Identifying Food Labeling Effects on Consumer Behavior

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We examine a large-scale mandatory food labeling regulation to identify its effects on consumer behavior. We take advantage of exogenous variation in product-labeling status arising from the gradual and asynchronous introduction of labeled products on store shelves many weeks before the regulation deadline. We combine individual-level scan data from a large retailer with on-the-shelf information on the actual warning-label status. We find that warning labels decrease purchase probabilities on breakfast cereals, but have no impact on chocolates or cookies. The effect is larger on medium-low socioeconomic groups and households with children. Results are consistent with information disclosure influencing consumers' choices when the advertised information is unexpected.

Keywords: Food Labeling, Consumer Behavior, Nutritional Information, Point-of-Sale Advertising

JEL Codes: D12, I12, I18

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1 Introduction

Obesity has rapidly become a first-order public health concern for governments around the world.[1,2] One approach that has gained prominence in recent years to help curb the global obesity epidemic is the use of nutrition labeling. As the scientific evidence linking obesity -and associated chronic diseases- and dietary habits has mounted, the World Health Organization (WHO) has forcefully advocated the use of nutrition labeling schemes and the provision of nutritional information as leading strategies to improve healthy food choices (WHO (2004)). In line with the WHO's recommendations, many countries have required food providers, such as supermarkets, to disclose calorie and nutritional content information (Hawkes (2004), WHO (2004)). However, consumers may misunderstand or misuse nutritional information impeding effective communication (Cowburn and Stockley (2005)). To overcome this problem, some retail stores have voluntarily provided simplified information on healthy products to persuade customers interested in improving their food choices at the point-of-sale.[3] More broadly, several countries are moving towards mandatory simple front-of-package labeling, focusing on unhealthy products, to change shoppers' behavior.

Despite its importance, identifying the effect of food labeling on consumer behavior has proved elusive to date. Bleich et al. (2017), for instance, review 53 studies on the impact of calorie labeling on consumer behavior and concluded that the lack of statistical power and strong designs challenge clear conclusions about the effects of calorie labels.[4] Moreover, the fact that most regulations are implemented at a single point in time poses additional challenges to pin down the effect of food labeling. For instance, before-after estimations need the unobserved components of consumer behavior to be time-invariant (Ippolito and Mathios (1995), Dumanovsky et al. (2011); Elshiewy and Boztug (2018), Nikolova and Inman (2015); Taillie et al. (2020)). Also, comparing regulated markets with other geographic locations (as control) requires unobservables to have a parallel trend across markets (Elbel et al. (2009), Bollinger et al. (2011), Finkelstein et al. (2011), Hobin et al. (2017)).

We take advantage of the gradual implementation of a comprehensive and mandatory food labeling regulation recently introduced in Chile to identify its effects on consumer behavior. The regulation was prominently featured in the international press (NYT (2018); Guardian (2020)) and described as "the world's most ambitious attempt to remake a country's food culture, and could be a model for how to turn the tide on a global obesity epidemic" by the New York Times. The new regulation established that products exceeding certain thresholds of critical nutrients should

[1] According to the Global Burden of Disease Study IHME (2013), the number of obese and overweight individuals rose by 28 percent in adults and 47 percent in children worldwide over the last 30 years.

[2] Cawley (2015) and Malnick and Knobler (2006) document the adverse consequences of obesity and other nutrition-related diseases on health and economic outcomes.

[3] The "Guiding Stars" system has been implemented by a few grocery stores in North America.

[4] See Kiszko et al. (2014) and Harnack and French (2008) for additional systematic reviews.

display mandatory warning labels by the end of June 2016. However, food suppliers gradually introduced the warning labels in different retail stores a few months before the regulation came into force. During this period, supermarkets began selling labeled products driven by stock availability in each store. We collected daily data on the label status of specific products (at the Universal Product Code (UPC)-level), and observe substantial variation in labeled and non-labeled products across time and supermarket stores, allowing us to avoid the identification problems present in the previous literature.

We estimate a demand model for differentiated products to identify the effect of warning labels on purchase probability using individual-level data from a big-box retailer. We focus on three product categories that were expected to be especially hard hit by the regulation: breakfast cereals, chocolates, and cookies. Our transactional scan data come from the loyalty card records of the retailer, representing nearly 80 percent of total sales. The variation in product-specific information across stores allows us to identify the warning label effect while controlling for price and including product and time fixed effects.

We find substantial heterogeneity in shoppers' responses to the warning labels across the three product categories we study. In the breakfast cereal category, the just-introduced warning label reduces the purchase probability of a labeled product by 12.5 percent (from a baseline of 2.4 percent). In contrast, we find no effects of the regulation on chocolates and cookies. This result is consistent with information disclosure being only effective when it adds new insights to the consumer initial information set (Loewenstein et al. (2014)).[5] In our case, consumers may respond to labelled products that are unexpectedly unhealthy, such as breakfast cereals. However, consumers do not change their behavior in categories such as chocolates and cookies, in which the warning labels did not provide additional information on products' healthfulness.

We study heterogeneous treatment effects across two dimensions: socioeconomic status (SES) and the presence of small children in the household. Both dimensions are relevant from a policy perspective as the regulation aims at improving the choices of lower-income households and families with young children, where obesity is more prevalent. We find that consumers who are likely to have children (frequent buyers of diapers and kids' snacks) and households living in areas predominantly inhabited by medium-low socioeconomic groups are more sensitive to the nutritional label. We also find that older people tend to be more sensitive to warning labels. Thus, the warning label may prove successful in targeting high-risk consumers in some food categories, at least partially.

By way of comparison, we further estimate the effect of the food labeling regulation using the standard pre-post analysis. In this case, the estimates of the label effect are positive, stressing the fact that unobservable time components can bias the results. We also conduct a placebo robustness test, in which we simulate the same gradual introduction of warning labels but in a period without

[5]Consistently, Hobin et al. (2017) find that people prefer more nutritious cereals after a nutritional guiding-stars system was implemented, but not for snacks.

any actual regulation. We find no warning labeling effect in our placebo test, reducing the chances of spurious factors affecting our results.

We also overcome the potential complication of consumers' misunderstanding and neglecting the information presented to them (Bollinger et al. (2018); Rotfeld (2009)). Our study takes advantage of a highly advertised regulation as confirmed by a survey to more than 3,000 customers at the exit of supermarket stores, which indicates that 73 percent of consumers identified products with the new food labeling before the law came into effect (CERET (2016)).

Our paper contributes to a vast literature studying the impact of food labeling on consumer behavior and point-of-sale advertising.[6] Similar to our work, Bollinger et al. (2011) estimate the effect of a mandatory nutrition labeling policy on purchase decisions of consumers in the actual market. They use transaction data from Starbucks to study the consequences of a law first implemented in New York City, which mandated the posting of calories on menus in chain restaurants. Bollinger et al. (2011) estimate the impact of the law by comparing the behavior of New York customers with those of other cities (Boston and Philadelphia) not affected by the regulation. They find that mandatory calorie posting causes average calories to decrease by 6 percent.

Other authors have implemented experiments to assess the effects of food labeling. Kiesel and Villas-Boas (2013) and Downs et al. (2009) study consumer responses to the provision of nutritional information in real market environments. Kiesel and Villas-Boas (2013) conduct a study in which they manipulate the information content of nutritional shelf labels in one product category (microwave popcorn) across five treatment stores selected by the supermarket chain and one "synthetic control group".[7] While the experimental setting allows the authors to compare labeled (versus unlabeled) popcorn as compared to the control stores, the selection on unobservables of their particular outlets remains a potential issue. In our study, stores were not participating in a voluntary experiment but under a mandatory regulation, which provides evidence on consumers' purchase behavior in stores of countries planning to introduce similar compulsory nutritional labels. We also add to this research by considering food categories that are a priority for mandatory nutritional labels from a health policy perspective. Downs et al. (2009) summarize the results from two experiments in which treated consumers receive different calorie information mimicking recent regulations. They find that the effects of calorie information provision are small and that the provision of calorie information may induce higher calorie consumption among dieters. One concern is that consumers may be aware of their participation in a study, potentially driving their attention to the new nutritional information. Our natural market setting with massive and detailed transactional data avoids potential biases from surveys and laboratory experiments as it captures the normal shopping behavior of consumers after the introduction of an exogenous change in information.

[6] Griffith and Nevo (2019) survey the quantitative marketing literature on nutrition labeling.

[7] Kiesel and Villas-Boas (2013) randomly assigned different "low" tag labels (a combination of low calorie, low fat, and low trans-fat) to each store. The authors use a synthetic control group to address the store selection issue, as the supermarket chain did not provide information on how they selected the five treated stores.

Finally, our paper contributes to the debate on mandatory information disclosure and its potentially heterogeneous effect across different segments of the population (Cawley et al. (2016)). Finding effective measures to address this dimension of inequality has been difficult. For example, Allcott et al. (2019) found that product availability does not explain the substantial purchasing differences of healthy products across income-groups in the US. We find that the labeling policy may be useful to change the purchasing behavior in specific food categories of lower socioeconomic consumers, who suffer more from obesity.

The remainder of this paper is organized as follows. Section 2 describes the nutritional warning information we study, institutional details and summary statistics of our supermarket data. Section 3 presents our demand model and econometric approach while Section 4 presents the results and robustness checks. Section 5 concludes.

2 Data and Institutional Background

2.1 The Chilean Law of Food Labeling and Advertising and its gradual implementation

Over the last few years, Chile introduced groundbreaking changes to its legislation regulating nutritional food labeling. The new regulatory framework put in place by the Chilean authorities was broadly aimed at improving point-of-sale nutritional information using simple interpretive front-of-package labeling.[8] Under the new regulations, pre-packaged food products whose contents of four critical nutrients –sugar, sodium, saturated fats, and calories[9] exceed certain thresholds must display standardized black labels warning that the product contains excessive levels of one or more of these critical nutrients.[10]

The warning labels take the form of front-of-pack octagons, resembling a black stop sign, displaying the legend *High in* followed by the name of the critical nutrient being exceeded.[11] Figure 1 displays the labels introduced by the law. The regulation is precise about the size of the warning labels and the position they must occupy to ensure saliency to the public. For instance, according to the law, a product which exceeds a critical nutrient limit and whose front pack exceeds 300 square centimeters (approximately 0.32 square feet) must include a warning label of dimensions 3.5 by 3.5 centimeters (about 1.38 by 1.38 inches). The law divided products into solids and liquids

[8]The law only affects packaged products and not bulk goods and unpackaged food such as bread.

[9]While calories are not, strictly speaking, a nutrient, we refer hereafter to all four food components regulated by the law (i.e., sugar, sodium, saturated fats and, calories) as nutrients for expositional convenience.

[10] Also, the new legislation regulated the advertising of the labeled products and their sales in schools. In particular, advertising of unhealthy tagged products targeting children under age 14 years was prohibited as was the sale of these products in or within 100 meters of a school.

[11] All the black stop signs included the name of the Ministry of Health. Mentioning the institution backing the nutritional message enhances the warning (Feunekes et al. (2008)).

and specified the thresholds for labeling a product in terms of a fixed quantity of the product (100 grams for solids and 100 ml. for liquids).[12]

The Chilean Law of Food Labeling and Advertising established a three-stage process over which products would be progressively labeled as ”High in” a critical nutrient. The initial phase began on June 26 of 2016, one year after the official order specifying the details of the new regulation was officially published. More stringent thresholds were mandated to be gradually introduced in June 2018 and June 2019. In this paper, we focus on the impact of the nutritional labels introduced during the first phase of the process.[13]

An international comparison puts Chile among the early adopters of a mandatory front-of-pack nutrition labeling law, an ambitious policy intervention that is being increasingly considered by other countries worldwide (Hawkes (2010), NYT (2018); Guardian (2020)). For example, Canada has begun discussing the adoption of a mandatory front-of-pack nutrition labeling system which, according to the initial specifications set by the Canadian Ministry of Health, would include several elements contained in the Chilean law.[14] Also, Australia, New Zealand, as well as several European countries have put in place graphical nutrition labeling systems. Among the countries that have already implemented mandatory front-of-pack nutrition labeling systems are Bolivia, Ecuador, Peru, and Mexico.[15]

The actual implementation of the new regulation plays a crucial role in our empirical strategy. The law mandating the introduction of the warning labels was approved in June 2012, but its implementation required the completion of several administrative and legal procedures.[16] The legislation was finally enacted in April 2015 and entered into force on June 26th of 2016.

There was an initial period of confusion about whether the stock of unlabeled products exceeding the limits of critical nutrients would be allowed after the June 2016 deadline. The authorities ruled that all products “High in” some nutrients would have to display the warning labels by June 26th of 2016 regardless of their manufacturing date. Stores that failed to comply with the new regulations by the deadline would be subject to fines. This clarification prompted large re-

[12]For further details on the design and threshold considered see Corvalán et al. (2013); Reyes et al. (2019).

[13]The thresholds for solid (liquid) products over the initial phase were defined as 350 (100) for calories; 800 (100) for sodium; 22.5 (6) for sugars; and 6 (3) for saturated fats.

[14] In a recent stakeholder engagement meeting organized by Health Canada, the authority required stakeholders to submit possible front-of-package nutrition symbols, which complied with three criteria included in the Chilean law. The three principles are: (1) follow the “high-in” approach; (2) focus on the three nutrients of public health concern (sugars, sodium, and saturated fats); and use only black and white colors (HC (2017)).

[15] In other nations, graphical nutrition labeling schemes are applied voluntarily. A pioneering intervention along these lines is the traffic light system implemented in the UK. The system was born as an initiative of the industry and has replicated by some retailers in France and Portugal (Hawkes (2010)).

[16]The final required modifications of the *Sanitary Regulations of Food*, which included the actual limits on critical nutrients and the precise specifications of the warning labels, were incorporated in Decree No. 13 of the Ministry of Health which was promulgated in April of 2015 and published in the Official Gazette in June 26th of 2015, establishing their implementation one year later.

tailers to demand delivery of labeled products several months in advance of the legal deadline. This process resulted in some products displaying the black warning label(s) simultaneously in some stores but not in others.

Our empirical strategy exploits this gradual implementation of the warning labels. Since retail stores received labeled products before the deadline set by the law, we can observe at a given point in time a product displaying a warning label in one store while the same product in a similar outlet being traded without the warning label.[17] This overlap of labeled and unlabeled products changing over time, coupled with observations of purchasing behavior at the UPC-store level, allows us to measure the impact of the food labeling on consumer behavior.

The assignment of labeled products to retail outlets is unlikely to have been manipulated by manufacturers, and it can be considered exogenous to consumers. Consistently, from several interviews we conducted with large suppliers of products directly affected by the regulations, we learned it was logistically impractical for them to determine which specific stores would end up receiving the labeled products. We discuss the observed implementation in the next subsection below.

2.2 Data Description

We partnered with a large chain of supermarkets in Chile[18] to study the impact of the nutrition labeling law on purchasing behavior. We were able to measure whether specific UPCs displayed warning labels on the shelves of six supermarket stores located in the two most populated regions of Chile over a period of gradual and asynchronous introduction of warning labels in supermarket stores. Our team of research assistants visited the stores before the legal deadline, during May-July 2016, took pictures of each product and then recorded in a spreadsheet the label status of each UPC and the type of warning label it displayed. On average, each store was visited 40 times over the period in which the warning-label status of a given UPC exhibited variation across stores.[19]

We combine our collected data on the presence of warning labels with consumer-level point-of-sale data, which include all items in consumers' shopping baskets, the prices paid for each item, and the date and time of the transaction. We identify individual consumers using customer membership in the retailer loyalty program. According to the retailer, purchases made through its loyalty program account for about 80 percent of its total revenues. Our consumer-level data also contains gender, age, and socioeconomic status (SES). The retailer classifies a customer into one of five SES categories (ABC1, C2, C3, D, and E) based on the specific street block where the customer resides using Census data. Also, our dataset includes historical data extending back to early 2015

[17] We identify a product based on its Universal Product Code, UPC.

[18] The Chilean supermarket industry is highly concentrated, with the three largest chains accounting for more than 90% of the market. Our data comes from one of the top-three supermarket chains.

[19] Our data also include transactions between June 26 and July 22, 2016, when the law was already in place.

with purchases made by the same set of customers in our primary dataset as well as demographic data on these consumers. We use data from May to July 2015, and from May to July 2016.

We focus on three product categories which were particularly affected by the regulation: Breakfast cereals, chocolates and cookies.[20] In each of these categories, we selected those UPCs among the top-30 in terms of market share which are consistently available throughout our time of analysis.[21] Figure 2 shows the evolution of warning labels per category in the six stores included in our sample. As expected, there is an upward trend in the number of labeled UPCs over time across all stores and categories.

We observe considerable variation in the food labeling implementation across products, stores, and time. Figure 3 shows the number of days in advance of the legal deadline when the warning labels were implemented for each of the selected products in a category. In effect, the figure displays average and standard deviation across stores of the number of days ahead of the deadline when the warning label was introduced. Within a category, products are ordered based on their market shares, with product 1 being the top market share product and the last product exhibiting the smallest market share among selected products. Importantly, the charts in Figure 3 do not suggest any clear pattern linking market shares with the timing of the introduction of warning labels across stores. For instance, product 7 in the top-left panel (breakfast cereal), was labeled on average 36.8 days in advance of the deadline (SD = 6.9), but it exhibited a warning label 43 days in advance in the first store, while the last store introduced the warning label 24 days before the deadline. This variability is even higher as some products varied their warning-label status over time within the same store.

To ensure mutually exclusive choices, we define as an eligible transaction those with no more than one item in the selected categories: breakfast cereals, chocolates, and cookies. Our final sample contains an average of 38,000 consumers per category, who made approximately 162,000 transactions in a given category. To reduce computational burdens, we drew a random sample of customers comprising 20% of all customers who purchase a UPC in a given category. The data used in estimation include between 4,817 customers (breakfast cereals) and 8,274 customers (chocolates). Since not all the top products were available in every store, the average choice set contains 18.32 products, implying 1,243,741 observations in total. Table 1 provides more details on the number of transactions and choices per category.

[20] We also collected data on juices and started collecting data on yogurt. However, only one product for juices and none for yogurts were labeled under the current law. Soft drinks are another relevant category, but these products were all labeled several weeks before we began collecting data on whether products displayed the new label (i.e., several months before the law came into force).

[21] Specifically, we included a top-market-share UPC if it was available at least 65% of the time in at least two stores over the period of study. Our analysis would be untractable if including the long tail of infrequently purchased products.

3 Demand Model

To estimate the impact of warning labels on consumer choice behavior, we specify a random utility model where label status enters as an additional product-specific attribute in the consumer's indirect utility function.[22]

In our setting, consumers visiting a store on a given day face a choice between J inside products in a category and an outside option (labeled $j = 0$). The inclusion of a no-purchase alternative allows us to investigate the effects of warning labels on category contraction. A key attribute describing a product in the choice set is whether or not the product displays a warning label. Formally, the utility of consumer $i = \{1, ..., N\}$ for food product $j = \{0, 1, ..., J\}$ in store $s = \{1, .., S\}$ at $t = \{1, ..., T\}$ is given by:

$$u_{ijst} = \alpha(y_i - p_{jst}) + \beta' x_{jt} + \gamma_i L_{jst} + \varepsilon_{ijst} \tag{1}$$

where y_i is consumer's income, p_{jst} is product j's price, and x_{jt} is a vector of product dummies and their interaction with time dummies. Of special importance in our setting is the label dummy, L_{jst}, which equals one if product j displays a warning label in a given (s, t) combination, and zero otherwise. ε_{ijst} is an iid random term with a Type I extreme value distribution function. We normalize the utility of the outside option to zero.

We introduce heterogeneity in the marginal (dis)utility of warning labels across consumers through the parameter γ_i. We assume the random coefficient of warning-labels follows a normal distribution given by:

$$\gamma_i \sim \mathcal{N}\left(\gamma, \sigma_\gamma^2\right) \tag{2}$$

where γ is the mean of the label coefficient and σ_γ^2 captures the dispersion of tastes in the population. Under these assumptions, the presence of a warning label can yield positive or negative utility to an individual consumer. A consumer might derive positive utility from the presence of a warning label, for instance, because it may allow her to make positive taste inferences.

The parameter α captures the marginal utility of income, and β is a vector of fixed effects that are also homogeneous across individuals.[23] We denote by $\theta = (\alpha, \beta, \gamma, \sigma_\gamma^2)$ the vector containing all the parameters of the demand model.

Estimation. We estimate a mixed logit model with repeated choices (Revelt and Train (1998, 2000))

[22]While in principle, the number and type (high in sugars, calories, sodium or saturated fat) of warning labels are other dimensions besides label status that might affect consumer choice, we observe almost no variation on these dimensions across products within a given category. Hence, they are mostly irrelevant for choice behavior within categories.

[23]We explore estimating heterogeneous price coefficients; however, the computational burden of the estimation and the subsequent difficulties in computing willingness-to-pay lead us to consider homogeneous price sensitivity. Instead, we explore heterogeneity on price sensitivity by examining the estimates using different sub-samples of consumers.

using detailed panel data on individual purchases over time. Denote by $y_{ist} = \{0, 1, ..., J\}$ the observed choice of individual i in store s at time t. The probability of purchasing product j is the integral over shocks ε that ensures that product j is the one that maximizes the utility given the choice set in the market. Conditional on $(\alpha, \beta, \gamma_i)$, we use the distribution of ε to obtain the standard logit formula for the conditional probability s_{ijst}. Formally:[24]

$$s_{ijst}(\alpha, \beta, \gamma_i) \equiv \mathbb{P}(y_{ist} = j \mid \alpha, \beta, \gamma_i) = \frac{\exp(-\alpha p_{jst} + \beta' x_{jt} + \gamma_i L_{jst})}{1 + \sum_{h=1}^{J} \exp(-\alpha p_{hst} + \beta' x_{ht} + \gamma_i L_{hst})} \tag{3}$$

Thus, conditional on $(\alpha, \beta, \gamma_i)$, the probability of the observed sequence of choices, y_{ist}, for individual i is given by:

$$S_i(\alpha, \beta, \gamma_i) = \Pi_{t=1}^{T} s_{i,y_{ist},st}(\alpha, \beta, \gamma_i) \tag{4}$$

The unconditional probability, P_i, is the integral of the conditional probability over all possible values of $(\alpha, \beta, \gamma_i)$, which depends on the distribution probabilities defined by the parameter vector θ.

$$P_i(\theta) = \int S_i(\alpha, \beta, \gamma_i) d\Phi(\gamma_i) \tag{5}$$

Since the integral in Equation (5) has no closed-form solution, we approximate $P_i(\theta)$ by using simulation methods:

$$SP_i(\theta) = \frac{1}{R} \sum_{r=1}^{R} S_i(\alpha, \beta, \gamma_i^r | \theta) \tag{6}$$

where $\{\gamma_i^r | \theta)\}_{r=1}^{R}$ is a sequence of R random draws, conditional on θ, following Equation (2). The estimated parameter, $\widehat{\theta}_{SLL}$ solves the following program:

$$\widehat{\theta}_{SLL} = \arg\max_{\theta \in \Theta} SLL(\theta) = \arg\max_{\theta \in \Theta} \sum_{i=1}^{N} \ln(SP_i(\theta))$$

See McFadden (1989) and Hajivassiliou and Ruud (1994) for further econometric details.

Customer-Specific Label Parameters. The estimation procedure outlined above provides us with information on the distribution of the label parameter for an individual consumer drawn at random from the population. To infer the label coefficients conditional on the choices and choice situations in a given subpopulation, we follow Revelt and Train (2000) and Train (2009). Let $h(\gamma_i | y_i, w_i, \gamma, \sigma_\gamma^2)$ denote the distribution of γ_i conditional on the sequence of choices y_i, vector of covariates w_i faced by consumer i and γ_i 's mean and variance. Using Bayes's theorem the

[24] Importantly, explanatory variables that are not product-specific (such as consumer's income y_i or potential store fixed effects) cancel out in the utility comparisons and thus, play no role in the purchasing probabilities.

conditional distribution of γ_i can be written as a function of known quantities as

$$h(\gamma_i|y_i, w_i, \gamma, \sigma^2_\gamma) = \frac{\mathbb{P}(y_i \mid w_i, \alpha, \beta, \gamma_i)\phi(\alpha, \beta, \gamma_i|\theta)}{\mathbb{P}(y_i \mid w_i, \theta)} \tag{7}$$

Using equation (7), the average label coefficient for the subpopulation of customers who choose y_i when facing covariate values w_i can be obtained as

$$\bar{\gamma}_i = \int \gamma_i \cdot h(\gamma_i|y_i, w_i, \gamma, \sigma^2_\gamma) d\gamma_i \tag{8}$$

where $w_i = \{p_{jst}, x_{jt}, L_{jst}\}_{\{\forall j,s,t\}}$ contains the sequence of prices and product characteristics faced by each individual i.

We use a transformation of $\bar{\gamma}_i$ to compute customers' aversion to warning labels in money terms. A customer's willingness to pay to avoid the warning labels is given by $\bar{\gamma}_i/\alpha$.

Heterogeneous Impact of Warning Labels. To examine heterogeneity in customers' distaste for warning labels, we examine how warning label coefficients covary with key sociodemographic variables. We use the following regression equation:

$$\bar{\gamma}_i = \delta' D_i + u_i \tag{9}$$

where D_i is a vector of demographic characteristics of consumer i, including age, socioeconomic background and a proxy for the presence of young children.

Identification. Our data offer unusual features suitable for the identification of the impact of warning labels on consumer behavior. Most research on the effects of food-labeling on consumer behavior cannot separately identify time effects from the labeling effect as the implementation of the regulation takes place simultaneously in all products and stores.

Our identification of parameter γ relies on warning-labels being tagged to the same product in different stores at different moments in time. This rich variation in the data allows us to identify the effect of labeling on purchasing behavior. For a given product at a given time, we have stores in which the product displays the warning-label and some other stores in which the same products do not. The differences in consumer purchasing probabilities between and within stores allow us to identify the warning-label effect, controlling for own and competitors' prices and a rich set of fixed effects.

The parameter β contains product fixed effects and the interaction between product and time fixed effects. Our product fixed effects will capture all the time-invariant product characteristics.

Our product-week interacted fixed effects will capture national marketing campaigns and any other activity that product-time specific but common across stores. For example, we can control for the massive advertisement for a particular brand of Easter eggs, and still, identify the warning-label effects in that weekend as long as we have stores with and without the regulated packaging for that specific product.

Identification of the price coefficient, α, relies on the standard price variation across time and products in the data. In effect, we observe price promotions (i.e., temporary price reductions) that differ across products and sometimes across stores. A typical concern is the potential price endogeneity. In our setting, prices are identical for those individuals in the same store and exogenous to consumers. Moreover, the retailer mostly follows a national pricing that uniform prices across stores in a given week. However, if the retailer is setting prices based on unobservables (to the researcher), our model would still be subject to price endogeneity. We resolve the problem by using monthly brand intercepts to control for monthly brand-specific characteristics, as suggested in Chintagunta et al. (2005).[25]

4 Results

We estimate the demand model laid out in the previous section for each of the product categories in our data, which were targeted by the regulation (i.e., breakfast cereals, cookies, and chocolates). Table 2 summarizes the results of the maximum simulated likelihood estimation for each category. All specifications include as controls the transaction price (at the UPC-level), a set of product dummies, and the interaction between product dummies and month fixed effects. We present cluster-robust standard errors at the store level to account for possibly correlated preference shocks across customers shopping in a given store.

We begin by noting that the estimated price coefficient is consistently negative and highly statistically significant across all three categories. Thus, as expected, more expensive products are less likely to be chosen, controlling for other factors.

Turning to the estimates for the distribution of warning label coefficients, we observe substantial differences across categories. The mean label coefficient is negative and highly statistically significant in the case of the breakfast cereal category but not significantly different from zero in the case of the cookies and chocolate categories. The estimate for the standard deviation of the warning label coefficients is, on the other hand, relatively high across all categories suggesting a high degree of heterogeneity across consumers in the disutility associated with warning labels.

The estimates for the distribution of warning-label coefficients indicate that warning labels have negative effects on choice in the breakfast cereal category, but no effects in the cookies and chocolate categories. To get a sense of the magnitudes involved, we compute the partial effects of

[25] Rossi (2014) presents a critical assessment of alternative strategies based on IV and control function approaches.

changing a UPC's label status from "no labeled" ($L_{ijt} = 0$) to "labeled" ($L_{ijt} = 1$) in the Breakfast Cereals category. Table 3 presents the matrix of own- and cross- partial effects of changes in label status on choice probabilities. Inside goods are coded from "A" to "U" and the outside option denoted by "NPO" (no-purchase-option). Entry (m, n) in the matrix corresponds to the change in the choice probability of the brand in column n (including the no-purchase-option) when the label status of the brand in row m changes from $L_{ijt} = 0$ to $L_{ijt} = 1$. We stress that this exercise corresponds to a counterfactual scenario in which a given UPC gets labeled while the remaining UPCs in the category remain unlabeled. Own-partial-effects are negative for all UPCs in the breakfast cereal category. On average, a change in label status reduces the own-choice-probabilities of labeled UPCs by approximately 0.002 probability points, which translates into a reduction of approximately 12.5% in the choice probability of a UPC. Turning to cross partial effects, we observe that customers substitute to other products outside the breakfast cereal category with probability 22.5%. Consumers substitute towards healthy cereals that remain unlabeled with probability 18.3%.[26]

Figure 4 provides further evidence on the heterogeneity in warning-label coefficients across consumers. The left-hand subfigure in Figure 4 depicts the density of customer-specific label coefficients in the breakfast cereal category conditional on the choices and choice situations we observe in our data (i.e., computed using Equation (8)). We see that the distribution is trimodal, with most of the probability mass located in the negative region. There is, however, a minor group of consumers who appear to have a strong preference for labeled products. The right-hand side subfigure in Figure 4 provides a picture of the heterogeneity in label-distaste measured in money terms. It displays the distribution of the willingness to pay to avoid warning labels (conditional on choices and covariate values observed in our sample) in the breakfast cereals category. Most customers are willing to pay positive amounts to avoid warning labels. On average, customers are willing to give away $1.61 to avoid warning labels, which is approximately 47% of the average price of a UPC in the breakfast cereals category.

Sources of Customer Heterogeneity. We further explore how the heterogeneity in the degree of label distaste relates to customer demographics. We focus on three demographic characteristics: household socioeconomic status, whether the household includes young children, and customer age. Previous literature suggests that higher-income, more educated individuals tend to respond to a greater extent to the presence of front-of-pack nutrition labels (Kim et al. (2001); Drichoutis et al. (2005)).[27] This disparity is essential from a policy perspective as the regulation should ideally be more effective across lower income groups where obesity is a more prevalent problem.

We use a classification of socioeconomic status (SES) provided by the retailer, which classifies

[26]The remaining 60.2 percent of probability of switching goes to products that we assume unlabeled but eventually will be labeled.

[27]Kim et al. (2001) find that females are more likely to read nutritional labels, and that label usage decreases with age and increases with income. Similarly, Drichoutis et al. (2005) find that consumers with lower income and education are more likely to report poor nutritional knowledge and label use.

a customer into one of five categories (ABC1, C2, C3, D, and E) based on the specific street block where the customer's residence is located. We define a customer as High-SES if she belongs to one of the two top strata of the socioeconomic scale (i.e., ABC1 or C2). To measure whether a household is likely to include small children, we examine a customer's purchase patterns in product categories, which are frequently bought by parents of young children. Namely, we classify customers as belonging to households with small children if they buy at least one item from the "diapers" or "fruit compotes" categories over the period of study.[28]

We examine the sources of heterogeneity in warning-label distaste by regressing our customer-level estimates of warning-label parameters on a vector of demographic characteristics as in Equation (9). Table 4 summarizes the OLS estimates. All sociodemographic variables are statistically significant, at least at the 5% level, as shown in Column (4) of Table 4.

The results reported in Table 4 indicate that warning-labels have stronger effects on lower SES customers relative to higher SES consumers as the coefficient on *High-SES* is positive and statistically significant. These results are in line with the objectives of policymakers and show that more straightforward information can succeed in closing nutritional disparities among households. Notice, that in our setting, the average price differences between labeled and non-labeled were negligible. Hence, substituting away from labeled cereals did not affect the budget constraints of the consumers. This may not be the case in other contexts. It should be stressed that, on average, both high- and low-SES customers decrease their likelihood of choosing products with warning labels.

Regarding the impacts of the warning-label valuations in families with young children, we find that the effects of food labeling are stronger among those households. In effect, after controlling for SES and age, having young children in the family leads the warning labels coefficient to decrease by 0.21 units, which is approximately one-fifth of the average coefficient. Finally, the *age* coefficient is negative and highly statistically significant, indicating that older customers tend to display a greater distaste for warning labels than younger customers, once we control for SES and family structure.

4.1 Placebo Tests

As a robustness check of our results, we conduct a placebo test in which we artificially introduce warning labels over a period predating the "intervention period" when the warning labels were actually implemented. Our falsification test uses data for the period January-February 2016 when no warning labels had been introduced in store shelves[29] and estimates the effects of placebo warning labels on consumer choice. Table 5 presents the results of the demand estimation for each

[28] We also explored including the subcategory of breakfast cereals for Kids in this definition but found that it did not contribute to the explanatory power of the variable.

[29] According to the supermarket chain and press reports of the time (Mostrador (2016)), manufacturers began delivering products carrying the warning labels in March 2016.

product category. As before, the price coefficient is negative and highly statistically significant across all categories. Importantly, the mean of the distribution of warning label coefficients is not statistically different from zero in any of the product categories, indicating the absence of placebo warning label effects for any of the categories. We conclude it is unlikely that spurious factors cause the effects of the warning label reported above.

4.2 Gradual Implementation versus Before-After

Our identification strategy relies on the gradual implementation of the warning labels over time and stores, allowing for time-specific unobservables. In this subsection, we quantify how sensitive the results are to this set of potential unobservables.

We compare our main estimates relative to an approach that does not exploit the gradual implementation of the warning labels. This alternative approach uses data before and after the regulation (July 2015 and July 2016, respectively) and assumes the absence of product-year specific unobservables. The primary source of identification of this approach is that the non-labeled products identify the year effect, and the labeled products identify the sum of the label and year effect. If unobservable factors affect a particular UPC in a given year (for example, different marketing campaigns, a different set of competitors, different allocations of supermarket stores shelf space, etc.), then the warning label estimates would be biased.

Table 6 presents the estimates for two of the studied categories (breakfast cereals and chocolates)[30] when using the before-after approach by considering two periods of different regimes: one episode with no warning labels (July 2015) and another episode with full implementation of the warning labels (July 2016).[31] We observe sizable changes in the results, stressing the quantitative importance of allowing for product-time-specific unobservables in the estimation. The mean of the warning label coefficient distribution is significantly positive for the two categories included in this exercise. Thus, we obtain substantial distortions in our estimates that highlight the importance of exploiting the gradual implementation of the food labeling law.

5 Conclusions

Providing consumers with simplified nutritional information is an increasingly favored policy option to induce healthier food choices (Hawkes (2010)). In this paper, we study the effects of a comprehensive nutrition labeling law enacted in Chile, which mandated the introduction of front-of-pack labels warning of the high levels of calories, sugars, sodium, and saturated fats contained in frequently-bought packaged goods. There was a strong and divided reaction in the

[30]Since all products in the cookie category are labeled after the legal deadline, we cannot estimate the mixed logit model as the warning labels are no longer alternative specific in the period after the regulation.

[31]We consider the same days of July in both years.

industry as the law added uncertainty on how consumers would respond to the new labeling. Whether consumers react to the implemented warning label regulation has profound managerial implications for the food industry, and policy lessons for the health authorities worldwide as the Chilean regulation has been singled out as an ambitious policy and followed closely by several countries.

A distinctive feature of our empirical setting is the rich variation we observe in the display of warning labels by narrowly defined products at a given point in time. This variation allows us to overcome a traditional challenge afflicting studies attempting to identify the effects of nutrition labeling policies using a before-after approach, namely the difficulty of disentangling the actual impact of the warning label on consumer choices.

Our estimates from three key product categories (in which most products were affected by the regulation) reveal heterogeneous responses from consumers to the nutritional information. We find a substantial reduction in purchase probabilities of labeled breakfast cereals. Instead, consumers tend not to substitute away from products displaying the warning labels in the chocolate and cookies categories. These results are consistent with interpretive nutritional information affecting consumer decisions when they provide decision-makers with new information regarding the nutritional content of foods. The effectiveness of this type of warning label may depend on whether consumers can discriminate between healthy and unhealthy labeled products within a product category. Importantly, the regulation severity allowed for non-labeled cereal products, whereas almost all UPCs in the chocolate and cookie categories ended up tagged as unhealthy products. The availability of healthier unlabeled substitutes will critically depend on how strict the regulation standards are.

Furthermore, our results suggest that purchase incidence by low socioeconomic groups and families with children are susceptible to be modified by the provision of simplified nutritional information. These findings are highly relevant for policymakers who typically target both groups, given their higher risk of developing obesity (especially given the alarming obesity rates among children (IHME (2013))). The effectiveness of the Chilean warning-label policy among low socioeconomic households could be driven by the fact that, in our setting, prices did not play a significant role as unlabeled and labeled cereals displayed similar price levels. Hence, substituting away from labeled breakfast cereals was not seriously affecting household expenditures.

While our empirical approach allows us to identify consumer responses to nutrition labeling in natural market environments, we are aware of its limitations. First, our study focuses on a single retail chain. To the extent that purchasing behavior and, in particular, the response to interpretative nutritional information may be different in other retailers, our results cannot be extrapolated to the population at large. We should emphasize, however, that our analysis used stores from the two most populated regions of the country, and the focus on one retail chain in no way compromises the internal validity of our findings. A second limitation is that we quantify the short-run impact of the intervention over the first few months of its introduction. Hence, we are unable to capture learning effects that may be taking place over a longer time horizon. However, this long-term effect may include many other elements other than the warning labels that could have affected food purchases. The law included other components, such as prohibitions to sell labelled products in schools, bans on the advertising of tagged products targeting children, and the removal of cartoons from cereal boxes (NYT (2018)), which were all implemented after June 2016. Even though all these changes were relevant for this particular policy (Taillie et al. (2020)), they do not allow separately identifying the effect of the warning labels on consumer choices. Moreover, information from supermarkets and the press had shown that suppliers did not change the product formulation before the law came into force, which they did afterwards (Kanter et al. (2019)). Understanding the consumer responses to nutritional labels will help to assess one of the main components of nutritional labeling policies and the marketing campaigns used in retail chains worldwide.

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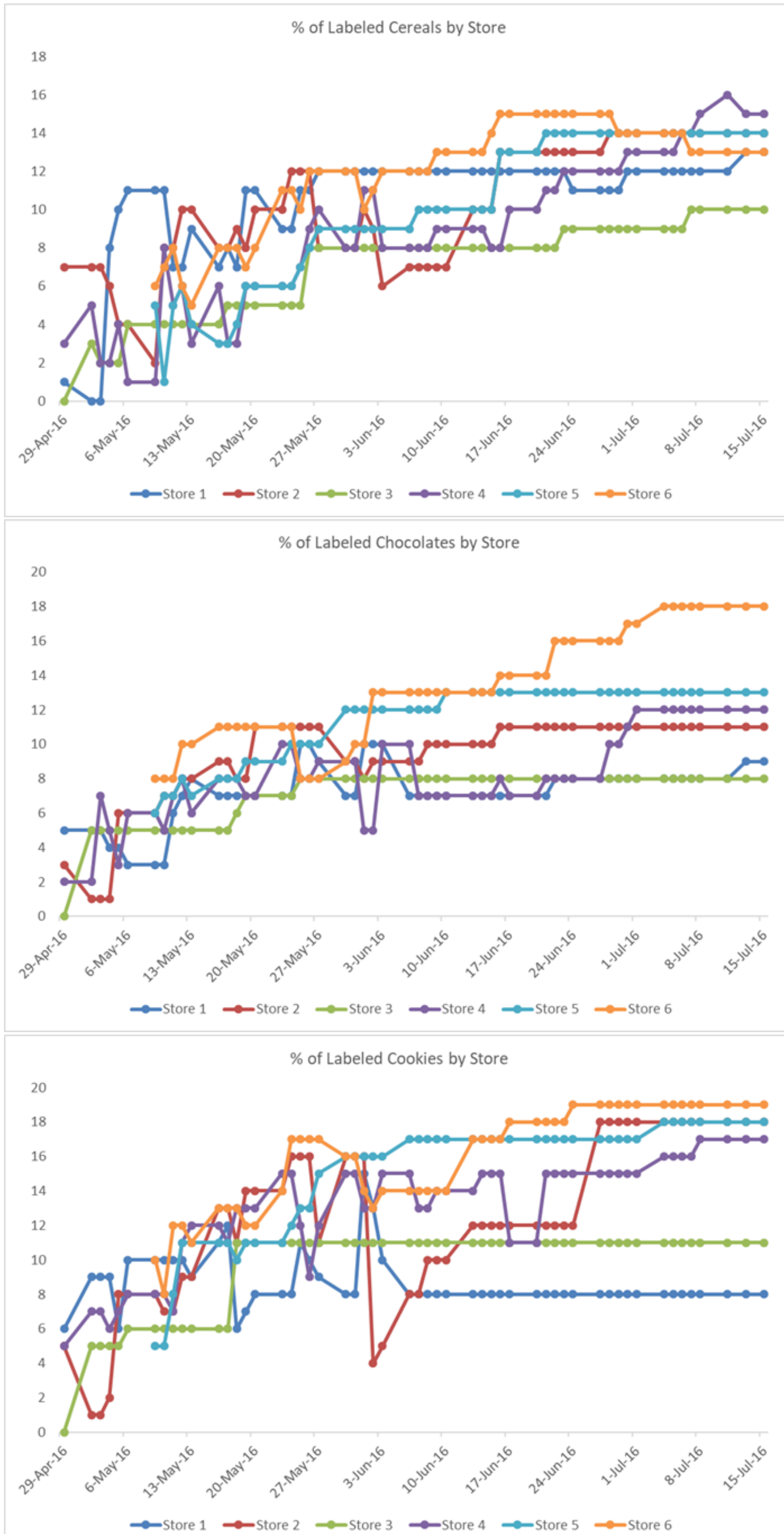
Figure 1: Warning Labels in Chile

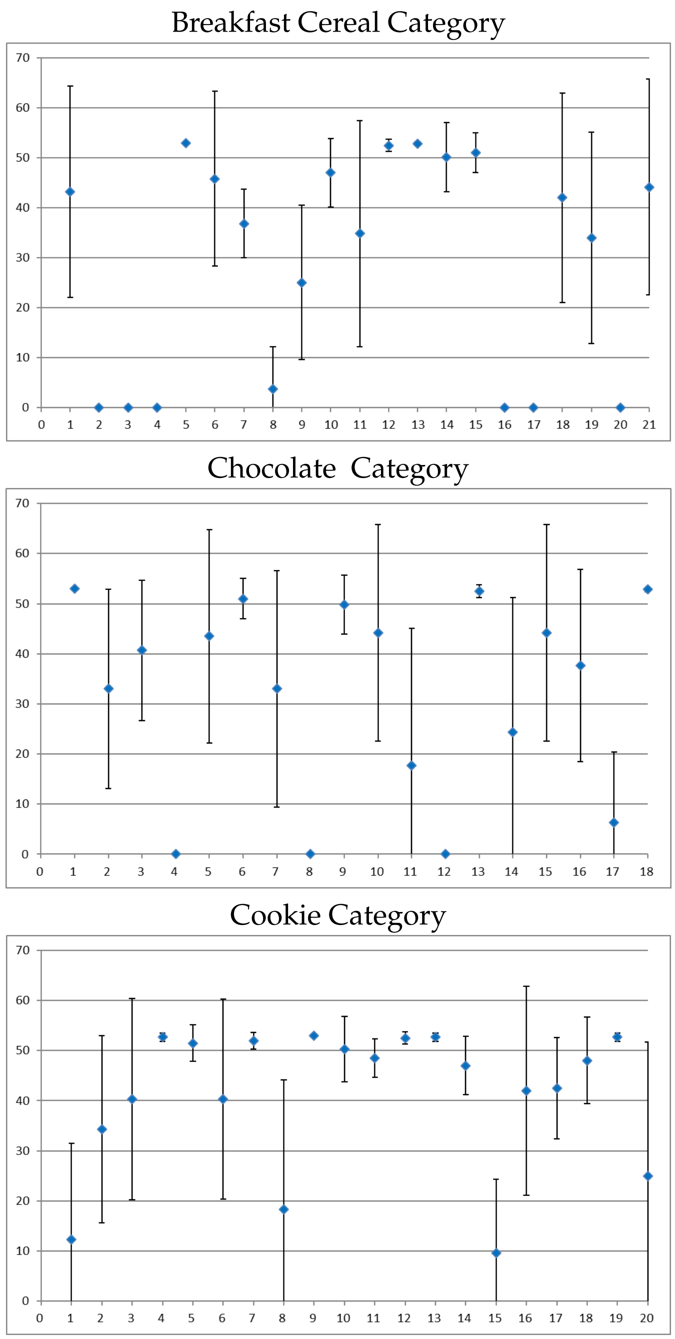
Notes: From left to right: High in Sugar, High in Calories, High in Saturated Fats and High in Sodium. At the bottom of each label it states Ministry of Health.

Figure 2: Evolution of the Number of Labeled products per store over time



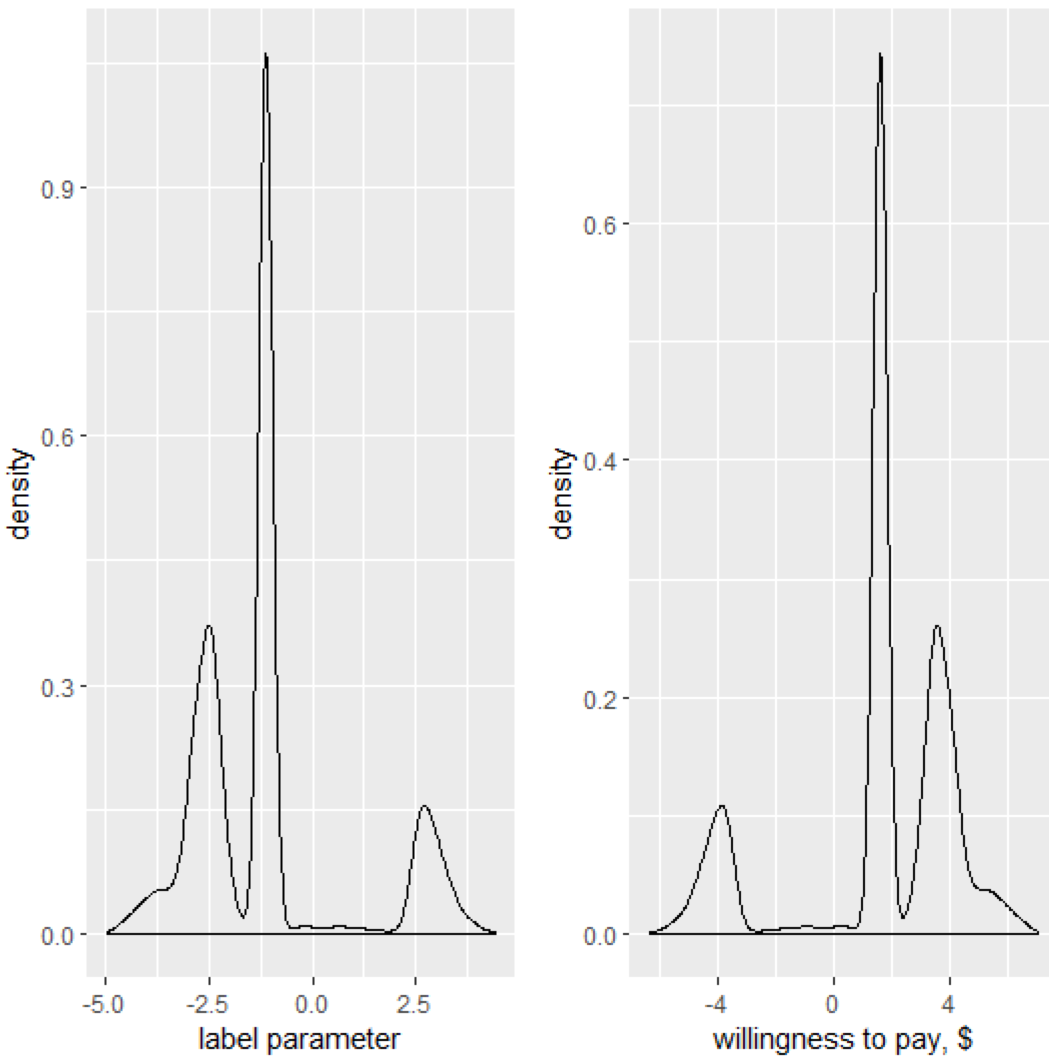
Notes: Y-axis is the number of labeled products, X-axis is the time line in weeks. Different colors different stores.

Figure 3: Timing of Warning Label Implementation Across Stores



Notes: X-axis displays each of the top products considered in each category. Y-axis is the number of days in advance of the actual implementation of the warning labels before the legal deadline. The blue dot represents the mean of the number of days in advance across stores for each product, and the error bars represent the corresponding variation (using the standard deviation). Dots at Y=0 correspond to unlabeled (healthy) products. Products are sorted by market share, being product 1 the SKU with the largest market share.

Figure 4: Distribution of Warning Label Coefficient and Willingness to Pay to Avoid Warning Labels in the Breakfast Cereal Category



Notes: Histograms based on the distributions of estimated utility coefficients in Equation (1). Left-hand side figure shows the estimated distribution of heterogeneous warning-label coefficients γ_i. Right-hand side figure shows the implied distribution of willingness to pay to avoid the warning-labels based on estimates of γ_i and price coefficient, α.

Table 1: Sample Size of Transactions and Choices

Categories	# Transactions	Avg. Choice Set	# Obs.
Breakfast Cereals	15,080	19.69	229,559
Chocolates	45,678	16.38	525,743
Cookies	36,216	18.89	488,439

Notes: To ensure mutually exclusive choices, we define as an eligible transaction those with no more than one item in the selected categories.

Table 2: Demand Model Estimates for Price and Warning Label Coefficients

	Cereals	Cookies	Chocolates
	(1)	(2)	(3)
Mean			
Price	-.00104	-.00144	-.00154
	(.00011)***	(.00026)***	(.00029)***
Label	-1.12652	.13834	-.37616
	(0.09423)***	(.23180)	(.30448)
Standard Deviation			
Label	3.68211	2.77844	2.79171
	(.260127)***	(.09086)***	(.14956)***
Fixed Effects:			
Product	✓	✓	✓
Product x Time	✓	✓	✓
# of individuals	4,817	6,550	8,274
# of choice situations	11,094	24,563	30,240
# of observations	229,559	488,439	525,743
Log sim. pseudolikelihood	-21976.364	-36105.017	-42830.093

Notes: Cluster-robust standard errors (at the store level) in parenthesis. P-values notation: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. We consider data from May to July 2015 and from May to July 2016.

Table 3: Marginal Effects of Warning Labels on Purchase Probabilities in the Breakfast Cereal Category

[Expressed in $(10^{-3})\cdot$ Probability]

	NPO	A	[B]	[C]	[D]	E	F	G	H	I	J	K	L	M	N	O	P	[Q]	R	S	T	U
A	0.334	**-2.160**	0.105	0.254	0.026	0.069	0.063	0.036	0.042	0.068	0.040	0.066	0.119	0.062	0.066	0.046	0.208	0.064	0.062	0.093	0.161	0.176
[B]	0.306	0.105	**-2.211**	0.308	0.029	0.066	0.059	0.032	0.046	0.061	0.033	0.069	0.102	0.055	0.056	0.039	0.246	0.072	0.053	0.085	0.215	0.172
[C]	0.179	0.277	0.333	**-4.323**	0.051	0.165	0.145	0.082	0.099	0.141	0.071	0.171	0.220	0.132	0.141	0.100	0.678	0.115	0.088	0.181	0.480	0.474
[D]	0.330	0.026	0.028	0.046	**-0.884**	0.016	0.018	0.012	0.016	0.022	0.016	0.020	0.046	0.021	0.020	0.015	0.039	0.044	0.035	0.036	0.045	0.032
E	0.207	0.068	0.065	0.151	0.016	**-1.426**	0.054	0.025	0.025	0.045	0.029	0.037	0.096	0.047	0.048	0.032	0.133	0.040	0.039	0.057	0.104	0.110
F	0.308	0.062	0.058	0.132	0.018	0.054	**-1.505**	0.026	0.025	0.048	0.034	0.036	0.101	0.050	0.050	0.033	0.116	0.049	0.046	0.061	0.099	0.099
G	0.212	0.036	0.032	0.073	0.012	0.025	0.026	**-0.898**	0.015	0.027	0.020	0.020	0.057	0.029	0.028	0.019	0.063	0.034	0.030	0.037	0.052	0.053
H	0.286	0.041	0.044	0.088	0.016	0.025	0.025	0.015	**-1.068**	0.029	0.018	0.027	0.053	0.025	0.026	0.019	0.075	0.044	0.037	0.043	0.073	0.059
I	0.441	0.067	0.060	0.127	0.022	0.045	0.048	0.027	0.030	**-1.669**	0.036	0.040	0.105	0.049	0.048	0.035	0.108	0.065	0.058	0.072	0.098	0.090
J	0.340	0.039	0.032	0.063	0.016	0.029	0.033	0.020	0.018	0.036	**-1.126**	0.026	0.079	0.036	0.034	0.024	0.054	0.047	0.043	0.048	0.057	0.051
K	0.302	0.066	0.068	0.155	0.021	0.037	0.036	0.020	0.028	0.040	0.026	**-1.464**	0.073	0.036	0.039	0.031	0.120	0.053	0.045	0.060	0.111	0.099
L	0.985	0.121	0.103	0.203	0.048	0.101	0.106	0.060	0.055	0.109	0.084	0.076	**-3.299**	0.121	0.109	0.076	0.173	0.134	0.142	0.150	0.174	0.168
M	0.396	0.061	0.054	0.119	0.021	0.047	0.050	0.029	0.026	0.049	0.037	0.036	0.155	**-1.587**	0.050	0.033	0.101	0.061	0.053	0.067	0.091	0.091
N	0.347	0.065	0.055	0.128	0.020	0.047	0.050	0.028	0.026	0.047	0.035	0.038	0.103	0.050	**-1.529**	0.035	0.104	0.054	0.051	0.062	0.090	0.093
O	0.274	0.045	0.038	0.090	0.015	0.032	0.033	0.019	0.019	0.035	0.024	0.030	0.072	0.033	0.035	**-1.112**	0.073	0.041	0.038	0.046	0.062	0.059
P	0.192	0.219	0.257	0.654	0.042	0.141	0.124	0.068	0.081	0.116	0.058	0.128	0.182	0.109	0.112	0.078	**-3.650**	0.094	0.074	0.153	0.400	0.369
[Q]	1.069	0.065	0.072	0.105	0.045	0.040	0.050	0.034	0.045	0.066	0.049	0.054	0.132	0.062	0.056	0.042	0.089	**-2.496**	0.108	0.107	0.128	0.078
R	0.821	0.063	0.053	0.081	0.036	0.039	0.046	0.030	0.038	0.059	0.044	0.046	0.138	0.054	0.052	0.038	0.070	0.107	**-2.085**	0.100	0.095	0.075
S	0.754	0.093	0.085	0.165	0.037	0.058	0.062	0.038	0.044	0.073	0.050	0.061	0.147	0.068	0.063	0.047	0.144	0.106	0.100	**-2.465**	0.143	0.129
T	0.652	0.166	0.222	0.457	0.052	0.108	0.104	0.054	0.078	0.102	0.060	0.117	0.176	0.094	0.093	0.064	0.393	0.131	0.097	0.147	**-3.640**	0.273
U	0.276	0.181	0.176	0.447	0.033	0.114	0.103	0.056	0.062	0.094	0.054	0.103	0.170	0.095	0.097	0.062	0.361	0.080	0.077	0.133	0.273	**-3.047**

Notes: The table presents the matrix of own and cross partial effects of changes in label status on choice probabilities. Changes in choice probabilities are presented amplified by a factor of 1000 to facilitate readability. Inside goods are labeled from "A" to "U" and the outside option is labeled "NPO" (no-purchase-option). Labels in brackets correspond to UPCs which were below the legal threshold required by the regulation. Entry (m, n) in the matrix corresponds to the change in the choice probability of the brand in column n (including the no-purchase-option) when the label status of the brand in row m changes from $L_{ijt} = 0$ to $L_{ijt} = 1$.

Table 4: Taste Heterogeneity in Warning-Labels and Customer Demographics

	(1)	(2)	(3)	(4)
High-SES	.1753	–	–	.2060
	(.0676)***			(.0680)***
Young Children	–	-.1427	–	-.2055
		(.0838)*		(.093)**
Age	–	–	-.0058	-.0079
			(.0018)***	(.0021)***
Constant	-1.2695	-1.1092	-0.8513	-.8761
	(.0561)***	(.0293)***	(.0898)***	(.1187)***
R-squared	0.0009	0.0009	0.0022	0.0064
# of obs.	3,596	4,817	4,817	3,596

Notes: The table presents the OLS estimates of a linear regression model where the dependent variable is the estimated warning-label coefficient conditional on choices and choice situations observed in the data. *High-SES* is a dummy variable equal to one if the customer's SES is ABC1 or C2; *Young Children* is a dummy variable equal to one if the customer's household have purchased items associated with small children; and *Age* is a customer's age in years. Robust standard errors in parenthesis. P-values notation: *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Placebo Test Estimates

	Cereals (1)	Cookies (2)	Chocolates (3)
Mean			
Price	-0.00061	-0.00254	-0.00108
	(0.00012)***	(0.00032)***	(0.00018)***
Label	-0.20225	-0.08092	-0.84333
	(0.170898)	(0.38646)	(0.51866)
Standard Deviation			
Label	3.06218	4.09645	3.24720
	(.26652)***	(.30158)***	(.44391)***
Fixed Effects:			
Product	Yes	Yes	Yes
Product x Time	Yes	Yes	Yes
# of individuals	3,086	4,645	5,376
# of choice situations	4,825	11,931	13,308
# of observations	96,725	241,682	231,465
Log sim. pseudolikelihood	-12156.3	-21548.9	-23126.3

Notes: Cluster-robust standard errors (at the store level) in parenthesis. P-values notation: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The placebo sample uses transactions in January-February in 2015 and 2016. No warning label was in place before March 2016.

Table 6: Demand Model Estimates using Before-After Approach

	Cereals (1)	Chocolates (2)
Mean		
Price	-.00070	-.00199
	(.00008)***	(.00021)***
Label	.36982	.63213
	(.09313)***	(.13818)***
Standard Deviation		
Label	2.58636	2.29241
	(.16088)***	(.13933)***
Fixed Effects:		
Product	Yes	Yes
Product x Time	No	No
# of individuals	4,486	8,477
# of choice situations	8,986	16,678
# of observations	192,384	298,649
Log sim. pseudolikelihood	-18306.571	-31897.782

Notes: Cluster-robust standard errors (at the store level) in parenthesis. P-values notation: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The demand estimation considers July 2015 (pre-treatment) and July 2016 (post-treatment period). Since all products in the Cookie category were labeled after the legal deadline, the warning labels are no longer alternative specific and preclude us from estimating the mixed logit model.