1987) even when this has no direct effect on future outcomes. The evidence of preference for coarse labels is not fully explained by this framework, that would allow heterogeneity across subjects (some of which would like to know more) but not necessarily that they wants to know something in between. Instead the result seems to fit well the idea of precision overload, with decision makers disliking information that is too precise and potentially confusing. The model discussed in Section 6 will provide a formal explanation of how both choices and preferences over types of information are consistent with this effect.

4.4 Response to Label Information

Why are detailed labels less effective than coarse ones? We want to look closer to the effect and study the underlying mechanism. The pair of graphs in Figure 13 offer two complementary ways to decompose the treatment effect. First, what is the effect conditional on product's calories? Second, what is effect conditional on labels' *information*? The first approach consider the products in isolation, since they can have low or high calories. The second approach focuses the products with respect to the current choice set and considers the choice of a low-calorie product with respect to the other options available.

The two types of analysis provide consistent and complementary insights about what drives the label effect. The first figure show that low-calorie (below median) are chosen sig-



(a) Products' calories and choice.

(b) Label information and choice.

Figure 13: Response to label information in different treatments. SE clustered at the subject-category level. Left: choice probability conditional on product's true calorie content. Right: change in choice probability for low-calorie products (compared with the Absent treatment) conditional on the inferred calorie difference (difference between expected amount of calories per serving, inferred from the labels).

nificantly more often in the Coarse treatment compared with either the Binary and Detailed treatments, with the largest differences in the middle range of values, 100 to 200 calories, while extreme calories do not display significant differences. This suggest that even in the control treatment subjects have a good sense of which products lie at the extremes of the interval, and label information is able to change their mind mainly for intermediate values.

The second figure indicates how subjects respond to differences between *implied* calorie labels in different treatments.[36] Calorie differences are calculated based on the information provided by the FOP label only. For example, in a trial with Binary labels the implied difference can be either 0 calories (when both products display the same label) or 100 calories (when one product displays Low and the other displays High).[37] This does not mean that the items have an exact difference of 100 calories: it could be less (e.g., 120 vs. 160 calories) or more (e.g., 80 vs. 220 calories), but in both these scenarios the products would display two different labels.

The vertical axis indicates the choice probability change in favor of the low-cal product with respect to the Absent treatment. In general we observe that larger implied difference lead to more frequent choice of healthy products. On one extreme, when two products display

[36] The difference between implied calorie differences Δc is defined as $\mathbb{E}[c_j] - \mathbb{E}[c_k]$ where j is the target product and k is the product with the highest amount of calories in the current choice set. Expectations are taken with respect to the information provided by the label.

[37] For choice sets with four items, differences are calculated with respect to the product with the highest number of calories

the same label (implied difference equal to zero), choices appear less healthy, and this can be explained by the search reduction discussed in Figure 9. We are interested in comparing the effect of Coarse and Detailed labels. The figure offers a visual decomposition of the treatment effect between small and large differences; response is not significantly different for values below 50 calories, but the response is weaker for larger differences. We can interpret this result in terms of lower sensitivity to the label information. A Wald test confirms that the difference across treatments is mostly driven by the change in the slope ($\beta_C = -0.00112$, $\beta_D = -0.00076$, $p = 0.022$) and not in the intercept ($\alpha_C = -0.0485$, $\alpha_D = -0.0446$, Wald test $p = 0.28$).

4.5 Heterogeneous Treatment Effect

Are these results differences across sociodemographic groups of respondents? I collect sociodemographic data, food habits, and calorie preferences for each subject and I compare the direction and size of the effect across groups. Table 6 contains the main results. For each group, I show three summary statistics: the baseline behavior (treatment Absent), the effect of coarse labels (difference between Coarse and Absent treatments), and the *marginal* effect of detailed labels (difference between Detailed and Coarse treatments). Results are expressed in number of calories (left) and probability of choosing a high-calorie product (right).

Two important patterns emerge from the table, and can be observed in Figure 14. First, the direction of the effect is robust across groups. We systematically observe a positive effect of coarse labels (lower calories) followed by a negative marginal effect of detailed labels (higher calories). Second, the magnitude and statistical significance of the effect are not equal across groups.

The comparison across groups highlight that food behavior and socioeconomic status mediate the label effect. For food behavior, we observe similar patterns for calorie preferences and food literacy index (FLI). Subjects who prefer low calories or have high FLI have higher baseline and larger response to the introduction of coarse labels. For socioeconomic status, coarse labels are more effective for subjects with low education and low income. These groups display a larger effects both in the comparison Absent-Coarse (positive) and Coarse-Detailed (negative effect).

These differences are consistent with the results highlighted in experiments that involve nudges; Mrkva et al. (2021) show that consumers with low SES, domain knowledge, and numerical ability are impacted more by nudges. This lead to a reduction of disparities when "good nudges" (designed to increase the choice of superior options) are introduced, but the opposite is also true when under "bad nudges." In the context of my study, this suggests that

Group	Avg. calories A	$A \rightarrow C$	$C \rightarrow D$	Pr. choose a high-calorie product A	$A \rightarrow C$	$C \rightarrow D$
All	143.06	-4.08***	2.63***	0.474	-0.051***	0.033***
	(0.64)	(0.96)	(1.02)	(0.008)	(0.012)	(0.012)
Prefer low calories	141.80	-3.98***	1.58	0.461	-0.051***	-0.020
	(0.83)	(1.18)	(1.23)	(0.010)	(0.014)	(0.015)
Prefer high calories	145.27	-3.34**	3.97**	0.489	-0.040**	0.049**
	(0.95)	(1.62)	(1.75)	(0.011)	(0.020)	(0.022)
FLI high	141.41	-4.45***	3.43**	0.460	-0.058***	0.045***
	(0.89)	(1.33)	(1.44)	(0.011)	(0.016)	(0.017)
FLI low	144.71	-3.38***	1.60	0.489	-0.040**	-0.017
	(0.90)	(1.35)	(1.41)	(0.011)	(0.017)	(0.017)
Education high	143.66	-2.77**	0.34	0.486	-0.037**	0.005
	(0.82)	(1.26)	(1.45)	(0.010)	(0.015)	(0.017)
Education low	142.46	-5.19***	4.60***	0.463	-0.062***	0.057***
	(0.97)	(1.42)	(1.42)	(0.012)	(0.017)	(0.017)
Income high	142.84	-3.11**	1.54	0.474	-0.041***	0.019
	(0.79)	(1.30)	(1.49)	(0.010)	(0.016)	(0.018)
Income low	143.37	-5.04***	3.57**	0.476	-0.061***	0.044***
	(1.05)	(1.44)	(1.40)	(0.013)	(0.018)	(0.017)

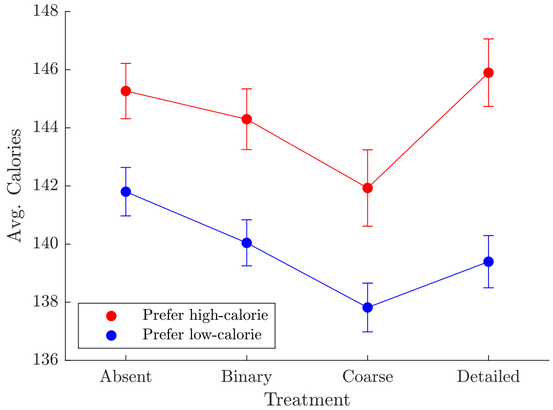
Table 6: Heterogeneous treatment effect. SE clustered at the subject-category level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. For each group (row) the table reports the treatment effect on calories (left) and probability of choosing a high-calorie product (right). Summary statistics indicate baseline values (Absent treatment), the effect of coarse labels (Absent to Coarse treatment), and the marginal effect of detailed labels (Coarse to Detailed treatment). High-calorie products: calories per serving above median in the current choice set.

detailed (complex) labels can be interpreted as bad nudges[38] and lead to higher disparity in choices.

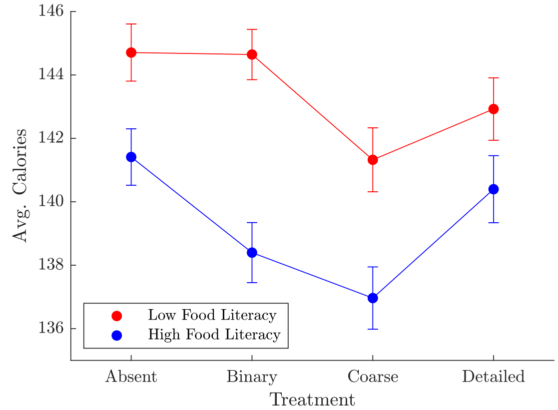
5 Bayesian Updating Model

The descriptive evidence from the experiment suggests that subjects might underreact to detailed labels' information, but this is not sufficient to rule out that their behavior is still consistent with the Bayesian updating model. Consider this example of a consumer who fully absorbs the detailed information and generates the observed U-shaped calorie pattern. The consumer prefers product with low calories and strongly dislikes very high calories (e.g.

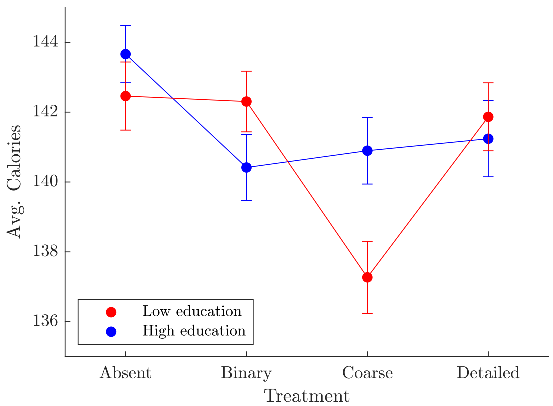
[38]Mrkva et al. (2021) study the effect of nudges that introduce a default option in a series of experiments in which a correct answer exists. They classify good and bad nudges based on the ex post outcome, i.e. if the default option is indeed the correct answer of the problem. In my experiment there is no explicit correct or wrong answer, and the intervention affects the information



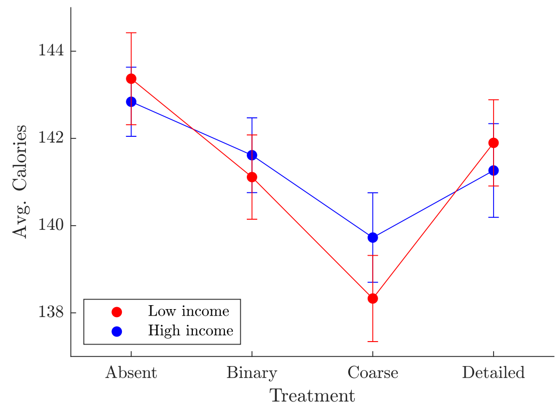
(a) Label choice probability (overall).



(b) Label choice probability (pairwise).



(c) Label choice probability (overall).



(d) Label choice probability (pairwise).

Figure 14: Heterogeneous treatment effect on calories per serving. Results are presented separately based on (a) calorie preferences, (b) food literacy, (c) education, and (d) income. Calorie preferences (a) are classified based on the preferred calorie amount (above or below 150 calories). The other three figures (b, c, and d) classify respondents based on the median split. Standard Errors clustered at the subject-category level.

above 220 calories). In the coarse scenario, they would avoid products in the fourth quartile, some of which are above 220 calories, but in the detailed scenario they would avoid only a fraction of them, and choose with positive probability high calorie products with 200 calories per serving, leading to a higher amount of calories selected.[39]

In this section I test whether the experimental dataset provides stronger evidence against

[39]Here is another example of a consumer who makes use of the detailed label information and end up choosing product with higher calories. A consumer considers two products, j and k, that in the coarse scenario are labeled as low-calorie (110-150 calories) and high-calorie (150-190 calories) respectively. Given a tradeoff between calories and other characteristics, suppose the consumer is indifferent between the two. Once the detailed information is provided, the consumer refines the beliefs and learns that j has 130-150 calories and k has 150-170 calories. The two products are more similar than expected, and the consumer chooses k, that contains more calories.

Group	Pr. Search	R. Time	Calorie Pref.	Label Pref.	Food Literacy
All	0.163	4.7	84.5	0.629	63.4
	(0.010)	(0.2)	(1.9)	(0.011)	(0.7)
FLI high	0.214***	5.3***	79.4***	0.679***	79.9***
	(0.016)	(0.2)	(2.5)	(0.014)	(0.5)
FLI low	0.109***	4.0***	90.1***	0.576***	45.6***
	(0.012)	(0.2)	(2.8)	(0.016)	(0.8)
Income high	0.163	4.5	82.9	0.642	66.8***
	(0.014)	(0.2)	(2.5)	(0.015)	(0.9)
Income low	0.163	4.9	86.2	0.616	59.9***
	(0.015)	(0.2)	(2.8)	(0.015)	(1.1)
Education high	0.170	4.8	81.2*	0.649*	67.8***
	(0.015)	(0.2)	(2.6)	(0.015)	(0.9)
Education low	0.157	4.6	87.4*	0.612*	59.6***
	(0.014)	(0.2)	(2.7)	(0.015)	(1.1)
Prefer low calories	0.177***	4.8*	58.3***	0.632	65.5***
	(0.012)	(0.2)	(1.3)	(0.012)	(0.8)
Prefer high calories	0.124***	4.2*	160.2***	0.621	57.4***
	(0.017)	(0.3)	(2.1)	(0.022)	(1.6)

Table 7: Heterogeneous responses across groups. For each group (row) the table reports the average and SE for search (probability of flipping the products' package), response time (expressed in seconds), preference over calories (peak of the preferences, with 60 for the lowest and 240 for the highest amount of calories), preference over types of labels (ranked based on precision and normalized in the range 0-1, with 0 for the Absent label and 1 for the Detailed labels), and Food Literacy Index (between 0, low, and 100, high). T-test for the differences between the two groups: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

the Bayesian updating model and in favor of the claim that subjects underreact to detailed labels. I do this by characterizing the choice task in the experiment as a choice problem under uncertainty about the products' characteristics. By taking this approach I am able to derive testable predictions about how consumers' beliefs are related across treatments. I use the experimental dataset to estimate the label fixed effects and test the predictions. The estimates will confirm what the descriptive evidence suggest; labels have larger weights on decisions in the coarse treatments, and subjects underreact to detailed label information.

5.1 Setup: Discrete Choice under Uncertainty

Preferences. I follow closely the setup used by Barahona et al. (2020) to characterize consumers who learn from label. The model consists of a distribution of consumers indexed by $i \in \mathcal{I}$ and a set of J products indexed by $j \in \mathcal{J}$. In each trial $t \in \mathcal{T}$ the consumer faces a choice set $\mathcal{J}_t$ and selects one product among those available. Trials can differ in the set of products offered $\mathcal{J}_t$ and in the prices of the products p_{jt}. Later I will introduce product labels, that can also differ across trials.

I assume that the utility derived by individual i when purchasing product j can be separate into three components:

$$u_{ijt} = \underbrace{h_i(c_j)}_{\text{health consequences}} + \underbrace{\delta_{ij}}_{\text{experience/taste}} + \underbrace{\alpha_i p_{jt}}_{\text{price}} \tag{1}$$

Products have c_j calories and the consumer has a mapping $h_i(c_j)$ from calories to utility that we can interpret as the part of utility related to health consequences. The second part is δ_{ij}, that represents the direct utility from consuming the product. The third part is $\alpha_i p_{jt}$ that captures the disutility from paying price p_{jt}, with α indicating the price elasticity.

Labels. I assume consumers do not observe the true calorie content c_j, but have beliefs about it based on initial knowledge and information conveyed trough labels. Label $l_{jt} \in \mathcal{L}_t$ provides information about product j in trial t according to a label regime $(\tau_t, \mathcal{L}_t)$. The label regime $(\mathcal{L}_t, \tau_t)$ is a pair of sets: a sorted set of label messages $\mathcal{L}$ (e.g. Low-Calorie and High-Calorie) and a sorted set of thresholds values τ that generate the partition of the calorie space into coarse labels (e.g. 0, 200, and 1000 calories).

Product j is assigned a label l_{jt} according to the label regime and based on its calorie content c_j.

$$l_{jt} = l_m \Leftrightarrow \tau_{m-1} \leq c_j < \tau_m \tag{2}$$

In lay terms, the product receives the m-th label message if and only if its calorie content lies in the m-th cell of the calories partition.

The consumer infers the calorie amount, and the associated health consequences, from the label and chooses the product that maximizes the expected utility

$$\mathbb{E}_c[u_{ijt}] = \mathbb{E}_c[h_i(c_j)|l_{jt}] + \delta_{ij} + \alpha_i p_{jt}$$

We are interested in the role of $\pi_{h|l_{jt}} := \mathbb{E}_c[h_i(c_j)|l_{jt}]$,[40] that represents the expected utility that depend on the label message (label utility thereafter). I assume that before observing any label the consumer is uninformed and holds prior beliefs follow the true distribution of calories across products $c \sim F_C$.

[40] To indicate belies and expected values I introduce a different notation from Barahona et al. (2020) and I use $F_{H|l}$ to indicate the posterior distribution given the label information, and $\pi_{h|l}$ to indicate the expected utility.

I assume agents observe accurately the label and interpret its meaning correctly. When a label is observed the consumer updates own calorie and health beliefs to the distribution $F_{C|l}$ and $F_{H|l}$ respectively, defined as

$$f_{C|l}(c) := f_C(c)\frac{Pr(l|c)}{Pr(l)} \qquad \text{and} \qquad f_{H|l}(h) := \int_c f_{C|l}(c) \cdot \mathbb{1}(h(c) = h)\, dc$$

and depend on the a priori probability of encountering the label $Pr(l)$ and the conditional probability $Pr(l|c)$ which is 0 for all the values of c that are associated with different messages.

5.2 Testable Predictions

Coarser Label and Information Refinement. In the experimental design I introduce treatments that differ from each other in the granularity of the label regime. Each treatment is a refinement of the previous one in the sense that each message is divided into multiple messages that convey the same information and more. I characterize formally this setup as a partition of the calorie space and I define when a label is coarser than another.

Consider two label regimes with thresholds τ and τ'. The label regimes based on τ' is coarser than the one based on τ if $\tau' \subset \tau$ - i.e. the set of values that determine the coarse labeling is a subset of those that determine the precise labeling.[41]

For each coarse label l'_c we can define the set $\mathcal{L}_{d|l'_c}$ of detailed labels that are feasible under l'_c

$$\mathcal{L}_{d|l'_c} := \{l_d \in \mathcal{L}_d : Pr(l_d|l'_c) > 0\}$$

where $Pr(l_d|l'_c)$ is the probability that a product with label l'_c in the coarse regime can receive the detailed label l_d, calculated according to the calorie distribution F_C.

Relation Between Labeling Regimes. We have all the ingredients to establish the relation between the expected label utility $\pi_{h|l}$ in different regimes. Consider a product that displays a specific coarse label $l'_c \in \mathcal{L}_c$ and with expected label utility

$$\pi_{h|l'_c} := \mathbb{E}_c[h(c)|l'_c] = \int_c h(c)\, dF_c(c|l'_c)$$

We want to express this value in terms of the detailed label utilities, if were were in a detailed

[41] We can define a partial ordering of the labels $\succ_p$ based on the precision of their cutoffs, and following the notation from above $\tau \succ_p \tau'$ structure generates a strict partition of the latter. This relation generates a surjection $\mathcal{L} \to \mathcal{L}'$: for each precise label $l \in \mathcal{L}$ there is one and only one corresponding coarse label $l' \in \mathcal{L}'$, but there can be multiple precise labels $l_1, l_2 \in \mathcal{L}$ associated to the same coarse label $l' \in \mathcal{L}'$. For example $\mathcal{L}' = \{A, B\}$ (coarse) and $\mathcal{L} = \{A+, A-, B+, B-\}$ (precise).

label regime with more granular label. It is useful to use the law of iterated expectations to rewrite

$$\pi_{h|l'_c} = \mathbb{E}[h|l'_c] = \mathbb{E}\big[\mathbb{E}[h|l'_c, l_d]\big] = \sum_{l_d \in \mathcal{L}_d} Pr(l_d|l'_c) \cdot \mathbb{E}[h|l'_c, l_d]$$

We are considering detailed labels that are partitions of the coarse ones, and this allows to simplify the expression in two ways. First, following the definition of feasible set we have $Pr(l_d|l'_c) = 0 \;\; \forall l_d \notin \mathcal{L}_d$. Second, the detailed labels are sufficient statistics for the posterior beliefs that leads to $\mathbb{E}[h|l'_c, l_d] = \mathbb{E}[h|l_d]$. We can now rewrite the value decomposition:

$$\pi_{h|l'_c} = \mathbb{E}[h|l'_c] = \mathbb{E}\big[\mathbb{E}[h|l'_c, l_d]\big] = \sum_{l_d \in \mathcal{L}_{d|l'_c}} Pr(l_d|l'_c) \cdot \pi_{h|l_d} \tag{3}$$

The value of the coarse label $\pi_{h|l'_c}$ is the convex combination of the *feasible* detailed labels $\pi_{h|l_d}$, weighted by the probability of encountering each detailed label.[42] The additional information provided by the detailed label can allow to make better choices. A consumer could be indifferent between two products when only coarse labels are available (based on taste and price only) but if the product have different detailed labels the consumer would break the tie in favor of the preferred one. The immediate consequence is that detailed information would increase the overall consumer welfare, and consumers should prefer receiving the most informative label. An additional consequence in the context of the experiment is that consumers who prefer lower calories would be more likely, on average, to choose low-calorie products when the labels are more precise.

Weaker Testable Predictions. The approach presented above has the advantage of providing a clear quantitative prediction that we can test under the assumption that participants assigned to different groups have the same distribution of preferences. On the other hand, it relies on a strong assumption that subjects use the correct probability distribution. We might doubt this assumption, and still use the setup to have a weaker version of the previous prediction based on the assumption that agents are using Bayesian updating to learn from labels, but are using a prior distribution of calories that is not necessarily the correct one. The label utility $\pi_{h|l_d}$ can still be expressed as a convex combination of the feasible detailed labels, but we have now full flexibility on the weights.

[42] The intuition can be presented with a simple numerical example. Consider a detailed regime with four labels $\{l_{d1}, l_{d2}, l_{d3}, l_{d4}\}$ (quartiles) and a coarse regime with two labels $\{l_{c1}, l_{c2}\}$ (below and above median) such that l_{d1} and l_{d2} are a refinement of l_{c1}. Given this partition of the distribution we have $Pr(l_{d1}|l_{c1}) = Pr(l_{d2}|l_{c1}) = \frac{1}{2}$. Suppose the expected utility for the detailed labels is $\pi_{h|l_{d1}} = 5$ and $\pi_{h|l_{d2}} = 1$, then $\pi_{h|l_{c1}} = \sum_{l_d \in \mathcal{L}_{d|l_{c1}}} Pr(l_d|l_{c1}) \cdot \pi_{h|l_d} = \frac{1}{2} \cdot 5 + \frac{1}{2} \cdot 1 = 3$.

A convenient way to express the prediction is that the utility of the coarse label lies between the lowest and highest values associated to the feasible detailed label, namely $\pi_{h|l'_{\underline{d}}} := min\{\pi_{h|l_d}\}_{l_d \in \mathcal{L}_{d|l'_c}}$ and $\pi_{h|l'_{\bar{d}}} := max\{\pi_{h|l_d}\}_{l_d \in \mathcal{L}_{d|l'_c}}$.

To recap, we have two predictions that we can test using the experimental dataset.

Prediction 1 (weak). Under the assumptions of Bayesian updating and any beliefs about the calorie distribution, we have the inequality prediction for the value of the coarse label $\pi_{l'_c}$:

$$\pi_{h|l'_{\underline{d}}} \leq \pi_{h|l'_c} \leq \pi_{h|l'_{\bar{d}}} \tag{4}$$

with boundaries defined as $\pi_{h|l'_{\underline{d}}} := min\{\pi_{h|l_d}\}_{l_d \in \mathcal{L}_{d|l'_c}}$ and $\pi_{h|l'_{\bar{d}}} := max\{\pi_{h|l_d}\}_{l_d \in \mathcal{L}_{d|l'_c}}$.

Prediction 2 (strong). Under the assumptions of Bayesian updating and correct calorie distribution, we have the equality prediction for the value of the coarse label $\pi_{l'_c}$:

$$\pi_{h|l'_c} = \sum_{l_d \in \mathcal{L}_{d|l'_c}} Pr(l_d|l'_c) \cdot \pi_{h|l_d} \tag{5}$$

5.3 Estimation

The experimental dataset provides an exogenous variation in the granularity of the label that I can use to test the predictions of the Bayesian updating model. For example, a product with 60 calories per serving is presented, according to the treatment, without label (Absent), or with a label that reports *Low Calorie* (Binary), *Very low calorie* (Coarse), or *3% calorie Daily Value* (Detailed).

In order to test the predictions on the expected utility I estimate the demand model

$$u_{ijt} = \underbrace{\lambda_{l_{jt}}}_{\text{label}} + \underbrace{\delta_j}_{\text{experience/taste}} + \underbrace{\alpha p_{jt}}_{\text{price}} + \underbrace{\varepsilon_{ijt}}_{\text{T1EV shock}} \tag{6}$$

The empirical model in Equation 6 is conceptually analogous to the theoretical model in Equation 1, but it relies on various homogeneity restrictions that are motivated by the features of the dataset. First, there is no explicit outside option in the study so I cannot separate the baseline product utility and the baseline health/label utility.[43] For clarity in the empirical model I express the first component of the utility as $\lambda_{l_{jt}}$ instead of $\pi_{h|l_{jt}}$ and I use

[43]For each product category, cereals and snacks, I normalize the value of the product with the highest amount of calories to 0.

the restrictions that the label utility derived from not observing any label is normalized to zero, and the average label utility within each treatment is also normalized to zero. Second, each subject is assigned to one treatment only, so it is not possible to separately estimate subject-level and treatment-level coefficients. To address this limitation I drop the subject-specific coefficients i and I assume homogeneous utility from labels λ_l, products δ_j, and price elasticity α. Different preferences across subjects and across trials are modeled using the preference shock term ε_{ijt} that I assume takes a Type 1 Extreme Value distribution. Finally, each product displays only one label in each treatment. There is no deception in the experiment, so a 60 calories product is never presented as high-calorie. If each product was presented with multiple types of labels in each treatment we would be able to estimate the label-product specific fixed effect, that captures how much subjects learn about each product through the label. That would be represent a stronger test, as it would not rely on the assumptions that, absent the label, subjects have the same initial beliefs for all the products.

The predictions introduced in the previous section can be now expressed with the notation of the empirical model.

$$\lambda_{l'_{\underline{d}}} \leq \lambda_{l'_c} \leq \lambda_{l'_{\bar{d}}} \quad \forall\ \lambda_{l'_c} \tag{7}$$

$$\lambda_{l'_c} = \sum_{l_d \in \mathcal{L}_{d|l'_c}} Pr(l_d|l'_c) \cdot \lambda_{l_d} \quad \forall\ \lambda_{l'_c}. \tag{8}$$

5.4 Estimation Results

I estimate $(\lambda_l, \delta_j, \alpha)$ using a maximum likelihood estimator, and I estimate the standard errors for the same coefficients using the bootstrap method.[44] The estimates of the label fixed effects λ_l are shown in Figure 15.

I provide now an interpretation of the estimates, deferring a formal test of the restrictions to the next subsection. The weak test on the Bayesian updating model restrictions requires the coarse label estimates to be within the range of feasible detailed label estimates.[45] The prediction is systematically violated for all the four coarse labels. The label estimates are scaled by the price elasticity. The interpretation is that subjects in the study are willing

[44] For the bootstrap estimation of the standard errors I use 1001 simulated dataset generate by random sampling with replacement from the original one.

[45] We can also test the restrictions binary-coarse and binary-detailed. The prediction is systematically rejected in the first case, but cannot be rejected in the second one. Binary and detailed labels' estimates have similar magnitude, but both of them have smaller values than the coarse ones.

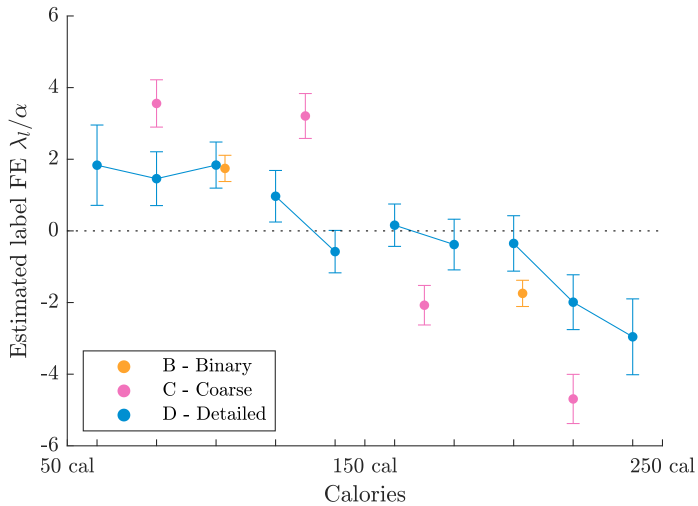


Figure 15: Estimates of the label fixed effect. Values estimated by maximum likelihood and bootstrap standard errors. ML label effect expressed in WTP λ_l/α, bootstrap SE. Blue lines indicate the groups of feasible detailed labels associated with every coarse label.

to pay about \$1.80 more for the same product when they observe the lowest-calorie binary label, \$3.40 for the lowest-calorie coarse label, but only \$2 more when they observe the lowest-calorie detailed label, with symmetric results for the highest values (binary -\$1.80, coarse -\$4.60, detailed -\$2.90).

5.5 Restricted Models and Model Selection

The Maximum Likelihood estimates show that the coefficients for the label weights in different treatments violate even weak predictions on the relation between treatments. In this section I consider an alternative approach to test the predictions by estimating different models, with and without restrictions. I run a model selection exercise to formally test the restrictions generated by the Bayesian updating model. I consider four nested model specifications.[46]

1. Unconstrained model.

2. Constrained model with inequalities (prediction 1).

3. Constrained model with equalities (prediction 2).

4. Constrained model with equalities (prediction 2) and flexible sensitivity (slopes).

[46] Models 1, 2, and 3 are nested, with model 3 providing the strictest restrictions. Models 1, 4, and 3 are also nested; model 3 is a special case of model 4 in which the fixed effects in all treatments have the same slope.

The equalities and inequalities for Models 2 and 3 follow the restrictions presented in Equations 7 and 8 and provide a formal test for the restrictions. Model 4 is not a direct test of the restrictions, but provide a quantitative measure of how differently subjects respond to information in different treatments. In this model agents are Bayesian and perfectly update own beliefs about h according to the label messages, therefore the label fixed effects follow the equality restrictions as in model 3. The key difference is that the sensitivity can be differ, meaning that the label fixed effect is multiplied by a treatment-specific coefficient $\omega_{\text{Treatment}}$ that is 1 in the Binary treatment and free in the Coarse and Detailed treatments.

Table 8 contains the maximum likelihood parameter estimates for different model specifications. The estimate of the price elasticity α is 0.052, with no significant differences across models, a low coefficient compared to what usually found in the empirical literature[47]. The table shows the estimated label fixed effects λ_l for the two most extreme labels in each treatment, expressed in terms of willingness to pay and with the coefficients shown in Figure 15 for model 1. The restrictions lead to very different estimates in the other models, with larger weights of the detailed labels (in all the models) or lower weights of the coarse labels (in models 3 and 4). Finally I show the summary statistics, average and standard deviation, for the product fixed effects. The product with the highest number of calories in each category is the implicit outside option of the choice model with $\delta_j = 0$. Positive average parameters confirm that even without labels products with lower calories are preferred, with large dispersion of the evaluations within each category.

Table 9 contains information about the model fit: maximized value of the log-likelihood of the data LL and the number of degrees of freedom dof. I use this information and the number of observations $N_{obs} = 68,454$ to calculate the Bayes Information Criterion (BIC) statistic for each model, defined as

$$BIC = -2LL + dof \cdot log N_{obs}.$$

The BIC penalizes the use of additional free parameters and allows to compare how well different models are fitting the data. The restricted model with free slope (model 4) is the preferred one under the BIC, as it leads to the lowest BIC value (138,834), followed by the unrestricted model (model 1). Models 2 and 3, that capture the two types of restrictions provided by the Bayesian updating model, have similar BIC (138,896 and 138,893) and the higher log-likelihood generated by model 2 is offset by the additional degrees of freedom by relaxing the equality restrictions. I calculate the Bayes factor for the models in the table

[47]In their study on response to the Chilean warning label reform, Barahona et al. (2020) estimate $\alpha = 0.05$ for products expressed in the amount of 100 grams, while the products used in the experiment are in the range 16-32 ounces, corresponding to 450-900 grams.

	(1)	(2)	(3)	(4)
Price Elasticity				
α	0.0520	0.0520	0.0519	0.0520
	(0.0068)	(0.0081)	(0.0089)	(0.0083)
Label FEs				
λ_{B1}/α	1.76	1.96	2.00	1.77
	(0.39)	(0.48)	(0.47)	(0.47)
λ_{B2}/α	-1.76	-1.96	-2.00	-1.77
	(0.39)	(0.48)	(0.47)	(0.47)
λ_{C1}/α	3.43	3.63	2.61	1.84
	(0.68)	(0.76)	(0.70)	(0.60)
λ_{C4}/α	-4.62	-4.16	-2.73	-2.38
	(0.74)	(0.87)	(0.70)	(0.67)
λ_{D1}/α	1.96	3.63	3.77	3.33
	(1.18)	(0.94)	(1.12)	(1.77)
λ_{D10}/α	-2.93	-4.16	-3.65	-2.79
	(1.14)	(1.08)	(1.15)	(1.75)
Product FEs				
$\delta_{cereals}/\alpha$ - Avg.	1.07	0.90	1.26	1.40
$\delta_{cereals}/\alpha$ - St.Dev.	4.10	4.16	4.13	4.10
δ_{snacks}/α - Avg.	0.43	0.25	0.61	0.76
δ_{snacks}/α - St.Dev.	3.65	3.63	3.65	3.68
Observations	68,454	68,454	68,454	68,454

Table 8: ML estimates in different model specifications and bootstrap standard errors. Price elasticity α; label fixed effects λ_l for the two labels at the extremes of the range in each treatment (e.g. B1 indicates the first label of treatment Binary, that is the one associate with lower calories); average and standard deviation of the product fixed effects δ_j for the two categories of products used in the study.

with respect to the unrestricted model. The Bayes factor is the multiplicative factor by which the relative posterior probability that $m2$ rather than $m1$ is the correct model of the data is increased by the observations in the dataset (see Burnham and Anderson (2002)). For any two models $\mathcal{M}1$ and $\mathcal{M}2$ the Bayes Factor K is defined as

$$logK_2 = \frac{1}{2}[BIC(\mathcal{M}1) - BIC(\mathcal{M}2)].$$

A Bayes factor of -12 points provides strong evidence against model 3. The data increase the relative posterior probability of the unrestricted model being the correct one by a factor of more than 150,000.[48] Models 2 and 4 consider weaker restrictions, either by considering

[48] A Bayes factor lower than -10 (higher than +10) is typically considered strong evidence against (in favor

inequalities (prediction 1 from the Bayesian updating model) or by relaxing the assumption of constant sensitivity to label information across treatments. The dataset provides strong evidence in favor of model 4, and against model 2. The high and positive Bayes factor indicate that the posterior probability of the free-slope model increases by a factor of more than 10^7.[49] The nonmonotonic effect of precision on choices could be consistent with learning when we take into account that treatments might differ in the sensitivity to label information. In the next section I explore this channel by considering a generalization of the updating model that can capture precision overload.

	Model	**-LL**	**dof**	**BIC**	**Bayes Factor**
1	Unrestricted	69,145	52	138,869	
2	Restricted (inequalities)	69,159	52	138,896	-13.66
3	Restricted (equalities)	69,190	46	138,893	-11.97
4	Restricted (eq + free slope)	69,150	48	138,834	+17.61

Table 9: MLE and model selection. LogLikelihood, degrees of freedom, Bayes Information Criterion, and Bayes Factor for the models discussed in text. Bayes Factor computed with respect to the unrestricted model.

6 Limited Attention Models and Precision Overload

The experimental data reject the Bayesian updating model and highlight three main features of the subject behavior that are at odds with the model predictions: precision effect, sensitivity to information, and preference for precision. First, increasing the precision of the message leads to a U-shaped effect on calories. If all consumers had a strict preference for low-calorie products we should observe a monotonic effect of precision of calories, as more and more ties can be broken in favor of the relatively healthier product. Second, subjects are more sensitive to the messages of coarse labels compared with detailed labels, whereas we would expect to find similar magnitude of the response to similar calorie differences.[50]

of) the alternative model, as it corresponds to a ratio of the likelihood equal to e^K. This result multiplied by the ratio of the prior probabilities of the two model being correct is equal to the ratio of the posterior probabilities of the models given the observations available.

[49] The model estimates a relative sensitivity to label information with weights $\omega_{\text{Binary}} = 1$ (benchmark), $\omega_{\text{Coarse}} = 1.88$, and $\omega_{\text{Detailed}} = 0.92$. The differences between treatments B and C and between C and D are large and significant. Additionally to the diminishing effect of detailed labels these results suggest a different interpretation; coarse labels could be the ones that increase the sensitivity to calorie information.

[50] The magnitude of the response should depend on the exact shape of the health-utility function $h(c)$ but in principle we would expect similar response to a 100 calories difference in different regimes. I consider the inferred calorie difference (difference between expected amount of calories) as a proxy of the inferred health-utility difference (difference between expected utility associated to the calories). The two measures

Third, in the experiment coarse labels with four possible messages are preferred to other labels with more and fewer levels. Bayesian agents who are able to fully understand the detailed message should always prefer the most precise label: if it is a sufficient statistic of the coarse one, the message is more informative and leads to higher expected utility, as shown in the Blackwell theorem (Blackwell (1953)) and discussed later in Section 8.

In this section I generalize the Bayesian updating model by relaxing the assumption that agents have perfect accuracy in observing and understanding the meaning of label messages. Consumers have a limited amount of cognitive resources that can be used to use the information contained in the label. After discussing how classic attention models are not able to capture the main results of the experiment, I gradually introduce the precision overload model in three steps. First, I introduce noise in the retrieval of the label information; I assume consumers can have limited ability to process the label information and can make mistakes. After, I add precision overload; detailed labels are harder to process and require more cognitive resources, leading to larger mistakes. Then, I show that precision overload emerges when retrieval noise is endogenous and agents face a cognitive cost that depends on the complexity of the message, regardless of the subsequent use. I conclude the section with a numerical exercise that shows how this approach can capture the main features of the experimental dataset.[51]

6.1 Classic behavioral models of attention

Attention and lack of it have been extensively studied and discussed in the psychology literature and have recently been incorporated in economics models. Salience and rational inattention provide two very different examples; they have been used to explain a variety of empirical and experimental features of human behavior but I want to highlight how they are not able to capture the new results presented in this paper.

Bordalo, Gennaioli and Shleifer (2012) introduce salience in the evaluation of multi-attribute options, including products (Bordalo, Gennaioli and Shleifer (2013)); they assume that the decision weights can be distorted based on the values of the different options in the choice set, with salient values (unusually far from the other ones) receiving more attention. This family of models does not provide a good explanation for the experimental results. Mainly, the model predicts that one attribute can become more salient once the values are (perceived as) further apart from the reference point. An increase in the precision of the label

are interchangeable only if the utility function is linear in the number of calories, but numerical simulations show that the results are qualitatively similar if we rule out extreme aversion towards specific calorie levels.

[51] The purpose of this section is not to fit the experimental data with this alternative model, as this is beyond of the scope of this paper and would require a richer dataset with a wider range of treatments.

can have a mixed impact on differences based on the choice set, but overall larger differences are more frequent than smaller ones, especially when two products share the same coarse label but would be assigned different detailed ones. In the eyes of the salience model this would generate larger responses to detailed labels, not smaller ones. Furthermore, the traditional salience model assumes that decision makers have access to the relevant information but distorts it in the process of evaluation and integration. The model emphasizes how attention is context-dependent, and some features can become salient through the addition of decoys, but this is not part of the experimental manipulation I am using to study food choice.

Rational inattention models like the ones used by Sims (2003) and Caplin and Dean (2015) look at attention as a costly resource that can be allocated to increase the accuracy of the decision maker. Rational inattention has been included in strategic settings in which the omniscient sender decides the signal structure to the inattentive receiver, as in Bloedel and Segal (2018) and Lipnowski, Mathevet and Wei (2020). In all these cases the attention cost refers to the accuracy of the information *used* in the decision process, not to the information *available*. Decision makers can freely dispose of excessive information - and therefore can also coarsen precise messages into simpler ones. Agents would always prefer receiving the most detailed signal and decide what to recall out of it instead of delegating the coarsening process to the principal. In the model I introduce in this section I will share the assumption of costly attention we typically encounter in the rational inattention literature, but in order to capture the role of complexity of detailed information I will introduce an additional cost that will reduce the cognitive resources available to the agent.

6.2 Generalized updating model with noisy information retrieval

I generalize the updating model by introducing noise in the retrieval of information about the products' labels. The agent is still Bayesian and makes optimal use of the information received, but now they can make mistake by recalling the wrong label, for example remembering that a product is high-calorie when instead it is low-calorie.

$$\underbrace{c}_{\text{Calories}} \rightarrow \underbrace{l}_{\text{True label}} \rightarrow \underbrace{\hat{l} \sim G_l}_{\text{Noisy label retrieval}} \rightarrow \underbrace{F_{c|\hat{l}}}_{\text{Beliefs (calories)}} \rightarrow \underbrace{F_{h|\hat{l}}}_{\text{Beliefs (health)}} \rightarrow \underbrace{\mathbb{E}[h|\hat{l}]}_{\text{Expected health}}$$

As in the model previously discussed, each product receives a label l based on its true number of calories c (unobserved), and the label information allows to refine the beliefs over the calorie amount. When the agent recalls the label from their memory, they recall it as $\hat{l}$, and they know that this might not be accurate. I assume the agent knows the distribution of the noisy retrieval G_l and makes use of the (noisy) label information to update the beliefs about calories (posterior beliefs distribution $F_{c|\hat{l}}$) and about the health (posterior beliefs distribution $F_{h|\hat{l}}$), leading to the expected health-utility component $\mathbb{E}[h|\hat{l}]$. In this section I model the noise as part of the memory storing-retrieval process. I discuss this further in Section 7, where I present two alternative interpretations that are consistent with the results I show here.

The nature of the noisy retrieval is conceptually different from the additive component ε that we already had in the model. ε can be interpreted either as preference shock (based on different preferences over time) or error in the evaluation of the product (based on the mismatch between ex-ante and ex-post utility of consuming a product), but in any case it represents a component of the utility function that is orthogonal to the other variables of interest. The noisy retrieval is instead naturally linked to the content of the label and affects decisions in two ways, stochasticity and sensitivity, both of them consistent with the results I want to capture in terms of leading to mistakes and to higher choice of high-calorie foods. Consider the scenario in which the agent evaluates two products (healthy-expensive and unhealthy-cheap) and that, noise being absent, they would always choose the healthy product. The direct effect of stochasticity creates variability in the product evaluations: there is a positive probability for the unhealthy product to be chosen because it is mistaken for a better one. The indirect effect on sensitivity to information is more subtle: label information retrieved from memory is not fully reliable, so the decision maker discounts it.

6.3 Precision overload

The main feature of this model is that messages with high precision can increase the number of mistakes and lead to worse choices, an effect that I call precision overload. For now I assume that accuracy is exogenously determined and in the next subsection I will show that this result emerges naturally when we consider an explicit cost for the recognition of precise, complex messages. When I presented the testable predictions on the relation between treatments, I assumed that the posterior beliefs $F_{c|l}$ were capturing only the residual uncertainty after observing correctly the label message. Under noisy retrieval the predictions typically do not hold anymore, because it is not guaranteed we can rewrite the calorie beliefs for the coarse label as convex combination of the detailed label ones. This applies even for the weak predictions on the bounds of values the estimates would take under the assumption of Bayesian updating but incorrect belief distribution. This should be immediately clear if we consider the extreme scenario in which coarse labels are always remembered correctly, whereas detailed labels are completely noisy and do not lead to any update with respect to the prior beliefs distribution. As a result, the weight λ_{l_d} would be the same across all the detailed labels (they all generate the same belief distribution).

Do we have evidence, from the experiment or the literature, supporting this effect? In both cases we have some indirect evidence. In the experiment response time data suggest that detailed labels make the decision more difficult compared to the other conditions. Figure ?? shows that subjects take on average 10% more time to make a choice in Treatment D, but there is no significant difference in the other three treatments (average response time 6 seconds per choice set). This effect is more broadly connected with the perception literature that analyzes the limits in the human ability to recognize and categorize stimuli (e.g. Pollack (1952)).

6.4 Costly information recognition and endogenous noise

In order to endogenize the precision overload effect, I introduce an explicit cognitive budget that decision makers can use to allocate attention.

$$\underbrace{C_{\text{Out}}\big(p(\hat{l}|l)\big)}_{\text{Cost for accurate retrieval}} + \underbrace{C_{\text{In}}(N_L)}_{\text{Cost for recognition}} \leq \underbrace{K}_{\text{Budget}} \tag{9}$$

The agent has K units of attention that can be used either to recognize (C_{In}, input process) and retrieve (C_{Out}, output process) information. The retrieval cost is conceptually the same as we typically encounter in rational inattention models. It depends on the joint distribution of true labels l and recalled labels $\hat{l}$, with more accurate retrieval being more costly. Mutual information is commonly used to provide a functional form to this component, but for the current setup it is sufficient to characterize this cost function as increasing in the accuracy of the information *used* in the decision process. The recognition cost captures the difficulty to process precise messages. I assume it is a weakly monotonically increasing function with respect to the number of possible labels. This cost depends on how the information is *presented*, not used, and the agent is forced to bear the cost regardless. If the number of labels is high enough, this might even exhaust the cognitive budget and do not allow for any use of the information. I assume the agent can only control the accuracy of the retrieval in the output cost, so we can rearrange the elements in equation 9 by expressing the net budget available for the accurate retrieval.

$$C_{\text{Out}}(p(\hat{l}|l)) \leq K_{\text{Out}} := K - C_{\text{In}}(N_l)$$

Without further restrictions I can only state that the budget available K_{Out} depends on the precision of the label structure, and the agent will have fewer resources available to retrieve information from memory. A simple numerical exercise will show how this setup can capture the three main results of the experiment.

6.5 Numerical exercise

I consider a scenario in which consumers maximize expected utility

$$\mathbb{E}[u_j] = -\mathbb{E}[c|\hat{l}_j] - \alpha \cdot p_j \tag{10}$$

by choosing one out of a pair of products. I assume a uniform prior distribution for calories and prices.[52] The accuracy of the information retrieval is endogenous and depends on the budget constraint expressed in Equation ?? with functional forms for the two types of costs $C_{\text{In}}(N_L) = \beta \cdot log_2(N_L)$ and $C_{\text{Out}}(p(\hat{l}|l)) = \mathrm{I}(l; \hat{l})$. The recognition cost C_{In} increases in the number of possible labels N_L: doubling the number of labels requires β additional attention units. The retrieval cost is calculated as mutual information between state (true label) and signal (retrieved label) as it is typically the case in the rational inattention literature. I restrict the conditional distribution of the retrieved labels to follow a simple functional form that can be expressed in terms of a single accuracy parameter γ.[53] The decision maker uses the highest accuracy γ given the cognitive budget constraints: with probability γ they remember the label accurately, otherwise they are equally likely to misremember any other label.

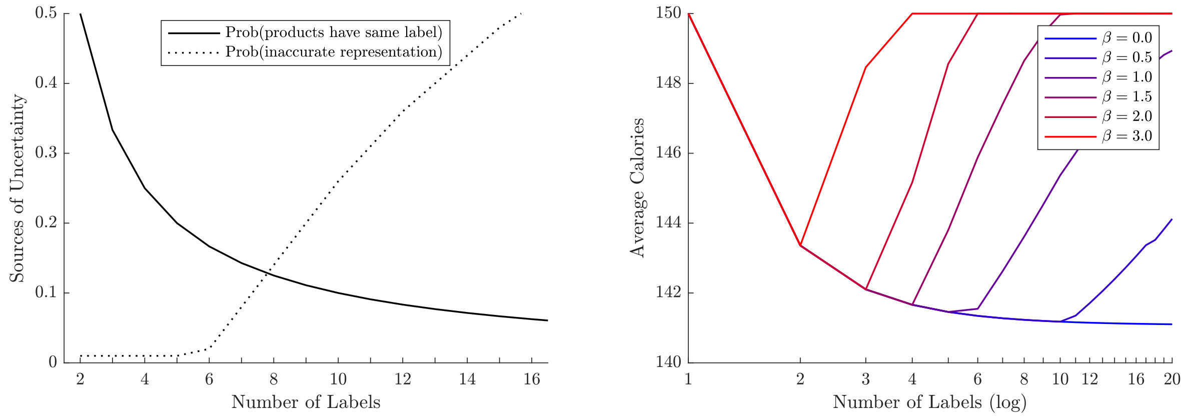
$$p(\hat{l} = l|l) = \gamma; \qquad p(\hat{l} = l'|l) = \frac{1-\gamma}{N_L - 1}, \ \forall l' \neq l$$

I am interested in how higher precision (more labels) affects quality of choice. The overall effect also depends on the parameters K (budget) and β (relative cost of recognition), with $\beta = 0$ characterizing a standard inattention model without precision overload. Figure 16.a shows the tradeoff between the two effects of higher precision. The solid line indicates the uncertainty reduction, since fewer pairs of products will display the same label (making it difficult to identify what is the healthier option). The dotted line captures the precision overload: the decision maker can correctly identify up to five labels, and mistakes gradually increase with larger numbers.

The three main results are shown in Figures 16.b and 17. First, the U-shaped precision effect. When the retrieval noise becomes too large compared to the precision of the label,

[52] For the simulations I use $c \sim Unif(50, 250)$ calories, $p \sim Unif(4, 6)$ dollars, price elasticity $\alpha = 200$. Calories and prices are i.i.d. across products in the choice set.

[53] A more general approach would allow the decision maker to choose a completely flexible conditional probability of the signal that depends on all the products in the choice set, but the current approach is sufficient to capture the main results of interest.

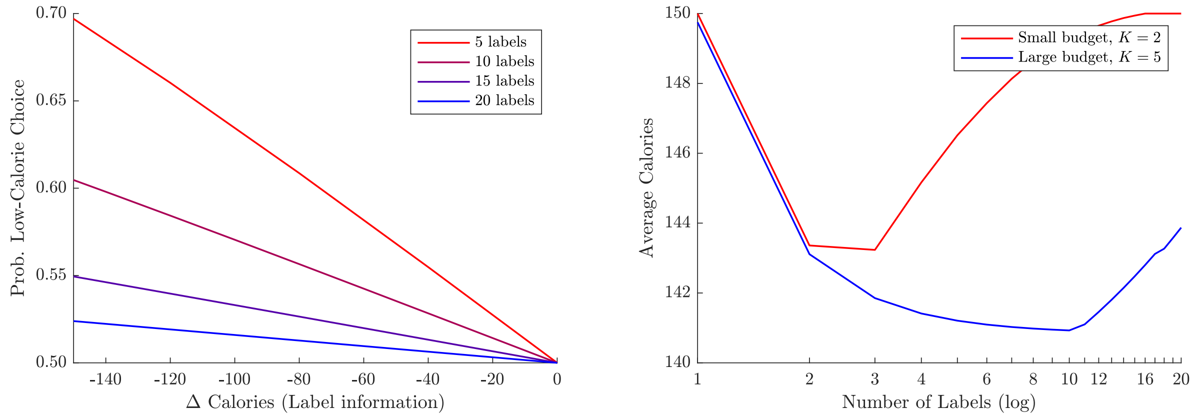


(a) Tradeoff simplicity-accuracy. (b) Result 1: U-shaped precision effect.

Figure 16: Numerical exercise. Left: Tradeoff between sources of uncertainty; parameters $K = 5$, $\beta = 1$. Right: Average calories per serving; budget $K = 5$, variable recognition cost β.

the number of calories increases even for agents who prefer fewer calories. Reducing the recognition cost parameter delays the saturation point and diminishes the severity of the overload problem, and when $\beta = 0$ calories diminish monotonically in the precision of the label.

The second result is the diminishing sensitivity to information. Figure 17.a shows that the probability of choosing the low-calorie product, after controlling for the inferred calorie difference, is lower when agents face more detailed labels. Also in this case the effect would disappear without precision overload: if we remove the recognition cost we see that choice probabilities are the same across labeling regimes, and only depend on the x-axis difference. The third result is that subjects in the experiment prefer coarse labels with intermediate level of details. Figure 17.b compares two agents with different budget constraints across labeling regimes. They are similar in the way that benefit from coarse labels up to a certain point and then gradually make worse choices after. But they differ in the bliss point, with the low-budget agent preferring three categories whereas the high-budget agent prefers ten. In the experiment, subjects with low food literacy show even stronger preference for coarse labels (two or four categories), and the same pattern emerges for subjects with low SES (low income or low education). A possible interpretation is that these subjects are not necessarily different in terms of preferences, but might find it more difficult to understand and make good use of the detailed information.



(a) Result 2: diminishing sensitivity to information. (b) Result 3: preference for coarse labels.

Figure 17: Numerical exercise. Left: Response to implied calorie differences; budget $K = 5$, recognition cost $\beta = 1$. Right: Average calories per serving; variable budget K, recognition cost $\beta = 1$.

7 Related Literature

This paper contributes to three separate streams of literature on food labels, consumer inattention, and coarse information.

Food labels play an important role in informing consumers and driving food choices. A vast and interdisciplinary literature has been studying the effect of food labels on consumer behavior using a combination of laboratory (Bix et al., 2015; Ono and Ono, 2015; Crosetto et al., 2020) and field studies (Dubois et al., 2020; Shangguan et al., 2019). Experimental evidence and surveys indicate that FOP labels can help consumers to identify healthier products. (Ikonen et al., 2020; Drichoutis, Lazaridis and Nayga Jr, 2006) There is no clear evidence on whether detailed information leads to healthier choices, and this is the primary question I am answering in this paper. The closest paper in the literature addressing a similar question is Crosetto, Muller and Ruffieux (2016). The authors use a 3x2 design to vary label types (coarse colors, precise numbers, or a combination of the two) and time pressure (with and without time constraint). They assign the task to assemble a dietary plan that respects specific nutritional objectives and report that detailed labels lead to higher accuracy in the task under free time, but results are not significantly different under limited time. Differently from their design, I focus only on one specific feature of the label, precision, on one single nutrient (calories), and I analyze the effect on consumer choices (instead of a task with an objective correct answer). The 2016 Chilean nutrient label reform allowed to study the effect of mandatory warning messages using secondary data (Barahona et al., 2020; Pachali et al., 2020). The empirical investigation shows a significant effect on consumer behavior through a combination of direct effect of the label and indirect effects through manufacturers' response, namely price change and ingredients reformulation. Chilean warning labels are binary; for each nutrient, a product either displays the warning or not. In principle, it is not clear whether the effects of the reform and their impact on consumer welfare would be larger by providing more detailed labels. My experimental results suggest this might not be the case, and that low-SES groups might be the ones that benefit the most from coarse information. A separate concern comes from the evidence that food labels could affect consumer behavior even when they provide no real content or confuse consumers. Wilson and Lusk (2020) show that consumers respond to meaningless nutritional messages, e.g. expressing higher willingness to pay for gluten-free orange juice despite the fact that all orange juices are gluten-free. This kind of evidence points out that labels' role might be a combination of information and persuasion, and that consumers might be confused about their real meaning. The precision overload model provides a general setup that is able to capture this effect: consumers might have imperfect ability to understand the message on the label and misuse confusing information.

Another relevant stream of literature studies the role of inattention in consumer behavior. When the goal of the regulator is to inform consumers, making the information available might not be sufficient if consumers are not attentive. We have experimental and observational evidence that consumers do not use all the information available and make costly mistakes. For example, Chetty, Looney and Kroft (2009) show that consumers underreact to taxes that are not salient. Evidence of inattention in store purchases also relate to base prices and promotions (Dickson and Sawyer, 1990), quantity surcharge (Clerides and Courty, 2017), and expiration dates (Hansen, Misra and Sanders, 2021). In my study the FOP label provide a coarser version of the calorie amount available on the BOP. If consumers were attentive and motivated to acquire that piece of information, we would not expect any response to the experimental manipulation. The results show that inattention might be enhanced by excess *precision* of the message. I define precision overload as the state in which precision inhibits the decision maker's ability to optimally determine the best possible decision: excessive precision can be confusing and lead to worse choices. In the experiment I do not have an objective definition of correct choices, as preferences are subjective, but I evaluate the difference across information treatment based on the policy maker's perspective (who want to reduce calories), the consumer perspective (based on the declared preferences over calories), and the general preference over types of labels (whether consumers prefer coarse or detailed labels, or none). Precision overload is analogous to other effects related to limited ability to process complex problems, such as choice overload (large number of options to choose from, Iyengar and Lepper (2000); Brown and Jeon (2019)) and information overload (large number of attributes to consider to evaluate each option (Lee and Lee, 2004; Ursu, 2018; Roetzel, 2019)).

The paper is motivated by the remark that coarse labels are widely used both by private companies that are profit-maximizer and public authorities that aim to protect and inform consumers. The theoretical literature has discussed various reasons according to which coarse information could be desirable when consumers are fully able to process the information (e.g. cheap talk models) or face a limited ability to update that depends on the actual use of information in the decision process (e.g. rational inattention models). The novelty in the model lies in considering how the complexity of the information can negatively affect the agents' ability to use it. Coarsening commonly emerges in principal-agent settings in which incentives are not aligned and sellers (signal senders) want to inflate the perceived quality of the product from the perspective of the consumers (receivers). This is the case in cheap talk models (Crawford and Sobel, 1982; Chakraborty and Harbaugh, 2010) and settings with verifiable disclosure (Milgrom, 2008; Rayo and Segal, 2010) in which pooling of multiple states is optimal. The idea of withholding information to benefit the sender is also discussed in the Bayesian persuasion literature (Kamenica and Gentzkow, 2011). Bloedel and Segal (2018) consider a persuasion model in which receivers are rationally inattentive and senders find it optimal to provide coarse information even when the goal misalignment is arbitrarily small. Lipnowski, Mathevet and Wei (2020) introduce an attention management model in which a benevolent principal can choose to withhold information to make the rationally inattentive agent focus on fewer issues. The agents would still prefer receiving detailed information, but higher welfare can be achieved under coarse signals. Other examples of coarsening emerge from voluntary certification (Lizzeri, 1999; Harbaugh and Rasmusen, 2018); even a benevolent authority might introduce a coarse and voluntary certification in order to incentivize sellers to opt in. The precision overload model provides a new explanation for the emergence of coarse labels even outside strategic settings. I consider consumers whose cognitive resources can be depleted because of the complexity (precision) of the information, regardless of its subsequent use. This means that agents do not have free information disposal; in particular they cannot coarsen information for free. If they could, having more granular information would always be desirable as it can gives the sender the freedom to choose between detailed and coarse signals.[54] The removal of the free information disposal assumption leads to a violation of Blackwell's theorem (Blackwell, 1953; Crémer, 1982): a detailed label, that

[54]Under free information disposal the agent that receives a signal σ about the state of the world s (calorie amount) would always be able to replace it with a weakly less informative (in the Blackwell order sense) signal σ' that is a garbling of σ. Given a (relatively) detailed labeling regime - defined according to the vector of threshold τ in the notation introduced in Section 5 - the label signals are deterministic and indicate the range of feasible calorie amounts.

is statistically sufficient to represent the signal of the coarse label, might be less informative than the coarse label itself. The detailed signal is statistically sufficient because it generates the coarse signal by pooling together messages that belong to the same partition cell. Blackwell information criterion instead relies on the expected utility from implementing the optimal action conditional on the signal. If the detailed message is associated to larger noise this can generate costly mistakes and reduce the expected utility. This violation can explain preference for coarse labels, that is one of the results I find in the experiment. Consumers might prefer coarse information because they are indeed able to make better choices with respect to what they themselves want. This does not exclude that in the real world many of these effects occur at once. The adoption of coarse labels can be due to a combination of demand for simplicity and attempts to guide consumer choices towards desirable behavior, for example healthier diets. Further motivations include the strategic dimension of the problem, with manufacturers responding with price changes (Pachali et al., 2020) or reformulation of the product characteristics (Barahona et al., 2020).

8 Conclusions

In this paper I studied the role of coarse and precise information if food labeling. The project is motivated by the question: what would happen if coarse labels were replaced with more detailed ones? In address this in the domain of food choice by conducting an experiment in which I manipulate labels with calorie information. Coarse-categorical labels are effective in helping consumers to choose products with fewer calories, but more detailed numerical labels are less effective. Also, subjects declare they would prefer coarse labels with intermediate level of precision. The choice data show that subjects are more sensitive to coarse information and suggest that they are learning less from detailed messages. Consistent with this result, the estimates of the label effect in a simple updating model highlight that coarse labels have systematically larger weights in the decision process. I generalize the updating model by introducing limited attention in the form or noisy retrieval from memory. Differently from other inattention model, I assume the agent has limited cognitive resources that are consumed by two types of cost: a retrieval cost, that depends on the accuracy of the information used to make the choice, and a recognition cost that depends on the complexity of the message. This model can characterize the precision overload effect and captures the main results from the experiment.

I acknowledge the limitations of the experiment and the model and I hope these results will encourage further exploration of the role of labels in new directions. In the experiment I compare the effect of coarse-categorical and detailed-numerical labels, and further studies are required to identify if the effect is driven by the different format of the label. In the real world high precision is typically associated with numerical information and it is possible that this alone represents a source of complexity of confusion for consumers. Similarly, the robustness of the experimental results can be tested with respect to additional dimensions. In the experiment I restrict choices to small groups similar products, for example two types of cereals. It is unclear if the effects would be larger with broader choice sets, with many products belonging to several categories. Other models of limited attention assume that consumers focus on small consideration sets and coarse labels might guide this type of progress. This kind of question is suitable for field experiments or further online or laboratory experiments that make use of process data, such as mousetracking or eyetracking. The general research question about information precision goes beyond food choice; energy efficiency, ethical products (e.g., certifications based on worker rights or production standards), and other health-related applications are suitable for further studies including analysis of the outcome of labeling reforms that intervene on the coarseness of information. The precision overload model I present is an extension of the general setup used in the rational inattention literature and does not aim to fully address the question on what are the necessary and sufficient conditions required to generate the precision overload effect. The introduction of an explicit cost related to the complexity of the messages motivates further experimental investigation and is closely connected to the evidence from the perception and cognitive science literature that highlight limited human ability to recognize and distinguish stimuli. One limitation of the current experiment and analysis is that we do not directly observe the true values of each option, but future studies can use other tasks (e.g., delegated choice tasks with explicit goals) or stimuli (e.g., abstract options with an explicit value in a simplified choice environment) to characterize the limits of human recognition and classification ability. Finally, the experimental results and model suggest that welfare analysis of information reform should take into account the response of consumers with limited attention and with heterogeneous response to the information intervention. Policy makers can use a variety of tools to promote healthier food choices, including banning, taxing, or labeling products deemed harmful for most of the consumers. If consumers are myopic and underestimate the future consequences, this can motivate a paternalistic approach such as sugar taxes. But if consumers are simply uninformed about the health consequences, the policy makers might want to focus on information provision. Standard information models would prescribe the adoption of the most precise labels, but excessive precision might deteriorate choice quality especially for consumers with low socioeconomic status. The design of simple and effective labels that inform consumers and help them choose what they themselves want will require further investigation.

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