Equilibrium Effects of Food Labeling Policies[a]

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Abstract: We study a regulation in Chile that mandates warning labels on products whose sugar or caloric concentration exceeds certain thresholds. We show that consumers substitute from labeled to unlabeled products—a pattern mostly driven by products that consumers mistakenly believe to be healthy. On the supply side, we find substantial reformulation of products and bunching at the thresholds. We develop and estimate an equilibrium model of demand for food and firms' pricing and nutritional choices. We find that food labels increase consumer welfare by 1.8% of total expenditure, and that these effects are enhanced by firms' responses. We then use the model to study alternative policy designs. Under optimal policy thresholds, food labels and sugar taxes generate similar gains in consumer welfare, but food labels benefit the poor relatively more.

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1. Introduction

Obesity rates in the world have tripled over the last half-century. Today, about 40% of the world's adult population is either obese or overweight (WHO, 2018). One increasingly popular policy tool governments are using to combat obesity are front-of-package labels, which are visual warnings placed prominently on the front of packaged food products. Unlike nutrition facts tables, which provide detailed information on the back of food products, food labels are simple symbols that clearly signal to consumers when a particular product is considered unhealthy. Since 2016, more than 25 countries have either implemented or are in the process of implementing country-wide mandatory food labeling policies (Barahona et al., 2022).

Several features of food labels make them popular. First, providing information to consumers is widely perceived as innocuous, in the sense that it can only improve consumer welfare. Furthermore, sugar taxes—the most prominent instrument to combat obesity—may be regressive (Allcott et al., 2019a). Finally, in settings in which some but not all agents act against their own interest, information interventions can be more efficient than taxes because their effects are better targeted (Bernheim and Taubinsky, 2018). Opponents of food labels, however, argue that they are ineffective in improving consumers' diet and impose an unnecessary burden on firms.

Most of this discussion focuses on consumers' responses to labels. However, firms' responses to the large-scale implementation of food labels may undo or even amplify some of their desirable properties. Food labels can, for example, affect product differentiation and market power. Firms may also use healthier ingredients in their products to avoid receiving labels, thus amplifying the positive effects on nutritional intake but also increasing consumer prices as a result of increased production costs. Taken together, the impact of large-scale food labeling regulations is ambiguous.

This paper studies the equilibrium impacts of food labels on consumers' purchases, firms' pricing and production decisions, nutritional intake, and consumer welfare. We combine descriptive analyses with a model of supply and demand for food and nutrients to quantify the impact of the Chilean Food Act of 2016, the first mandatory nationwide food labeling regulation implemented in the world. The regulation mandates that food manufacturers put warning labels on all of their packaged food products that surpass a threshold concentration of sugar, calories, sodium, or saturated fat.

To study how the regulation affected consumer choice, we use scanner data on purchases made in Walmart, the largest food retailer in Chile, from 2015 to 2018. The data contain information on prices, quantities, and consumer demographics such as gender, age, and income. To shed light on mechanisms, we surveyed 1,500 consumers and elicited their beliefs over the nutritional content of products. Finally, we use scanned nutrition facts tables of products before and after the policy to study strategic reformulation decisions by firms. We thus have a rich window into consumer demand and beliefs, as well as firm behavior.

We focus our analysis on the breakfast cereal market. Cereal is well suited for this analysis because it is a well-defined category with little substitution across other food categories, substantial labeling variation across products, and one in which food labels may be particularly informative due to consumers' nutritional content misperceptions. We extend the analysis to other product categories in Barahona et al. (2022).

Three key findings arise from our descriptive analysis. First, we show that consumers substituted from labeled to unlabeled products. Second, we find that the change in demand is primarily driven by updates in consumer beliefs. Products that consumers already knew had high sugar or caloric concentration only experienced a small and temporary drop in demand. However, products that consumers previously believed to be low in sugar and calories but received a label under the labeling policy experienced a persistent 40% decrease in demand relative to unlabeled products. In line with a Bayesian updating model, this result suggests that labels are more effective when they provide new information to consumers. Third, we find that suppliers responded to the regulation by reformulating their products and changing prices. To avoid labels, many firms modified the nutritional content of their products to be just below the regulatory thresholds and decreased sugar and caloric concentration by 11.5% and 2.8%, respectively. We also document a 5.5% increase in prices of unlabeled products relative to labeled ones due to the regulation.

Motivated by these findings, we develop and estimate a model of supply and demand for food and nutrients. On the demand side, consumers care about the price, taste, and healthiness of products. Healthiness, however, is not observed, and consumers may have poorly calibrated beliefs about products' nutritional content. Food labels help consumers by providing them with a binary signal about the true nutritional content of products, which allows them to make better-informed purchasing decisions. On the supply side, firms strategically set prices and nutritional content to maximize profits. Food labels create a sharp discontinuity in demand at the policy threshold, which induces firms to reformulate their products to avoid labels. However, reducing the concentration of critical nutrients is costly, and may cause firms to raise prices.

Our model highlights two sources of inefficiency that arise due to incomplete information. First, consumers may make mistakes when choosing what to buy. Second, firms do not have incentives to produce healthier items if they cannot credibly inform consumers about product healthiness. Thus, food labels may reduce inefficiencies by improving consumer choice and incentivizing suppliers to produce healthier goods.

We use our model to quantify the impact of the Chilean Food Act on nutritional intake and consumer welfare. To analyze how equilibrium forces change the effectiveness of food labeling policies, we simulate three progressively more flexible counterfactuals, each of which we benchmark against a no-intervention counterfactual.

First, we study the effects of food labels in the absence of supply-side responses. We find that the regulation reduces sugar and caloric intake in the cereal market by 6.8% and 0.6%, respectively, resulting in average gains in consumer welfare equivalent to 1.1% of total cereal expenditure. The changes in consumer welfare are driven by a combination of a healthier diet, fewer dollars spent, and an increase in the consumption of less tasty products (e.g., oatmeal).

Second, we allow firms to optimally set prices in response to the policy but not to change the nutritional content. As in Villas-Boas et al. (2020), we use this counterfactual to assess the role of product differentiation and market power. Under this counterfactual, prices of unlabeled and labeled products go up and down, respectively, with average prices remaining relatively constant. Gains in consumer welfare relative to the no-intervention counterfactual are 7% lower than in the absence of supply-side responses.

Third, we allow firms to optimally reformulate their products to avoid receiving labels. This counterfactual recovers the full effect of the policy. Overall, we find that high-in-taste products become healthier but more expensive due to higher production costs. Consumer welfare gains under this counterfactual are 70% larger than in the absence of supply-side responses.

We then use our model to study optimal policy design. We show that ignoring supply-side effects can lead to substantially different outcomes. Considering only demand-side effects, a social planner who wants to maximize consumer welfare should set a threshold that maximizes the information provided by labels. However, when accounting for supply-side responses, the social planner wants to set a lower threshold to provide stronger incentives for firms to improve the nutritional content of their products. By taking supply-side responses into account, the social planner can reduce sugar intake by an additional 38% and increase consumer welfare gains by 20% relative to the outcome under the threshold that maximizes information.

Overall, our descriptive and model results suggest that food labels are more effective when consumers have mistaken beliefs about products' healthiness, consumers value healthiness, reformulation that does not substantially change products' taste is feasible, and regulatory thresholds are set so that they provide useful information to consumers and encourage product reformulation.

Finally, we compare food labels with other popular policy instruments, such as sugar taxes. When compared with sugar taxes, food labels present both advantages and disadvantages. They tend to be more progressive and better targeted, but are less effective against non-informational market imperfections, such as lack of self-control or fiscal externalities.

This paper contributes to several strands of the literature. It adds to a large literature that studies consumer choice in settings of imperfect information (Hastings and Weinstein, 2008; Abaluck and Gruber, 2011; Abaluck, 2011; Woodward and Hall, 2012; Handel and Kolstad, 2015; Allcott and Knittel, 2019). Moreover, it contributes to the literature that examines how providing nutritional information affects consumer demand. This includes consideration of the effects of advertising (Ippolito and Mathios, 1990, 1995; Dubois et al., 2017); nutritional information on menus (Wisdom et al., 2010; Bollinger et al., 2011; Finkelstein et al., 2011); and food labeling regulations (Kiesel and Villas-Boas, 2013; Zhu et al., 2015; Allais et al., 2015). Previous research has also highlighted the importance of firms' strategic responses to nutritional information policies by adjusting prices (Villas-Boas et al., 2020) and reformulating products (Moorman et al., 2012; Lim et al., 2020). Our paper contributes to these studies by providing evidence of and quantifying the equilibrium effects of national information policies, by allowing firms to vary prices and nutritional characteristics of the products they sell.

Other concurrent work has also studied the Chilean Food Act. Using a before-after analysis, Taillie et al. (2020) document a significant decline in purchases of labeled beverages following the policy's implementation. Araya et al. (2022) take advantage of the staggered introduction of labeled products in store inventories and find that labels decrease demand in the breakfast cereal category, but not for chocolates or cookies. Pachali et al. (2022) study price adjustments and conclude that prices of labeled products increased due to increased product differentiation. Alé-Chilet and Moshary (2022) provide evidence of bunching just below regulatory thresholds and conclude that reformulation reinforces the policy's effects by lowering the caloric content of cereal. Our paper goes further along several dimensions. First, we develop an equilibrium framework that allows both price adjustments and product reformulation. This is crucial in assessing the overall role of equilibrium responses to food labeling policies. Second, we show that beliefs over nutritional content are a primary driver of consumer behavior and explicitly incorporate them in our model. This allows us to provide a welfare evaluation of the policy. Third, we use our model to answer additional policy-relevant questions, such as the design of optimal policy thresholds and the comparison of food labels with sugar taxes. Barahona et al. (2022) combine the insights of this paper with analysis of other product categories and discuss the effectiveness of food labeling policies in different settings.

Our work also relates to the literature on quality disclosure and certification that studies the effect of third-party disclosure on consumer choice and seller behavior (Dranove et al., 2003; Jin and Leslie, 2003; Greenstone et al., 2006; Dranove and Jin, 2010; Roe et al., 2014; Houde, 2018; Vatter, 2021) and to the literature in industrial organization that estimates demand models under endogenous product characteristics (Ackerberg and Crawford, 2009; Draganska et al., 2009; Fan, 2013; Wollmann, 2018).

Finally, we contribute to a broader literature that studies how governments can help consumers make better nutritional choices. Allcott et al. (2019) study whether improving access to healthy food in poor neighborhoods can decrease nutritional inequality, Dubois et al. (2017) analyze the effect of advertising on junk food consumption, and several other papers study the effects and design of taxes for sugar-sweetened beverages and calorie-dense food products (Falbe et al., 2015, 2016; Silver et al., 2017; Allcott et al., 2019a; Lee et al., 2019; Taylor et al., 2019; Dubois et al., 2020; Aguilar et al., 2021). Our paper focuses on a different policy instrument and shows that it can be an effective tool to improve diet quality and combat obesity.

The remainder of the paper is organized as follows. Section 2 describes the setting and the data. In Section 3, we provide descriptive evidence to illustrate the main mechanisms through which food labels can reduce the intake of critical nutrients. In Sections 4 and 5, we present and estimate the demand and supply model, respectively. We present our main counterfactual exercises in Section 6 and conclude in Section 7.

2. Setting and data

2.1. *The Chilean Food Act*

In 2015 the Chilean legislature, concerned about the growing obesity problem, passed Law 20.606 (hereafter, the Food Act) to improve nutritional choices. The Act imposed new regulations on how food manufacturers could package and advertise food products. An important part of the Act was a food labeling system, which prominently informs to consumers which products are considered unhealthy.[1] The Food Act sought to enhance consumers' decision-making by providing easy-to-process information about the healthiness of food products.

The Food Act established threshold values for sugar, calories, sodium, and saturated

[1] The Food Act also included a ban on selling, distributing, or advertising labeled products in schools, and a ban on advertising labeled products aimed at children younger than 14 years old.

fat concentration and mandated suppliers to place a warning label on the front of their packaged products for each nutrient threshold surpassed. The thresholds were implemented in three stages, with each stage setting stricter threshold values than the last. Due to data limitations, we focus on stage 1, which was implemented in June of 2016 and established limits of 22.5 grams of sugar and 350 kcal per 100 grams of product.[2]

2.2. *Data*

We restrict our attention to breakfast cereal because it is a well-defined category with substantial labeling variation; around 60% of cereal products received at least one label. Breakfast cereal is also a category in which consumers tend to have inaccurate beliefs about the healthiness of products. This feature is important because, as shown below, beliefs play a critical role in the extent to which labels impact shoppers' decisions. In certain other categories, such as soft drinks, products have already long been categorized as diet and non-diet, and consumer beliefs about nutritional content are thus more closely aligned with reality.[3]

2.2.1. *Walmart data*: To capture prices and quantities, we use scanner-level data provided by Walmart-Chile. Walmart is the largest food retailer in Chile and accounts for more than 40% of supermarket sales. Our data contain all transactions that occur in any Walmart store in Chile between May 2015 and March 2018. Every transaction identifies products at Universal Product Code (UPC) level and contains information about price, revenue, product name, brand name, and discounts. We can track buyers enrolled in Walmart's loyalty program and link them to individual characteristics, such as gender, age, and household income. We supplement these data with additional information about product and store characteristics also provided by Walmart.

Since our data only cover purchases at Walmart and most consumers may also purchase a large share of their groceries from other retailers, we restrict our analysis to regular Walmart customers. Our final sample consists of 524,000 consumers who visited a Wal-

[2]The law was first approved in Congress in 2012 and its details were finalized and announced in June of 2015, one year before Stage 1. Stages 2 and 3 took place in June of 2018 and 2019, respectively. The thresholds were established based on the 90th percentile of the distribution of the concentration of critical nutrients from non-processed food products using data from the United States Department of Agriculture (USDA). As far as we know, the choice of thresholds was not influenced by the industry's lobby. The legislation only applies to processed and packaged foods. This means that products that do not have any added sugar, sodium, saturated fat, honey, or syrup do not receive a label, even if they are above a given threshold. For example, even though oats have a caloric content above 350 kcal/100 g, they did not receive a label.

[3]In Barahona et al. (2022), we extend the analysis to several other categories. We also study potential between-category substitution effects and find no evidence of it.

mart store at least once every 8 weeks during the study period. The average customer in our panel is 48 years old, and 69% are women.[4] In the first year of data, from May of 2015 to May of 2016, the average customer buys cereal 11 times and spends a total of $25 on it.

2.2.2. *Nutritional Information*: Nutritional data for packaged products come from two sources: (a) pre-policy data collected by the Institute of Nutrition and Food Technology (INTA) at the University of Chile, and (b) post-policy data that we collected and digitized ourselves. The data comprise information on 94 cereal products, which represent 94% of total cereal revenue.

2.2.3. *Consumer beliefs*: We conducted a survey to elicit consumers' beliefs about the nutritional characteristics of all cereal products in the absence of food labels. We implemented the survey in Argentina using Qualtrics in August 2019 and surveyed a total of 1,500 individuals. We asked consumers to provide their best estimate of the sugar and caloric concentration of all cereal products and to state how confident they were about their answers. Using this information, we elicit the first and second moments of consumer beliefs about each product's nutritional content. We also collected information about the gender, age, and household income of survey respondents.

We find that, on average, individuals have relatively accurate beliefs about the concentration of sugar in cereal. The correlation between actual sugar content and respondents' stated beliefs is 0.76. However, respondents' beliefs about the caloric concentration of cereal were less aligned with reality; the correlation between the actual and predicted caloric concentration is only 0.26.

3. Descriptive evidence

This section provides descriptive evidence of the impact of the food labeling policy on nutritional intake, consumer choice, and firm behavior. For our analysis, we define a product as the union of UPCs that share the same product name and brand. For example, we assign all *Honey Nut Cheerios* the same product ID regardless of their box size. In total, our sample contains 94 unique cereal products (produced by 14 firms): 39 did not receive a label and 55 received a high-in-calories label, of which 21 received an additional high-in-sugar label. No cereal products received a high-in-sodium or high-in-fat label in

[4]The sample is fairly representative of the Chilean urban population, with high-income consumers slightly overrepresented. A third of consumers are in the bottom 50% of the national income distribution, a third between the 50th and 85th percentiles, and a third in the top 15%.

our sample period. Our main analysis focuses specifically on caloric and sugar intake. We assign labels to a product based on its 2018 nutritional content.

Three key facts emerge from the evidence presented below. First, consumers decreased demand for labeled products relative to unlabeled ones. Second, products that were perceived as healthy but received labels experienced the largest decline in demand. Third, suppliers responded to the policy by reformulating their products and changing prices.

3.1. *Changes in equilibrium quantities*

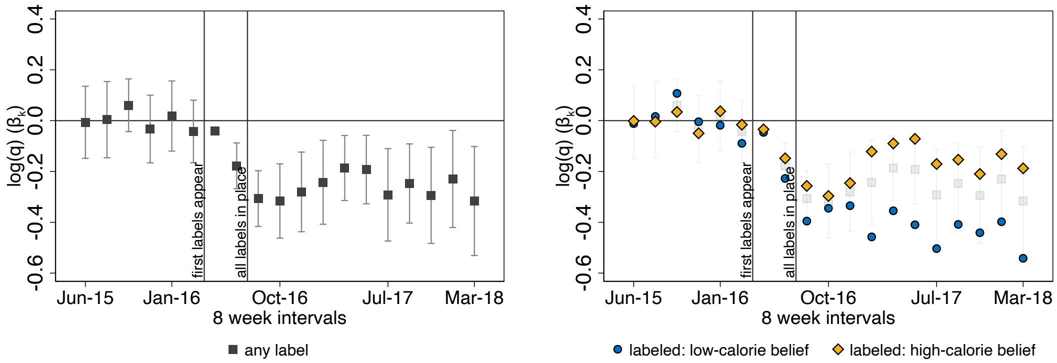
We quantify the effects of the policy on demand by using an event-study design. We aggregate our data into product-store-period data bins (where a period is defined as eight consecutive calendar weeks) and estimate the following regression:

$$\log(q_{jst}) \;=\; \sum_k \beta_k \cdot L_j \cdot \mathbb{1}\{k=t\} + \gamma \cdot \log(p_{jst}) + \delta_{js} + \delta_t + \varepsilon_{jst}, \tag{1}$$

where q_{jst} denotes the grams of product j sold in store s in period t, p_{jst} refers to the product's price per 100 grams of cereal, and L_j is an indicator variable that takes the value of one if the product has one or more labels. Finally, δ_{js} refers to product-store fixed effects and δ_t to period fixed effects. We normalize the β_k coefficients so that their average value over the pre-policy period is equal to zero. Observations are weighted by product-store pre-policy revenues. Products that do not appear in the pre-period have zero weight and are thus excluded from the estimation sample. Standard errors are clustered at the product level.

Figure 1(a) displays the results of estimating Equation (1). In the pre-period, the coefficients are small and not significantly different from zero. After the regulation was implemented, the quantity of labeled products sold relative to unlabeled ones decreased by an average of 26.4%. The impact of the legislation does not seem to change over time. This suggests that labels shifted consumer purchases away from labeled products, with the effect lasting throughout the entire period covered by our sample.

3.1.1. *The role of beliefs*: To investigate how information and beliefs shape consumer choices, we use the beliefs survey described in Section 2.2.3. We use the elicited beliefs about caloric concentration to test for heterogeneity in the impact of labels. If labels provide useful information for consumers, then products for which labels come as a surprise (i.e., products that consumers believed were low in calories but are actually high in calories) should experience a larger drop in demand. We thus split our sample of labeled products into two groups: products below the median in the distribution of beliefs (20



(a) By labeling status (b) By labeling status and prior beliefs

Figure 1: Relative changes in equilibrium quantities

Notes: This figure presents the coefficients of our event study regressions. Panel (a) presents the β_k coefficients from Equation (1). Panel (b) displays the coefficients from Equation (2). Coefficients in blue circles, yellow diamonds, and light gray squares denote β_k^l, β_k^h, and β_k estimates, respectively. The vertical segments delimit the 95% confidence intervals. We run the regressions on the sample of 68 ready-to-eat cereals that show up in the pre- and post-policy periods. The sample consists of 27 unlabeled and 41 labeled products for a total of 194,510 observations.

products) and products above the median in the distribution of beliefs (21 products). We use indicator dummies for each of these groups (denoted by Low_j and $High_j$) to estimate the following equation:

$$\log(q_{jst}) = \sum_k (\beta_k^l \cdot L_j \cdot Low_j + \beta_k^h \cdot L_j \cdot High_j) \cdot \mathbb{1}\{k = t\} + \gamma \cdot \log(p_{jst}) + \delta_{js} + \delta_t + \varepsilon_{jst}, \quad (2)$$

where all variables and specification details are defined as in Equation (1).

Results from Equation (2) are shown in Figure 1(b). Coefficients in blue circles and yellow diamonds denote β_k^l and β_k^h estimates, respectively. Coefficients in light gray squares denote β_k coefficients from Equation (1). Products that consumers believed to be high-calorie (yellow diamonds) saw an initial drop in demand that faded 6 months after the policy implementation. In contrast, products consumers thought were relatively healthy but actually received a label (blue circles) saw a persistent decrease in demand of around 40%.[5] These empirical findings suggest that labels are especially effective for products about which consumers are more misinformed.

[5]The difference between the average value of $\hat{\beta}_t^l$ and $\hat{\beta}_t^h$ in the post-policy period is significant at the 98% confidence level.

3.2. *Changes in nutritional content and prices*

To study whether firms responded to the labeling policy by reformulating products, we compare the distribution of nutritional content before and after the policy was implemented. In 2016, 55 cereal products were above the threshold for caloric concentration. In 2018, 13 of those products reduced their concentration of calories to below the threshold, with eight of them bunching at the threshold of 350 kcal per 100 grams. We observe a similar pattern when we look at sugar concentration. In 2016, 27 regulated products were above the threshold. In 2018, 9 of these reduced their sugar content to be below the threshold and 6 reduced it to between 20 and 22.5 grams of sugar per 100 grams of cereal (see Online Appendix A, Figure A.1). This suggests that firms chose to respond strategically to the labeling policy, bunching at the threshold to avoid receiving a label.

This bunching results in a net reduction in the caloric and sugar concentration of cereal products offered in the market. The weighted average of the caloric concentration of products decreased from 383.6 to 372.8 kcal per 100 grams, while the weighted average of the sugar concentration of products decreased from 21.54 to 19.06 grams of sugar per 100 grams of cereal; weights are assigned by pre-policy revenue.

In Online Appendix B, we show that labeled products saw an average decrease of 5.5% in prices relative to unlabeled products. This may be explained by a combination of firms increasing markups on unlabeled products that now face higher demand (and vice versa) and an increase in marginal costs of unlabeled products due to reformulation. We find no evidence of firms responding by changing product assortment or package size.

4. Demand for breakfast cereal

We now develop and estimate a model of supply and demand for cereal that can explain the descriptive facts presented above. We use the model to answer policy-relevant questions such as what the total effect of the policy was in terms of consumer welfare and per capita nutritional intake, where the optimal threshold should be set, and how warning labels compare with sugar taxes.

4.1. *Demand model*

Our demand model consists of a continuum of risk-neutral consumers, indexed by $i \in \mathcal{I}$, who are divided into two bins defined by being above or below the median household income in our sample. We refer to them as low- and high-SES consumers and denote them by their type $b \in \{l, h\}$. We refer to each store-period combination as a "market" and index it by t. There are J products indexed by $j \in \mathcal{J}$ and one outside good (i.e. the option to buy no product). Each product j is produced by a firm $f \in \mathcal{F}$ and characterized by (r_j, p_{jt}, w_{jt}), where r_j is is a vector of indicator variables denoting the subcategory the product belongs to (plain, sugary, chocolate, granola, oatmeal); p_{jt} is its price in market t; and w_{jt} is its vector of nutritional content.

Our model departs from the standard random coefficients demand model (e.g., Berry et al., 1995; Nevo, 2001) in an important way. We allow the nutritional content, w_{jt}, to affect utility through the negative long-run health consequences of consuming unhealthy goods. Nevertheless, because nutritional content may not be directly observed by consumers, their choices are based on their beliefs about it. As a consequence, consumer choices do not necessarily maximize consumer utility, which leaves space for government interventions with the potential to improve consumer welfare.

We assume that the utility derived by individual i when purchasing product j can be split into three main components:

$$u_{ijt} = \underbrace{\delta_{ijt}}_{\text{experience/taste}} - \underbrace{\alpha_i p_{jt}}_{\text{price paid}} - \underbrace{w'_{jt}\phi_i}_{\text{health consequences}} . \tag{3}$$

The first component, denoted by δ_{ijt}, corresponds to the aspect of utility that comes from the experience of consuming product j and is assumed to be observed by consumers when making the decision to buy the product. It is a function of the product's characteristics (e.g., sweetness, mouthfeel, smell) and other individual-level and time-varying demand shocks (e.g., idiosyncratic preferences for some products, hunger relief, food craving). In particular, we assume that

$$\delta_{ijt} = r'_j\beta_i + \delta_{jb} + \delta_{T(t)b} + \delta_{S(t)b} + \xi_{jtb} + \epsilon_{ijt}, \tag{4}$$

where β_i represents individual preferences for different subcategories; δ_{jb}, $\delta_{T(t)b}$, and $\delta_{S(t)b}$ are product, period, and store fixed effects, respectively, all specific to each consumer type; and ξ_{jtb} is a product-market-type specific idiosyncratic demand shock. ϵ_{ijt} is a consumer-specific demand shock that jointly follows a generalized extreme value distribution that follows the distributional assumptions of a one-nest nested logit model, where all inside goods are in the same nest. We denote the intra-nest correlation by ρ. We assume that $\beta_i \sim \mathcal{N}(0, \Sigma_\beta)$.

Note that this model specification does not allow the experience aspect of the utility to vary with changes in nutritional content, w_{jt}. As we will discuss later, we restrict firms to reformulations that maintain the taste of products constant. In other words, when changing w_{jt}, firms replace critical nutrients with alternative ingredients that maintain the sweetness, mouthfeel, smell, and other perceivable attributes.

The second element in the utility function, $\alpha_i p_{jt}$, corresponds to the disutility derived from paying price p_{jt} for product j. The parameter $\alpha_i \sim \log \mathcal{N}(\alpha_b, \sigma_\alpha)$ governs the price elasticity.

Finally, $w_{jt}'\phi_i$ corresponds to the negative long-term health consequences of consuming unhealthy products. The parameter $\phi_i \sim \log \mathcal{N}(\phi_b, \Sigma_\phi)$ represents the marginal damage perceived by consumer i from consuming additional critical nutrients w_{jt}.[6] Consumers do not know the true nutritional content, w_{jt}, but have prior beliefs, π_{ij}, about it. We assume that prior beliefs, π_{ij}, follow a normal distribution $\mathcal{N}(\mu_{jb}, \Omega_{jb})$. This allows both moments of the beliefs distribution to vary across products and consumer type. Additionally, we assume that the non-diagonal elements of Ω_{jb} are zero. This implies that sugar labels do not change beliefs about calories and vice versa.

Based on their beliefs, consumer i chooses the product that maximizes their expected utility:

$$\mathbb{E}_{\pi_{ij}}[u_{ijt}] \quad = \quad \delta_{ijt} - \alpha_i p_{jt} - \mathbb{E}_{\pi_{ij}}[w_{jt}|L_{jt}]'\phi_i, \tag{5}$$

where $\mathbb{E}_{\pi_{ij}}$ denotes the expectation operator over prior beliefs π_{ij} and $L_{jt} \in \{\text{pre-policy}, \text{no}, \text{yes}\}$ denotes the label status of product j in market t. We assume that consumers form their beliefs by using the observed labels (or lack thereof) and applying Bayes' rule.[7]

We denote the set of consumers that choose product j in market t by

$$\Theta_{jt} \quad = \quad \{i \in \mathcal{I}_t : \mathbb{E}_{\pi_{ij}}[u_{ijt}] \geq \mathbb{E}_{\pi_{ki}}[u_{ikt}], \ \ \forall k \in \mathcal{J}_t\}, \tag{6}$$

where $\mathcal{J}_t$ is the set of products available in market t, which includes the outside good, and $\mathcal{I}_t$ is the set of consumers who shop at least one time in supermarket $S(t)$, which we normalize to have mass one. The market share of product j in market t is given by $s_{jt} = \int_{i\in\Theta_{jt}} di$, while the share of consumers of type b who prefer product j in market t is given by $s_{jtb} = \int_{i\in\Theta_{jt}\cap b} di / \int_{i \in b} di$.

Modeling beliefs in our setting is essential. A model that ignores beliefs and in which labels enter into the utility function directly can lead to misleading conclusions. Only

[6] Note that ϕ_i does not need to be the same for consumers and the social planner. So far, we are mostly interested in modeling consumer behavior. In Section 6, in which we discuss the normative implications of the model, we extend it to accommodate additional market imperfections such as lack of self-control or time inconsistency.

[7] We assume that consumers do not take into account product reformulation. We make this assumption for two reasons. First, interviews with consumers in Chile suggest that they did not realize that products may be bunching at the regulatory nutritional thresholds. Second, this assumption simplifies the calculation of consumers' posteriors and the solution of the market equilibrium.

including a label dummy for the post-policy period would not capture the heterogeneity in responses that we observe in Figure 1(b). In the cereal market, products with a high-in-sugar label are also products that were already known to be high in calories and sugar. As a result, the products most affected by the policy were those that got a high-in-calories label but not a high-in-sugar one and were believed to be low in calories. A model that assumes beliefs away would have interpreted this result as consumers disliking high-in-calorie labels but liking high-in-sugar ones. Once we consider beliefs, we find that consumers dislike high concentrations of both calories and sugar. Not fully capturing the effects in demand would also lead to misleading incentives from the supply side when choosing which products to reformulate.

In Online Appendix C, we explore the implications of the main assumptions embedded in our demand model. We investigate the importance of using a static model, excluding salience effects, assuming invariant taste, and disregarding advertisement effects. We justify these modeling decisions and show that our primary findings are robust to modifying these assumptions.

4.2. *Estimation and identification*

To estimate the model, we aggregate the data at the product-store-period-consumer-type level. We estimate the model using the generalized method of moments proposed by Berry et al. (1995), but fixing consumer-type-level shares, s_{jtb}, at the observed levels. The estimating moment conditions are given by $\mathbb{E}[\xi_{jtb} Z_{jtb}] = 0$, where ξ_{jtb} is the demand shock from Equation (4) and Z_{jtb} are instruments that we describe below. We now discuss what variation in the data identifies each parameter and what instruments we use to exploit such variation.

4.2.1. *Price coefficient*: To identify α_b, the first moment of the price coefficient, we construct simulated instruments using the price of cereal inputs (Backus et al., 2021). We collected the ingredients list of each cereal product, with the corresponding percentages of the main ingredients on them (e.g., Cheerios has 29% of corn, 21% of wheat, and 8% of oats), and combined it with historical price data on commodities from www.nasdaq.com to run the following regression:

$$p_{jt} = \sum_k \beta_k \upsilon_{kt} \varsigma_{kj} + d_j + d_{T(t)} + d_{S(t)} + \eta_{jt}, \tag{7}$$

where υ_{kt} is the price of commodity k in period $T(t)$ and ς_{kj} is the share of commodity k contained in product j in the pre-policy period. We include product, period, and store fixed effects. Commodities are corn, wheat, and oats. We then construct a price predictor given by

$$\hat{p}_{jt} = \sum_k \hat{\beta}_k \upsilon_{kt} \varsigma_{kj} + \hat{d}_j + \hat{d}_{T(t)} + \hat{d}_{S(t)}. \tag{8}$$

We use $\hat{p}_{jt}$ as an instrument for p_{jt}. It captures changes in prices that come from changes in commodity prices, and that are orthogonal to unobserved changes in demand. Since α_b takes different values for each consumer type, we interact the instrument with a consumer-type dummy.

4.2.2. *Preferences for beliefs about health consequences*: The identification of ϕ_i, the preferences over the perceived health consequences of consuming sugar and calories, and (μ_{jb}, Ω_{jb}), the parameters that govern the distribution of beliefs, is more difficult. In order to separate beliefs from preferences, we use information from the survey. We assume that the responses collected by the beliefs survey are informative about the ranking of and relative distance between μ_{jb} and μ_{kb}—the first moment of beliefs about the nutritional content of two different products—but that their absolute levels may be wrong.[8] We allow for the first moment of beliefs to be determined by $\mu_{jb} = \tilde{\mu}_{jb} + \mu$, where $\tilde{\mu}_{jb}$ is the average survey response regarding the expected value of nutritional content of product j among consumers of type b, and μ is a free parameter in our model that shifts the expected value of the nutritional content of all products among all consumers by a constant amount.[9]

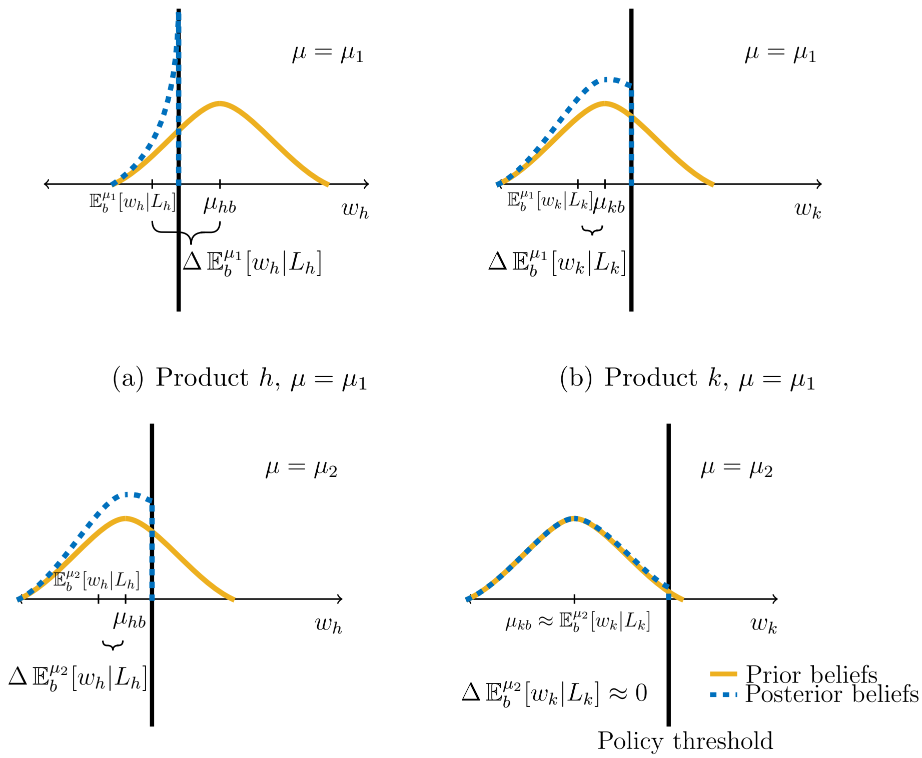
We take Ω_{jb}, the second moment of beliefs about the nutritional content of each product, directly from the answers on the survey.

Combining the responses from the survey with the Bayesian model adds enough structure to jointly identify ϕ_b and μ. Figures 2 and 3 provide the intuition behind our identification strategy. To explain it, we illustrate the model prediction of changes in expected utility for two products, h and k (with $\tilde{\mu}_{hb} > \tilde{\mu}_{kb}$), at two parameter values, $\mu = \mu_1$ and $\mu = \mu_2$ (with $\mu_1 > \mu_2$).

In Figure 2, we plot the distribution of prior and posterior beliefs for products h and k conditional on not receiving a label. For ease of exposition, we assume that $\Omega_h = \Omega_k$.

[8] We rely on the survey data for information on the relative levels, but not on the absolute levels of believed nutritional content of each product. We piloted three different survey designs, varying the reference products shown to respondents. We found that the levels of consumer responses were sensitive to the choice of the reference points, but the ranking and relative distance between answers for different products were robust across the survey designs.

[9] We normalize the elements of $\tilde{\mu}_b$ to have mean zero and the same variance as w^{pre} across products. The normalization implies that, in terms of changes in expected utility, a change in beliefs of 1 standard deviation is equivalent to a change in nutritional content of 1 standard deviation if nutritional content was observed. μ is measured in standard deviations and is constant for both nutrients.



(a) Product h, $\mu = \mu_1$ (b) Product k, $\mu = \mu_1$

(c) Product h, $\mu = \mu_2$ (d) Product k, $\mu = \mu_2$

Figure 2: Model-implied change in beliefs about about nutritional content, w, for products h and k at different values of μ upon not receiving a label

Notes: The figure illustrates the changes in beliefs about nutritional content, w, for products h and k when they do not receive a label. Product h is believed to have a higher concentration of the critical nutrient, w, than product k. Larger values of μ shift the distribution of beliefs to the right. In each panel, the yellow solid line represents the distribution of prior beliefs and the blue dashed line represents the distribution of posterior beliefs. In panels (a) and (b), we plot the distribution of prior and posterior beliefs when $\mu = \mu_1 > \mu_2$ for products h and k, respectively. In panels (c) and (d) we plot the distribution of prior and posterior beliefs when $\mu = \mu_2 < \mu_1$ for products h and k, respectively. The figure shows that changes in beliefs upon not receiving a label are larger when μ is larger. Moreover, the differences in changes in beliefs between products h and k is also larger when μ is larger.

In panels (a) and (b), we plot beliefs when $\mu = \mu_1$, and in panels (c) and (d) when $\mu = \mu_2$. To recover posterior beliefs (dashed lines), we truncate prior beliefs at the policy threshold, which is invariant to μ. We denote the absolute change in the expected value of w_j induced by the labeling policy at parameter value μ by $\Delta\,\mathbb{E}^{\mu}[w_j|L_j]$, where $j = \{h, k\}$. Intuitively, $\Delta\,\mathbb{E}^{\mu_1}[w_j|L_j] > \Delta\,\mathbb{E}^{\mu_2}[w_j|L_j]$ for $j = \{h, k\}$ when $\mu_1 > \mu_2$. Moreover, $\Delta\,\mathbb{E}^{\mu_1}[w_h|L_h] - \Delta\,\mathbb{E}^{\mu_2}[w_h|L_h] > \Delta\,\mathbb{E}^{\mu_1}[w_k|L_k] - \Delta\,\mathbb{E}^{\mu_2}[w_k|L_k]$ for all (h, k) such that $\tilde{\mu}_{hb} > \tilde{\mu}_{kb}$. This nonlinear behavior of $\Delta\,\mathbb{E}^{\mu}[w_j|L_j]$ with respect to $\tilde{\mu}_{jb}$ and μ allows us to identify μ separately from ϕ_b.

We use Figure 3 to illustrate how the nonlinearity of $\Delta\,\mathbb{E}^{\mu}[w_j|L_j]$ with respect to $\tilde{\mu}_{jb}$

and μ helps us identify these parameters. The figure shows the change in expected utility from consuming product j as a function of $\tilde{\mu}_{jb}$. The solid line corresponds to $\mu = \mu_1$ and the dashed line to $\mu = \mu_2$. Different values of μ have different implications for the relative difference between the change in expected utility of products h and k. For large values of μ, the increase in expected utility from consuming product h will be larger than that from consuming product k. For small values of μ, the increase in expected utility will be small and similar for the two products.

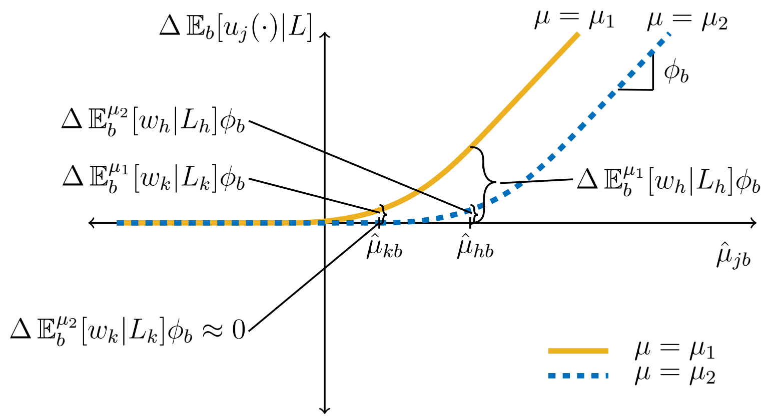


Figure 3: Model-implied change in expected utility for product h and k at different values of μ upon not receiving a label

Notes: The figure illustrates the change in expected utility from consuming product j as a function of $\tilde{\mu}_{jb}$ for two different values of μ, where $\tilde{\mu}_{jb}$ is the average survey response regarding the expected value of nutritional content of product j among consumers of type b. The yellow solid line conveys this relationship for $\mu = \mu_1$ and the blue dashed line for $\mu = \mu_2$. The figure shows that different values of μ imply different changes in expected utility for products that do not get a label. Lower values of μ translate into small changes in expected utility for a broader set of products.

Changes in expected utility present a kink-like structure, where μ determines the position of the kink in the $\tilde{\mu}_{jb}$ space. All unlabeled products to the left of the kink will experience small changes in expected utility. All unlabeled products to the right of the kink will experience an increase in expected utility. For products to the right of the kink, the increase in expected utility will be larger when $\tilde{\mu}_{jb}$ is higher. The differential change in expected utility between products implies a differential change in observed market shares. The shape of the change in observed market shares will identify the position of the kink and, therefore, the value of μ. The parameter ϕ_b, on the other hand, will determine the rate at which the change in expected utility increases with $\tilde{\mu}_{jb}$, which is given by the slope of the right side of the curve in Figure 3. Thus, ϕ_b will be identified by the relative differences in the changes of observed demand between products on the right side of the kink.

To bring this to the data, we first construct a predictor, $\hat{L}_{jt}$, of whether a product gets labeled or not that is uncorrelated with potential demand shocks, ξ_{jtb}. The predictor uses the cereal categories r_j and the pre-policy nutritional content as inputs, and estimates a random forest model to avoid overfitting. Distance from the policy threshold in the pre-policy period and heterogeneity in the cost of departing from the threshold driven by r_j explain most of the bunching, which provides us with an instrument that is highly correlated with labeling status. We then split products into different bins based on answers on the survey regarding the first moments of beliefs, $\tilde{\mu}_{jb}$. We denote these bins by B_μ. As illustrated in Figure 3, the model provides sharp predictions about how demand should change as a function of prior beliefs μ_{jb} and label status L_{jt}. By minimizing the moments $\mathbb{E}[\hat{L}_{jt} \times B_\mu \times \hat{\xi}_{jtb}]$, we impose conditions over $\hat{\xi}_{jtb}$ that prevent the patterns in Figure 3 from being explained by differential demand shocks. Without these moment restrictions, our model could explain the fact that products believed to be low in calories but which received a high-in-calories label experienced a reduction in demand, by assigning negative demand shocks to such products in the post-policy period. These moment conditions prevent such distribution of shocks, and thus identify ϕ_b and μ.

4.2.3. *Preference heterogeneity*: Finally, we need to identify Σ_β, σ_α, Σ_ϕ, and ρ, which are the parameters that govern the substitution patterns between different products and to the outside good. To do so, we construct three sets of market-level instruments. The first two sets of instruments exploit changes in competitors' cost-shifters, which through changes in prices should shift the probability that consumers substitute from one product to the other. The third set of instruments exploits the entrance of new products to the market that induce changes in the competitive environment. Let τ_{jt} be the first time a given product enters supermarket $S(t)$. Then, the three set of instruments are given by

$$z_t^{r,1} = \underset{j\in r,t}{\text{mean}}\{\hat{p}_{jt}\}, \qquad z_t^{r,2} = \underset{j\in r,t}{\text{pctile}^{20,80}}\{\hat{p}_{jt}\}., \qquad z_t^{r,3} = \sum_{j\in r,t} \mathbb{1}\{t \geq \tau_{jt}\}.$$

The first set of instruments corresponds to the average price predictor of all products in each cereal category r and market t. The intuition behind the instrument is that when commodities usually used in a given subcategory, r, are cheap, consumers will be more likely to substitute toward products in that subcategory. For example, if oat prices in a given period are low, we should expect to see more substitution toward oat products in that period.

The second set of instruments corresponds to the 20th and 80th percentiles of the price predictor among all products in a given cereal category r and market t. These instruments work in a fashion similar to the first set of instruments, but add additional moments of the predicted price distribution of competitors' products, which increases statistical power.

The third set of instruments exploits the timing of the entrance of different brands into different stores. These instruments measure the total number of products from each subcategory, r, that have ever entered store $S(t)$ before period $T(t)$. The identifying assumption is that the first entry of a product at the supermarket level is not correlated with demand shocks. We believe this is a reasonable assumption given that Walmart is increasing its assortment in many product categories, including cereal (see Online Appendix B). At the beginning of the sample period, there are on average 52 products available in each market. By the end of the sample period, the average number of available products per market grows up to 73 products. Empirically, the increase in product assortment is not correlated with the timing of the policy. The intuition behind the instruments is that when more products are available and variety increases, consumers are less likely to substitute toward the outside option, which helps us to identify ρ.

4.3. *Results*

Our estimated demand parameters are presented in Table 1. Our estimates imply an average own-price elasticity of -3.1, with a higher absolute elasticity among low SES households (-3.33 vs. -2.74). We also find that products in the same subcategory, r_j, are closer substitutes. We present the matrix of own- and cross-price elasticities of the most important products from each subcategory in Online Appendix A, Table A.1. These elasticities imply median markups—defined as the ratio of price minus marginal cost to price—of 46% in the pre-policy period.[10] These results are similar to those in previous papers that estimate demand for cereal in the U.S. market and find elasticities between -2.3 and -4.3 and median markups of 34%-42% (Nevo, 2001; Michel and Weiergraeber, 2018; Backus et al., 2021). Our estimates are also comparable to accounting estimates provided by the Chilean antitrust agency, which estimates markups of 45% for the largest cereal brand in Chile (FNE, 2014).

The estimates for ϕ_i indicate that an average consumer is willing to pay 9.9% and 7.6% of the average price of cereal to reduce the sugar and caloric concentration of products, respectively, by 1 standard deviation (12 grams of sugar and 25 kilocalories per 100 grams of cereal, respectively), while keeping the taste constant. For example, *Original Cheerios* contains 5 grams of sugar per 100 gram, while *Honey Nut Cheerios* contains 32.5 grams of sugar per 100 grams. According to our model, consumers would be willing to pay \$0.7 more for a 550 grams family size box of *Honey Nut Cheerios* if it contained the sugar content of *Original Cheerios* but kept its own taste. In Figure 4, we show the distribution

[10] We present the full distribution of markups in Online Appendix A, Figure A.2.

Table 1: Estimated demand parameters

Panel A: Preferences for price and healthiness (α_i, ϕ_i)								
	First moments				Second moments			
	low-SES		high-SES		low-SES		high-SES	
Price (α_i)	$\bar{\alpha}_l$	0.255***	$\bar{\alpha}_h$	0.189***	σ_{α_l}	0.152***	σ_{α_h}	0.113***
		(0.072)		(0.059)		(0.034)		(0.036)
Sugar (ϕ_i^s)	$\bar{\phi}_l^s$	0.013***	$\bar{\phi}_h^s$	0.013**	$\sigma_{\phi_l^s}$	0.054	$\sigma_{\phi_h^s}$	0.055
		(0.004)		(0.005)		(0.151)		(0.153)
Calories (ϕ_i^c)	$\bar{\phi}_l^c$	0.026***	$\bar{\phi}_h^c$	0.025***	$\sigma_{\phi_l^c}$	0.028	$\sigma_{\phi_h^c}$	0.028
		(0.007)		(0.008)		(0.019)		(0.017)

Panel B: Individual preferences for different subcategories (Σ_β)									
Plain		Sugary		Chocolate		Granola		Oatmeal	
$\sigma_{\beta_{r_1}}$	0.058	$\sigma_{\beta_{r_2}}$	0.195	$\sigma_{\beta_{r_3}}$	0.215	$\sigma_{\beta_{r_4}}$	0.036	$\sigma_{\beta_{r_5}}$	0.295
	(0.145)		(0.186)		(0.139)		(0.167)		(0.361)

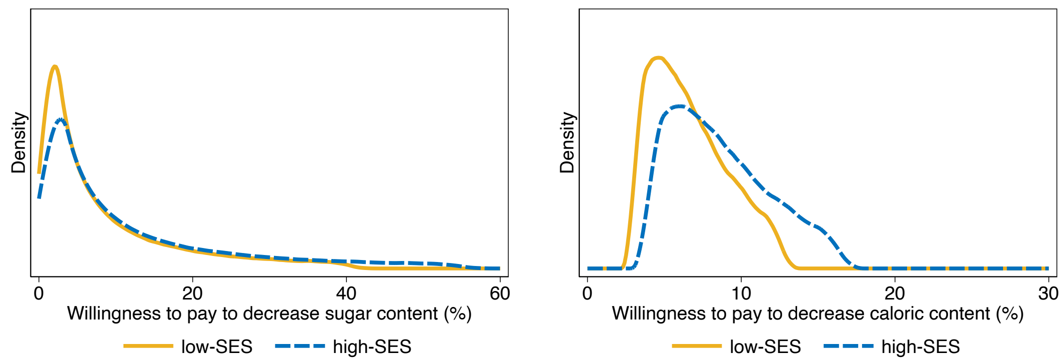
Panel C: Remaining parameters (ρ, μ)		
Nest parameter	ρ	0.959***
		(0.004)
Beliefs shifter	μ	-0.129***
		(0.019)

Notes: Nutritional content is measured in grams of sugar and kilocalories per gram of cereal, and prices in dollars per 100 grams of cereal. Subscripts l and h correspond to parameters for low- and high-SES consumers, respectively. For random parameters $x_i \in \{\alpha_i, \phi_i, \beta_i\}$, we report their average $\bar{x}$ and standard deviation σ_x. Standard errors are calculated using the delta method and reported in parentheses.

of willingness to pay among low- and high-SES consumers to reduce the sugar and caloric concentration of products by 1 standard deviation, while keeping the taste constant. We find substantial consumer heterogeneity, especially for preferences over sugar content.

We find an intra-nest correlation of $\rho = 0.96$, which suggests that there is little substitution from inside goods to the outside good. This should be taken with caution as it is larger than that estimated in the previous literature. However, we show in Online Appendix A, Figure A.3, that our main results are qualitatively similar when we impose a lower value of ρ.[11] Finally, μ shifts beliefs about sugar and caloric concentration by 0.13

[11] At face value, the estimated substitution to the outside option would have unrealistic implications for how a monopolist in this market would behave. It could also affect the interpretation of our tax counterfactual as the overall demand for cereal would be insensitive to higher taxes.



(a) Sugar

(b) Calories

Figure 4: Willigness to pay to reduce sugar and caloric concentration for low- and high-SES consumers

Notes: The figure presents willingness to pay, as a percentage of the average price of cereal, among low- and high-SES consumers to reduce the sugar and caloric concentration of products by 1 standard deviation while keeping the taste constant. To calculate willingness to pay, we use the following formula: $\text{wtp}_i = \frac{\phi_i}{\alpha_i}\frac{sd(w_{jt})}{\bar{p}_{jt}}$. The parameters that govern the distributions of ϕ_i and α_i are reported in Table 1.

standard deviations downward.[12]

5. Supply: pricing and nutritional content

5.1. *Supply model*

Each firm f has a bundle of products $\mathcal{J}_f$ that it can produce. To produce a given product j, firms use two types of inputs: critical nutrients w_{jt} (e.g., sugar), and other inputs m_{jt} (e.g., sucralose, polyols).[13] The taste of a product depends on the concentration of these inputs and is given by a product-specific production function $\delta_j(w_{jt}, m_{jt})$. We restrict firms to reformulations that maintain the product's taste, $\bar{\delta}_j$, constant. That is, when firms reformulate their products, they choose inputs to always achieve the same level of sweetness, crunchiness, smell, etc. This is consistent with industry participants' descriptions of how reformulation was accomplished.[14] Since taste, $\bar{\delta}_j$, is invariant, firms

[12]We plot the estimated values of μ_{jb} in Online Appendix A, Figure A.4. Regarding Ω_j, its diagonal elements range from 20-40$\left(\frac{\text{g}}{100\text{ g}}\right)^2$ for sugar and 200-325$\left(\frac{\text{kcal}}{100\text{ g}}\right)^2$ for calories.

[13]Note that other inputs, m_{jt}, might also have adverse health consequences. In our model, we let the policymaker decide what nutrients are considered harmful (i.e., what nutrients are included in the vector w_{jt}) and assume all other inputs to be harmless.

[14]We interviewed the consumer product managers of the two largest cereal companies. They confirmed that an explicit goal of the reformulation process is that the new version of the product is indistinguishable from the previous one. To achieve this, firms follow several steps that include conducting expert focus groups and randomized blind tests.

need to choose w_{jt} and m_{jt} such that

$$\delta_j(w_{jt}, m_{jt}) = \bar{\delta}_j \tag{9}$$

The cost of producing a product depends on the nutritional content w_{jt}, other inputs m_{jt} and an additive cost-shifter ϑ_{jt}:

$$\tilde{c}_{jt}(w_{jt}, m_{jt}) \quad = \quad p_w w_{jt} + p_m m_{jt} + \vartheta_{jt}. \tag{10}$$

From Equations (9) and (10) we can redefine the marginal cost of producing product j as

$$c_{jt}(w_{jt}) = p_w w_{jt} + p_m m_j(w_{jt}, \bar{\delta}_j) + \vartheta_{jt}, \tag{11}$$

where $m_j(w_{jt}, \bar{\delta}_j)$ is the inverse function of $\delta_j(w_{jt}, m_{jt})$ in Equation (9), provided that $\delta_j(w_{jt}, m_{jt})$ is invertible.

Let ν_j, which we will call the *bliss point* of product j, be the value of w_{jt} that minimizes marginal cost (i.e., ν_j is such that $\nabla c_{jt}(\nu_j) = 0$). The bliss point is an attribute of the product and corresponds to the concentration of critical nutrients that product j should have to achieve taste $\bar{\delta}_j$ at minimum cost. In the cereal market, for example, we should expect *Honey Nut Cheerios* to have a higher bliss point for sugar than *Original Cheerios*, since the former is a sweetened version of the latter.

Departing from the bliss point is possible but costly. For example, after the food labeling policy was introduced, firms in the breakfast cereal market replaced sugar with artificial alternatives such as sucralose and polyols.[15] This reformulation results in a more expensive product, captured in our model by the functional form of $c_{jt}(w_{jt})$. For each product, we approximate the marginal cost function by a second-order Taylor polynomial around the bliss point, such that

$$c_{jt}(w) = \underbrace{\bar{c}_{jt}}_{\text{baseline cost}} + \underbrace{(w - \nu_j)'\Lambda_j(w - \nu_j)}_{\text{change in cost due to reformulation}}, \tag{12}$$

where $\Lambda_j = \begin{bmatrix} \lambda_j^s & 0 \\ 0 & \lambda_j^c \end{bmatrix}$ with $\lambda_j^n > 0$ for $n \in \{s, c\}$ and all products j. We assume that λ_j^n is drawn from a lognormal distribution with parameters $(\mu_\lambda^n, \sigma_\lambda^n)$, where $\mu_\lambda^c = \bar{\mu}_\lambda^c + \vartheta_\lambda^c \nu_j^s$ while $\mu_\lambda^s = \bar{\mu}_\lambda^s$. This allows for the cost to reformulate calories to depend on the baseline

[15] We collected data on specific ingredients of 17 out of the 20 products that reformulated in our sample. We found that after the policy is implemented, 47% start using maltitol (a type of polyols), 29% sucralose, and 35% stevia.

sugar concentration of the product. However, having zeros on the non-diagonal elements of Λ_j implies that the costs of marginally reducing sugar and caloric concentration are not correlated. These assumptions are consistent with the data, where we find low correlation between caloric and sugar content and between changes in these induced by reformulation, but we find that high-in-sugar products were less likely to reformulate calories.

The firm's profit maximization problem is given by

$$\max_{\{p_{jt}, w_{jt}\}_{j \in \mathcal{J}_{ft}}} \quad \sum_{j \in \mathcal{J}_{ft}} (p_{jt} - c_{jt}(w_{jt})) \cdot s_{jt}(\mathbf{p_t}, \mathbb{E}_\pi[\mathbf{w_t}|\mathbf{L_t}]), \tag{13}$$

where s_{jt} is the market share of product j in market t, which depends on the vector of all prices $\mathbf{p_t}$ and all individuals' expectations about the nutritional content of all products in the market, $\mathbb{E}_\pi[\mathbf{w_t}|\mathbf{L_t}]$. In the absence of any government intervention, the firm chooses

$$w^*_{jt} = \nu_j \tag{14}$$

$$p^*_{jt} = c_{jt}(w^*_{jt}) + \Delta^{-1}_{(j,\cdot)}\mathbf{s_t}, \tag{15}$$

where the (j, k) element of Δ is given by

$$\Delta_{(j,k)} = \begin{cases} \frac{-\partial s_k}{\partial p_j} & \text{if } k \in \mathcal{J}_{ft} \\ 0 & \text{otherwise,} \end{cases} \tag{16}$$

and $\Delta^{-1}_{(j,\cdot)}$ is the jth column of the inverse of Δ. Equation (14) states that firms will choose the nutritional content of product j to be equal to its bliss point.[16] Equation (15) implies price-cost markups given by $\Delta^{-1}_{(j,\cdot)}\mathbf{s_t}$, where $\Delta^{-1}_{(j,\cdot)}$ takes into account that by increasing price j, demand for other products produced by firm f might increase.

When the food labeling regulation is in place, the demand function $s_{jt}(\mathbf{p_t}, \mathbb{E}_{\mathcal{I}_t}[\mathbf{w_t}|\mathbf{L_t}])$ becomes discontinuous in w_{jt} at the threshold. Firms have incentives to reduce the nutritional content of products whose bliss points are to the right of, but close to, the threshold. By marginally increasing the production cost of a product close to the threshold, firms can choose w_{jt} to be right below the threshold, thus changing consumers' conditional expectations and inducing large increases in demand. This explains the bunching observed in the data.

In Online Appendix D, we explore the implications of the main assumptions embedded in our supply model. We study the importance of the firms choices' timing in choosing

[16] In the absence of any policy, demand does not depend on w_{jt} or m_{jt}. In that case, the firm's optimal decision is to choose a combination of w_{jt} and m_{jt} that minimizes marginal cost.

prices and nutritional content and of assuming that reformulation does not change the taste of products but increases marginal cost. We justify these modeling decisions and show that our primary findings are robust to modifying these assumptions.

5.2. *Estimation*

To estimate the supply model, we need to recover three key parameters: (a) the marginal cost of producing a product in the absence of reformulation, $\bar{c}_{jt}$, (b) the products' bliss points, ν_j, and (c) the cost of reformulating, Λ_j, which is determined by $(\bar{\mu}^n_\lambda, \sigma^n_\lambda, \vartheta_\lambda)$.

We recover $c_{jt}(w^*_{jt})$ and ν_j from the firm's first-order conditions (Equations (14) and (15)). We then estimate $\bar{\mu}^n_\lambda$, σ^n_λ, and ϑ_λ by exploiting variation in firms' decisions to bunch.

Using our demand estimates, we compute the equilibrium at the current parameters and labels. We then ask, for each product, what would be the value of λ^n_j that would render firm $f(j)$ indifferent between choosing the bliss point level ν^n_j or having product j bunching at the threshold, keeping all other products' nutritional content decisions fixed. We denote the indifference value by $\tilde{\lambda}^n_j$. Then, the probability that product j bunches in nutrient n is given by $P_{B^n_j} = Pr(\lambda^n_j \leq \tilde{\lambda}^n_j)$.[17]

We estimate $(\mu^n_\lambda, \sigma^n_\lambda)$ for $n \in \{s, c\}$ and ϑ_λ via GMM by imposing that the difference between the probability of bunching, $P_{B^n_j}$, and whether a product bunches or not, B^n_j, has mean zero and is uncorrelated with the product's bliss point ν_j:

$$
\begin{aligned}
\mathbb{E}[(B^n_j - P_{B^n_j})] &= 0 \quad \text{for } n \in \{s, c\} \\
\mathbb{E}[(B^n_j - P_{B^n_j})\nu^n_j] &= 0 \quad \text{for } n \in \{s, c\} \\
\mathbb{E}[(B^c_j - P_{B^c_j})\nu^s_j] &= 0.
\end{aligned}
$$

Once we estimate $(\mu^n_\lambda, \sigma^n_\lambda)$, we calculate $\bar{c}_{jt}$ by solving

$$
\bar{c}_{jt} = c_{jt}(w_{jt}) - \mathbb{E}_\lambda[(w_{jt} - \nu_j)'\Lambda_j(w_{jt} - \nu_j)|B_j]. \tag{17}
$$

5.3. *Results*

Our estimated supply parameters are presented in Table 2. To interpret these parameters, we calculate $\mathbb{E}[\lambda^n_j|B^n_j = 1]$, the expected value of λ^n_j conditional on product j

[17] Note that λ^n_j is not point-identified. From the data, we learn that for products bunching in nutrient n, $\lambda^n_j \leq \tilde{\lambda}^n_j$, and that for products not bunching in nutrient n, $\lambda^n_j > \tilde{\lambda}^n_j$. However, we cannot recover the exact value of λ^n_j. Treating λ^n_j as a random coefficient drawn from a known distribution allows us to overcome this identification problem.

bunching in nutrient n. We find an average value of $0.151\frac{\text{¢}}{(\text{g}/100\text{ g})^2}$ in the case of sugar and $0.016\frac{\text{¢}}{(\text{kcal}/100\text{ g})^2}$ in the case of calories. The average reduction in sugar concentration among products bunching in sugar is 8.2 grams per 100 grams, while the average reduction in caloric concentration among products bunching in calories is 24.9 kilocalories per 100 grams. Putting everything together, our model finds that the average expected increase in marginal cost for products bunching in any nutrient is 2.8¢ per 100 grams, which is equivalent to 4.4% of the average price of cereal.

Table 2: Estimated supply parameters

Panel A: Costs to reformulate sugar					
$\bar{\mu}^s_\lambda$	-1.832**	σ^s_λ	1.143*		
	(0.839)		(0.677)		
Panel B: Costs to reformulate calories					
$\bar{\mu}^c_\lambda$	-2.349	σ^c_λ	1.874 *	ϑ^c_λ	1.546**
	(1.946)		(0.967)		(0.687)

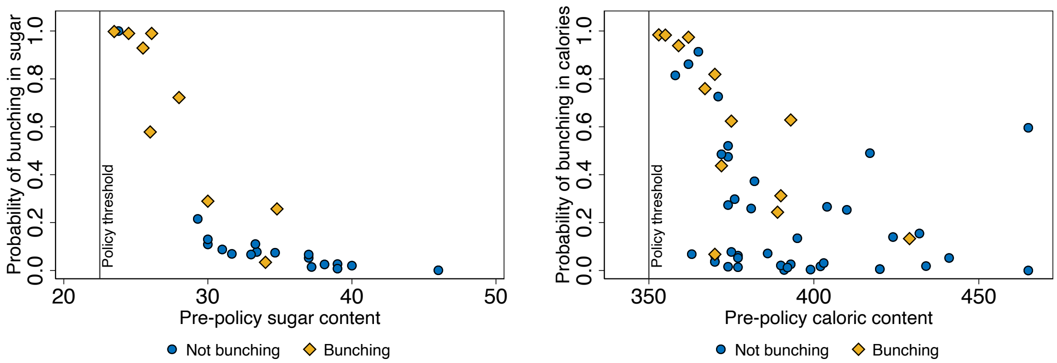
Notes: The table presents the estimated parameters that govern the distribution of $\Lambda_j = \begin{bmatrix} \lambda^s_j & 0 \\ 0 & \lambda^c_j \end{bmatrix}$, the cost of reformulating sugar and calories. We assume that λ^n_j is drawn from a lognormal distribution with parameters $(\mu^n_\lambda, \sigma^n_\lambda)$, where $\mu^c_\lambda = \bar{\mu}^c_\lambda + \vartheta^c_\lambda \nu^s_j$ while $\mu^s_\lambda = \bar{\mu}^s_\lambda$. To estimate the parameters, we measure nutritional content in 10 grams of sugar and 100 kilocalories per 100 grams of cereal, respectively. Standard errors are presented in parentheses. $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

To assess the accuracy of our estimates, we run a regression to calculate how our estimates of marginal cost, $c_{jt}(w^*_{jt})$, differ between products that did and did not bunch at nutritional thresholds and compare them with the change in marginal cost implied by our estimated supply parameters that govern Λ_j. To do this, we estimate the following equation:

$$c_{jt}(w^*_{jt}) = \beta \cdot B_j \cdot Post_t + \delta_{js} + \delta_t + \varepsilon_{jt}, \tag{18}$$

where $c_{jt}(w^*_{jt})$ is computed using the firm's first-order conditions, B_j is a dummy indicating whether product j is bunching in the post-period, and δ_{js} and δ_t are product-store and period fixed effects, respectively. The estimated coefficient $\hat{\beta}$ from Equation (18) suggests an average change in marginal cost of 3.1¢ per 100 grams, slightly larger than the 2.8¢ per 100 grams derived from Equation (17) of our model.

We also compare the model-based predicted probability of each product bunching in a given nutrient with what actually happened in the data. Figure 5 shows the probability of bunching predicted by the model for each product to the right of the policy threshold. Products in gray are products that bunched in the data and did not receive a label. Products in color are those that did not bunch. The model predicts correctly that products ex ante closer to the threshold are more likely to bunch.



(a) Sugar

(b) Calories

Figure 5: Predicted probability of bunching

Notes: The figure shows the predicted probability of each product bunching in sugar and calories as a function of the pre-policy nutritional content and the distance from the regulatory threshold for each critical nutrient. In Panel (a), we focus on sugar content. Products in yellow diamonds are products that bunched in the data and crossed the sugar policy threshold. Products in blue circles are products that did not bunch and received a "high-in-sugar" label. In Panel (b), we focus on caloric content. Products in yellow diamonds are products that bunched in the data and crossed the calorie policy threshold. Products in blue circles are products that did not bunch and received a "high-in-calorie" label.

In Online Appendix A, Figure A.5, we also show that our model correctly predicts that products for which prior beliefs about nutritional content were lower have a higher probability to bunch.

6. The impact of food labeling policies

In this section, we use our model to evaluate the effects of food labeling policies on nutritional intake and overall welfare. We start by simulating the Chilean Food Act under several counterfactuals that isolate different economic forces. We then study optimal policy design and compare food labels with sugar taxes, which is the most prominent alternative policy instrument.

6.1. *Equilibrium effects of food labels*

We estimate the effects of the Chilean Food Act on consumer choices, firms' production and pricing decisions, nutritional intake, and consumer welfare. To disentangle the roles of demand and supply in changes in nutritional intake and consumer welfare, we run four counterfactuals. The first counterfactual, denoted by (0), *no intervention*, corresponds to the case in which no policy is in place. To isolate demand forces, we compare the no-intervention benchmark with a situation in which products receive labels according to the regulatory thresholds and suppliers are not allowed to respond. We denote this counterfactual by (1), *demand only*. We then compute counterfactual (2), *price response*, in which—in addition to receiving labels—we allow suppliers to optimally choose prices while keeping nutritional content constant. We use counterfactual (2) to measure additional changes in consumer welfare driven by competition and product differentiation, which can either decrease or increase prices. The differences in consumer welfare between (1) and (2) are thus ambiguous. Finally, we compute counterfactual (3), *equilibrium*, in which we also allow firms to change the nutritional content of their products. This corresponds to the equilibrium model presented in Sections 4 and 5. The expected change in consumer welfare from counterfactual (2) to (3) is also ambiguous. Although firms improve product quality by reducing the concentration of critical nutrients, production costs increase, which leads to higher prices for consumers. Whether the policy under counterfactual (3) increases or decreases consumer welfare relative to (0) is therefore an empirical question.

To estimate consumer welfare, we cannot use a standard revealed preferences approach, because in our setting consumer choices do not necessarily maximize utility. We follow Allcott (2013), who offers a framework to calculate consumer welfare in situations in which consumers' ex ante expected utility differs from what they actually experience when consuming their chosen alternative. To do so, we define consumers' utility from the perspective of the social planner as

$$u_{ijt}^{SP} = \delta_{ijt} - \alpha_i p_{jt} - w_{jt}' \phi_i \lambda. \tag{19}$$

The social planner's utility from Equation (19) differs from the expected utility function consumers use to make choices in Equation (5) in two different ways. First, the social planner's utility depends on the true nutritional intake w_{jt} rather than the expected one. Second, we allow the social planner to disagree with consumers about the marginal damage of consuming additional critical nutrients by multiplying ϕ_i by a constant λ. This allows our model to accommodate additional market imperfections, such as externalities in the form of financial health-care costs or internalities in the form of self-control problems, time-inconsistency, or misperceptions about the individual damage caused by critical nutrients, ϕ_i. For the main part of our analysis, unless otherwise stated, we focus on results for the case in which $\lambda = 1$ (i.e., in which there are no additional market imperfections). Equation (19) makes specific normative assumptions and does not allow, for example, for models in which "ignorance is bliss" (i.e., consumers are better off not knowing that they are engaging in harmful behavior) or in which labels affect utility in some other way.[18]

Average consumer welfare in market t under counterfactual (x) is given by

$$CW^t(x) = \sum_j \left\{ \int_{\Theta_{jt}^{(x)}} \frac{1}{\alpha_i}(\delta_{ijt} - \alpha_i p_{jt}^{(x)} - w_{jt}^{(x)} \phi_i \lambda) di \right\},$$

where $p_{jt}^{(x)}$ and $w_{jt}^{(x)}$ are the price and nutritional content of product j in market t in counterfactual (x). $\Theta_{jt}^{(x)}$ is the set of consumers who prefer product j in counterfactual (x). Since taste is constant, δ_{ijt} does not vary across counterfactuals. The total mass of potential consumers is normalized to be one in each market. We present the average change in consumer welfare between counterfactuals (x) and (0) in Figure 6, and decompose it between how much of it is driven by changes in nutritional intake, changes in dollars spent, and changes in the average taste of products that are consumed.

We find that moving from a counterfactual with no intervention, (0), to one in which products get labeled but suppliers do not respond, (1), increases average consumer welfare by \$0.27 a year. This corresponds to 1.1% of the average yearly expenditure on cereal products. In the absence of supply-side responses, consumers shift demand from products high in critical nutrients to those low in critical nutrients. Since in the breakfast cereal market caloric and sugar content are positively correlated with prices, consumers end up consuming products that are cheaper but, according to the model, have lower taste (e.g., oatmeal).

We then allow firms to optimally set prices in response to the policy by simulating counterfactual (2). Under this counterfactual, we find that prices of unlabeled products go up while prices of labeled products go down. Overall, prices increase by 0.05% on average and gains in consumer welfare relative to counterfactual (0) are \$0.25 a year per capita (7% lower than under counterfactual (1)).

Under counterfactual (3), firms not only choose prices, but also the nutritional content of their products. We find large gains in consumer welfare from reducing caloric intake, mostly driven by products that become healthier due to reformulation.[19] Gains

[18] Readers who disagree with this normative model can take home the positive results of our model: the changes in nutritional intake, the changes in dollars spent by consumers, and the changes in the taste of the products consumers choose. The normative model just adds weights to these positive results to aggregate them into a single index we call welfare.

[19] Changes in consumer welfare from reducing sugar intake are negative. On one hand, firms reformulate products to have a lower concentration of sugar. On the other hand, more products are unlabeled in

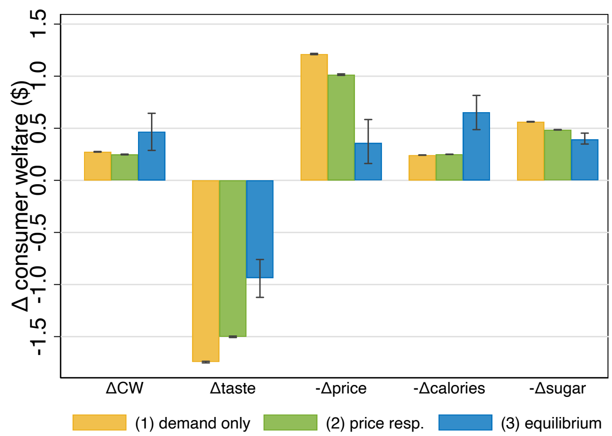


Figure 6: Changes in consumer welfare under different counterfactuals

Notes: The first three bars of the figure show the changes in consumer welfare from counterfactual (0) to counterfactuals (1), (2), and (3), respectively. The remaining bars decompose these changes into changes in taste/experience of consuming cereal, changes in price paid, changes in calorie intake, and changes in sugar intake. Each bar is normalized to show the contribution of each dimension to consumer welfare in dollars. For example, a positive value for the contribution of caloric intake means that consumers are consuming lower quantities of calories under that counterfactual. We present 90% confidence intervals from the Monte Carlo simulations. Counterfactual (3) has larger confidence intervals due to variation in Λ_j that does not show up when firms do not reformulate products.

in consumer welfare due to lower intake of critical nutrients are 30% larger than under counterfactual (1). However, reformulation increases production costs, which leads to higher prices. The net effect is an average gain in consumer welfare of \$0.46 a year under counterfactual (3), which is 70% larger than under counterfactual (1).

On the firm side, average yearly profits per capita increase by only \$0.01, with substantial heterogeneity across firms. While some firms increased their profits by around 10%, others lost more than 20%. Who wins and who loses is closely related to how labels shift consumer beliefs. Firms with products that were believed to be healthy but ended up labeled experience the highest losses. This may explain why some firms opposed the Chilean Food Act so strongly when it was first implemented.

Finally, we consider an additional counterfactual in which consumers are perfectly informed about the nutritional content of products. This exercise informs us about the total welfare losses due to lack of information in the cereal market, and allows us to assess how well food labels approximate the best-case scenario of perfect information. We find that the food labeling policy achieves 8% of the consumer welfare gains that would be obtained under the perfect information counterfactual.

counterfactual (3), which means that the average sugar concentration among unlabeled products is higher. The latter effect offsets the potential benefits of the former effect.

6.2. *The design of food labeling policies*

We now study the design of food labeling policies. We take the binary-signal structure of the policy as given, and study how nutritional intake and consumer welfare vary under different regulatory thresholds. Intuitively, in the absence of supply-side effects, thresholds should be set such that labels' informativeness is maximized. When supply-side responses are considered, policymakers can choose a different regulatory threshold that induces larger reductions in critical nutrients. To clarify the analysis, we simplify our model to only allow misinformation regarding sugar content.[20]

We focus our analysis on counterfactuals (1), demand-only responses, and (3), the equilibrium model. Figure 7(a) shows the gains in consumer welfare under counterfactuals (1) and (3) for different policy thresholds. A naive policymaker who seeks to maximize consumer welfare but ignores equilibrium effects would set the policy threshold at 16.5 grams per 100 grams, the value at which consumer welfare is maximized under counterfactual (1). Consumer welfare under counterfactual (3), however, is maximized at 8.5 grams per 100 grams, at which point it is 20% larger than under the naive threshold.

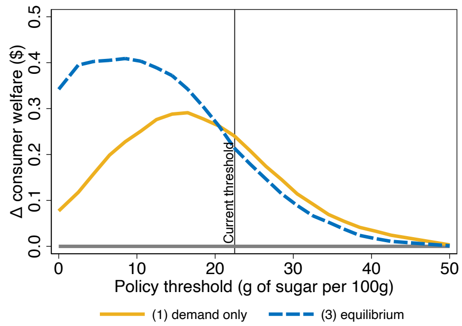
6.3. *Food labels vs. sugar taxes*

We exploit the richness of our model to compare the effectiveness of food labels against sin taxes. We focus on sugar taxes, a widespread policy used in more than 40 countries (Allcott et al., 2019b). Most sugar taxes are structured as a per-ounce tax on any product with added sugar. However, Allcott et al. (2019b) recommend using tax designs that depend on the amount of sugar instead of the amount of product, to encourage consumers to switch to lower-sugar products and producers to reduce sugar content. We follow this tax structure. We assume that consumers observe the final after-tax price of products and cannot infer the concentration of critical nutrients by looking at prices. This is a reasonable assumption in our context, since sales taxes are not observed by consumers in Chile. We use ψ to denote the marginal value of public funds. To calculate consumer welfare, we distribute the tax money to consumers through a lump sum transfer (i.e., $\psi = 1$).

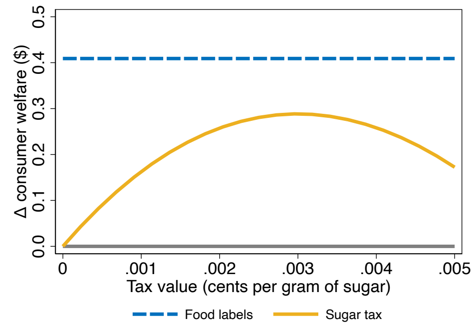
Extending the model from Section 5 to include sugar taxes, the firm's problem is given by

$$\max_{\{p_{jt}, w_{jt}\}_{j \in \Im_j}} \quad \sum_{j \in \Im_j} (p_{jt} - c_{jt}(w_{jt}) - w_{jt}\tau) \cdot s_{jt}(\mathbf{p_t}, \mathbb{E}[\mathbf{w_t}])$$

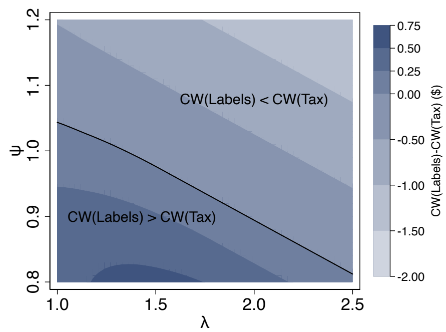
[20] We assume consumers are perfectly informed about the nutritional content of calories in all counterfactuals.



(a) Food labels



(b) Sugar taxes



(c) Policy comparison

Figure 7: Changes in consumer welfare under food labels and sugar taxes

Notes: Panels (a) and (b) plot the average change in consumer welfare under counterfactuals (1) and (3) relative to counterfactual (0). Panel (a) shows the gains in consumer welfare under a food labeling policy at different regulatory thresholds, and panel (b) shows the gains in consumer welfare under different tax values. Panel (c) shows a contour plot that represents the difference in gains in consumer welfare between a food labeling policy and sugar taxes as a function of λ, the parameter that accounts for additional market imperfections, and ψ, the marginal value of public funds under counterfactual (3). For each value of λ and ψ, we choose policy thresholds and tax values that maximize consumer welfare. In the bottom-left side of the box, consumer welfare gains under a food labeling policy is larger than under optimal sugar taxes (CW(Labels) $>$ CW(Tax)). In the upper-right side of the box, consumer welfare gains under a food labeling policy is smaller than under optimal sugar taxes (CW(Labels) $<$ CW(Tax)).

where τ is the tax per gram of sugar and p_{jt} is the final price paid by consumers. From the first-order conditions, we have

$$\begin{aligned} \nabla c_{jt}(w_{jt}^*) &= -\tau \\ p_{jt}^* &= c_{jt}(w_{jt}^*) + \tau w_{jt}^* + \Delta_{(j,\cdot)}^{-1} \mathbf{s_t}, \end{aligned}$$

where the (j,k) element of Δ is given by equation (16). In this setting, firms have incentives to deviate from the bliss point, ν_j, and reduce the nutritional content of their products to pay lower taxes. Moreover, the price equation has an additional term given by the tax, which is proportional to the sugar content, and gets passed on to consumers through higher prices.

In Figure 7(b), we present gains in consumer welfare at different tax values. The optimal sugar tax (i.e., the tax that maximizes consumer welfare) is set at 0.3¢ per gram of sugar. This is not far from the value of sugar taxes implemented in some U.S. cities.[21] Gains in consumer welfare with optimal sugar taxes are 29.5% lower than under food labels at the optimal policy threshold.

We find that taxes are 31% more effective at reducing sugar intake than food labels. However, they do this at a greater direct financial cost to consumers. Under the optimal tax level, consumers spend 2.6 additional dollars a year in taxes, equivalent to 7.5% of the total expenditure on cereal. Because taxes collected are relatively high, our results are sensitive to the choice of ψ, the marginal value of public funds.

Note that in contrast to food labels, sugar taxes are granular instruments, which are levied more heavily on products with higher levels of sugar. This is important for two reasons. First, sugar taxes have the potential to incentivize firms to reformulate all of their products in order to pay lower taxes, especially those with higher sugar content. Second, the effects of sugar taxes do not depend on consumers' beliefs. This makes taxes particularly appealing when λ, the parameter that accounts for additional market imperfections, is high.

6.3.1. *Sensitivity to different values of λ and ψ*: We take our values for λ from Allcott et al. (2019a), who estimate externalities from consuming sugar-sweetened beverages to be 0.8¢ per ounce, and internalities—which include the type of misinformation analyzed in this paper—to be around 1¢ per ounce. Taking into account that the median sugar-sweetened beverage has 3.25 grams of sugar per ounce, the additional marginal damage from consuming a gram of sugar is between 0.25¢ (only externalities) and 0.55¢ (externalities + internalities). In our model, this corresponds to $\lambda = 1.5$ and $\lambda = 2.1$, respectively.

The marginal value of public funds, ψ, can vary substantially depending on how tax money is spent. Hendren and Sprung-Keyser (2020) find that a large variety of policies targeted at adults in the United States have marginal values of public funds that range from $\psi = 0.8$ to $\psi = 1.2$.

In Figure 7(c), we show the values of λ and ψ for which labels are better than taxes and vice versa. Intuitively, larger values of λ favor taxes since they are better designed to deal with market imperfections not directly related to misinformation regarding w_{jt}.

[21] Philadelphia and Berkeley are the first two cities to pass a sugar tax in the U.S. In Berkeley, there is a 1¢ tax per ounce of sugar-sweetened beverages, equivalent to 0.32¢ per gram of sugar in the case of Coca-Cola. In Philadelphia, the tax is 1.5¢ per ounce, equivalent to 0.48¢ per gram of sugar.

Taxes, however, impose a large burden on consumers who end up spending more on cereal. If the marginal value of public funds ψ is small, the resources collected through taxes will not contribute much to the total welfare. The smaller the value of ψ, the less effective taxes will be.

6.3.2. *Heterogeneity in beliefs*: In settings with heterogeneous agents, food labels can be more efficient than sugar taxes because their effects can be better targeted. To illustrate this point, consider a simple model in which half of the consumers have miscalibrated beliefs and the other half have accurate beliefs (i.e., $\mu_{jb} = \nu_j$, $\Omega_{jb} \to 0$). We call them uninformed and informed consumers, respectively. To gain intuition, let us focus on the case in which there are no supply-side responses. Ideally, the regulator would like to implement a targeted policy that only applies to uninformed consumers (e.g., food labels or sugar taxes for the uninformed population only). Although implementing a targeted policy is usually not possible, food labels will only affect the decisions of uninformed individuals and not those of consumers who are informed and were already making optimal choices, even when the instrument is not itself targeted. Taxes, on the other hand, are blunt instruments that generally change the actions of all consumers, and benefit some while hurting others.

6.3.3. *Distributional consequences*: The progressivity or regressivity of a policy depends on how the benefits (e.g., more information, correction of biases) and the costs (e.g., the burden of tax payments) vary across the income distribution. Two key parameters in our model are crucial in determining the incidence of each policy.

The first parameter is the extent to which low-SES consumers are more or less inclined than high-SES consumers to prefer products that are high in sugar. While food labels improve consumer welfare by providing information about the healthiness of products, taxes correct consumer behavior by inflating the prices of products that are high in sugar. If low-SES consumers prefer high-in-sugar products more than high-SES consumers do, then they will be charged disproportionately higher taxes. Depending on how the tax revenue is spent by the government, sugar taxes can benefit high-SES consumers relatively more. In the United States, for example, consumers with household incomes below \$10,000 purchase 25% more grams of added sugar per calorie than do households with incomes above \$100,000 (Allcott et al., 2019). Sugar taxes are therefore more likely to be regressive than food labels.

The second parameter is the extent to which low-SES consumers are more or less informed than high-SES consumers regarding the nutritional content of products. An advantage of food labels relative to sugar taxes is that the former can be better targeted toward the uninformed population. Using survey data, Allcott et al. (2019a) find that U.S. consumers with household income below $10,000 score 0.82 standard deviations lower than consumers with household income above $100,000 on a nutrition knowledge questionnaire, which renders food labels more progressive than sugar taxes.

7. Conclusion

In this paper, we study the equilibrium effects of food labeling policies on nutritional intake and consumer welfare. Three key findings arise from our empirical analysis. First, the food labeling regulation caused consumers to substitute from labeled to unlabeled food products. Second, products that were perceived as healthy but received labels experienced the largest decline in demand. Third, suppliers responded to the policy by changing prices and reformulating their products.

We develop and estimate an equilibrium model of supply and demand for food and nutrients and use it to calculate the effects of food labeling policies on nutritional intake and consumer welfare. We find that food labels can be an effective way to improve diet quality and combat obesity. Our analysis shows that food labels are more effective when consumers have mistaken beliefs about products' healthiness, consumers value healthiness, reformulation that does not substantially change products' taste is feasible, and regulatory thresholds are set so that they provide useful information to consumers and encourage product reformulation.

We then use our model to compare food labels with sugar taxes. When compared with sugar taxes, food labels present both advantages and disadvantages. We show that food labels are more effective for tackling misinformation, but less effective for dealing with other market imperfections such as fiscal externalities, lack of self-control, or time inconsistency. Food labels are more progressive than sugar taxes, especially in settings in which the poor tend to consume more sugary products or in which the poor are more misinformed about the nutritional content of available products.

Our analysis shows how a theoretical framework combined with data can inform the design of policies to combat obesity by identifying and measuring the most relevant economic forces at work. Our model can accommodate a variety of settings and can be used to study the effects of food labels in categories other than cereal. It also provides a useful framework for comparing food labels with alternative policy instruments.

Food labels are a new and promising policy tool with the capacity to improve diet quality. While this paper covers important features of food labels, several unanswered questions remain. First, this paper focuses on a policy design in which labels act as a binary signal. New research suggests that more granular labels can be more effective in improving diet quality (Ravaioli, 2021). Second, food labels can incentivize firms to design new healthy products targeted to more informed consumers, which improves the bundle of available products in the long run. Finally, measuring long-run outcomes on health and wellbeing will be crucial in assessing the effectiveness of food labels.

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Online Appendix for:

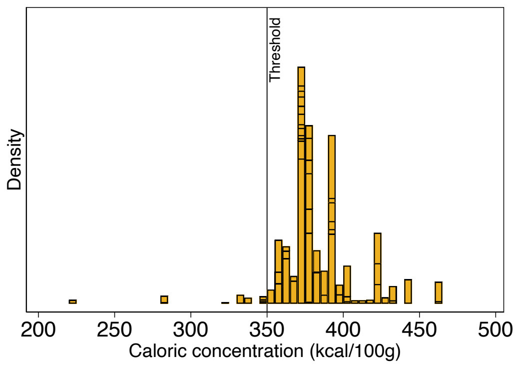
Equilibrium Effects of Food Labeling Policies

(Not for publication)

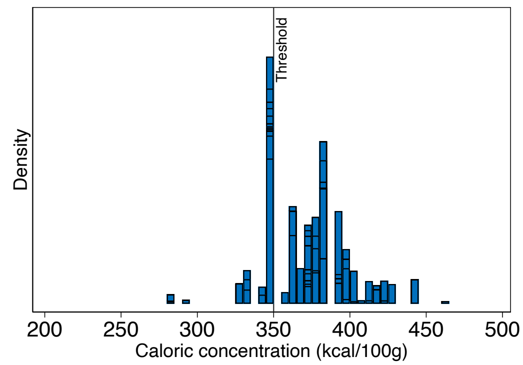
Nano Barahona Cristóbal Otero Sebastián Otero

February 11, 2023

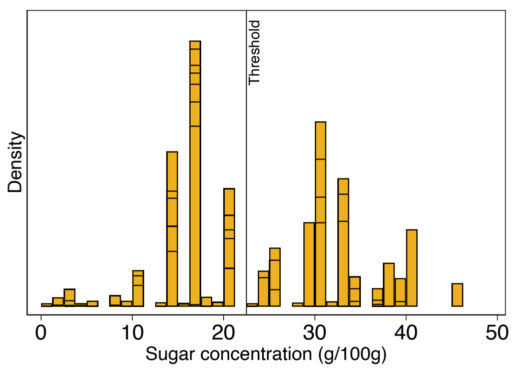
Appendix A: Additional Figures and Tables



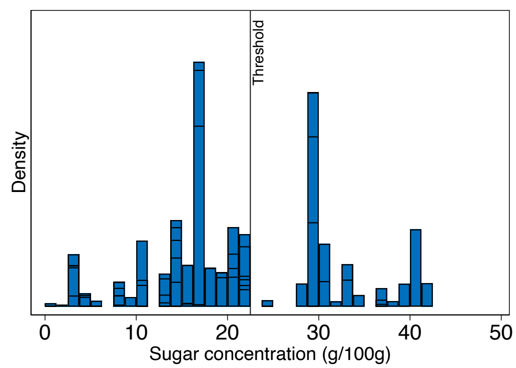
(a) Distribution of calorie content in 2016



(b) Distribution of calorie content in 2018



(c) Distribution of sugar content in 2016



(d) Distribution of sugar content in 2018

Figure A.1: Distribution of caloric and sugar concentration pre- and post-legislation

Notes: This figure plots the distribution of calories and sugar per 100g for cereal products before and after the policy implementation. Horizontal black lines inside the bars identify different products. Observations are weighted by pre-policy revenue. We exclude oatmeal products, which do not have artificially added critical nutrients, as they are exempted from the regulation and do not reformulate their products.

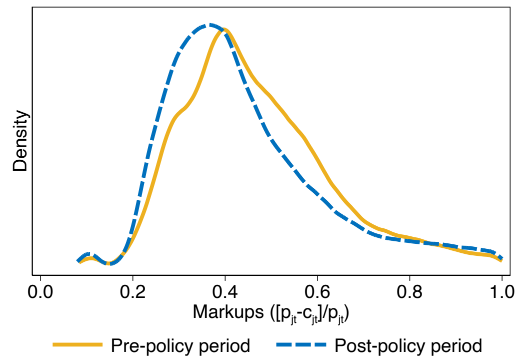
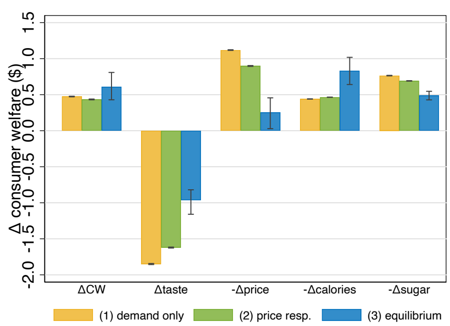
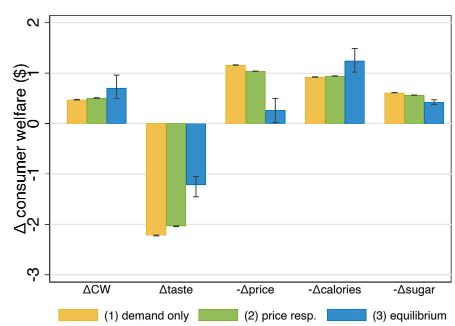


Figure A.2: Distribution of markups

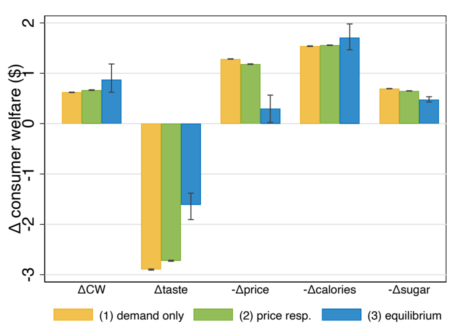
Notes: This figure shows the distribution of markups—defined as the ratio of price minus marginal cost to price—across products and markets before and after the policy implementation.



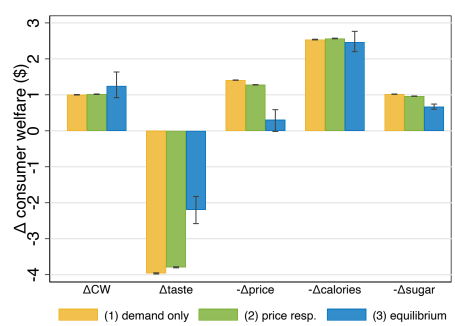
(a) $\rho = 0.9$



(b) $\rho = 0.8$



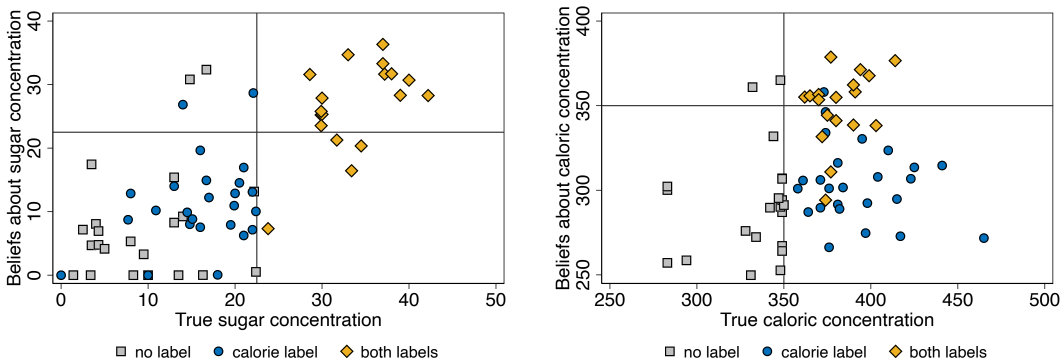
(c) $\rho = 0.7$



(d) $\rho = 0.6$

Figure A.3: Changes in consumer welfare under different values of ρ

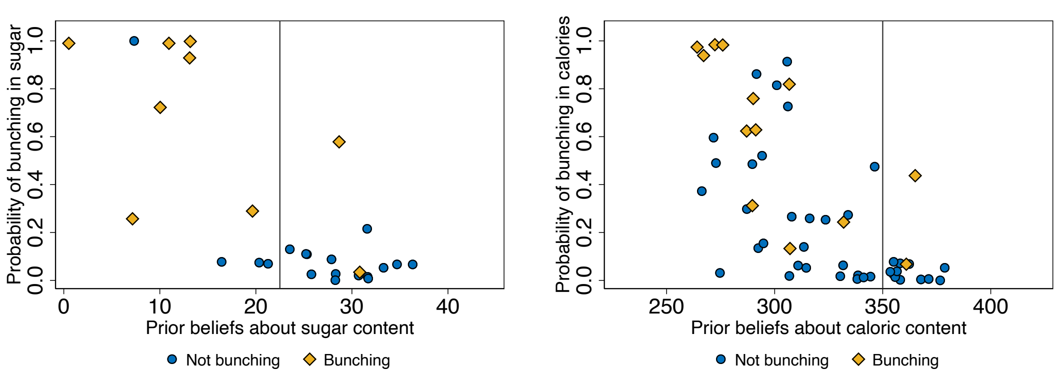
Notes: This figure replicates the findings from Figure 6 by imposing different values of ρ. For each panel, we fix ρ at 0.9, 0.8, 0.7, and 0.6, respectively. For each value of ρ, we estimate all other parameters from the demand and supply models presented in Sections 4 and 5. We then run our main counterfactuals and calculate the changes in consumer welfare under the different parameters. We show that our main results are qualitatively similar when we assume lower values of ρ.



(a) Sugar (b) Calories

Figure A.4: Beliefs about nutritional content vs true post-policy nutritional content

Notes: This figure shows the estimated average belief (between low- and high-SES consumers) about each product's nutritional content against the true post-policy period nutritional content. Vertical and horizontal lines correspond to the value of the policy threshold in both spaces. Gray-square products did not receive any label, blue-circle products received a high-in-calorie label, and yellow-diamond products received a high-in-calorie and a high-in-sugar label. We exclude products that do not show up in the pre-policy period or are exempt from the policy.



(a) Sugar (b) Calories

Figure A.5: Predicted probability of bunching as a function of prior beliefs

Notes: The figure shows the predicted probability of each product bunching in sugar and calories as a function of the average prior belief about their nutritional content. In Panel (a), we focus on sugar content. Products in yellow diamonds are products that bunched in the data and crossed the sugar policy threshold. Products in blue circles are products that did not bunch and received a "high-in-sugar" label. In Panel (b), we focus on caloric content. Products in yellow diamonds are products that bunched in the data and crossed the calorie policy threshold. Products in blue circles are products that did not bunch and received a "high-in-calorie" label.

Table A.1: Median price elasticities

		Share (%)	Elasticities									
			Plain		Sugary		Chocolate		Oatmeal		Granola	
			(1)	(2)	(4)	(5)	(7)	(8)	(10)	(11)	(13)	(14)
Subcategory: Plain												
Fitness, Nestlé	(1)	0.77	-3.104	0.157	0.078	0.054	0.010	0.047	0.213	0.062	0.024	0.017
Quadritos, Quaker	(2)	0.66	0.173	-4.069	0.079	0.056	0.105	0.050	0.205	0.059	0.022	0.016
Corn Flakes, Nestlé	(3)	0.61	0.173	0.166	0.082	0.056	0.103	0.048	0.201	0.061	0.020	0.015
Subcategory: Sugary												
Trix, Nestlé	(4)	1.57	0.032	0.030	-3.224	0.484	0.014	0.007	0.068	0.020	0.005	0.004
Zucaritas, Kellog's	(5)	1.27	0.032	0.031	0.687	-3.113	0.015	0.007	0.063	0.018	0.005	0.004
Zucosos, Nestlé	(6)	0.69	0.032	0.030	0.673	0.486	0.015	0.007	0.068	0.020	0.005	0.004
Subcategory: Chocolate												
Chocapic, Nestlé	(7)	4.27	0.022	0.021	0.008	0.005	-1.996	0.361	0.066	0.019	0.003	0.003
Milo, Nestlé	(8)	1.55	0.022	0.021	0.008	0.005	0.779	-3.070	0.065	0.019	0.003	0.003
Mono Balls, Costa	(9)	0.94	0.020	0.019	0.007	0.005	0.778	0.356	0.064	0.018	0.003	0.002
Subcategory: Oatmeal												
Avena Instantanea, Quaker	(10)	5.8	0.084	0.073	0.066	0.043	0.121	0.055	-0.813	0.075	0.041	0.033
Avena Instantanea, Vivo	(11)	1.98	0.083	0.072	0.066	0.043	0.122	0.055	0.255	-0.831	0.041	0.034
Avena Tradicional, Quaker	(12)	1.55	0.084	0.073	0.066	0.043	0.122	0.055	0.255	0.074	0.041	0.033
Subcategory: Granola												
Granola Miel y Alm., Quaker	(13)	0.55	0.032	0.028	0.018	0.013	0.020	0.009	0.143	0.038	-2.880	0.223
Granola Miel y Alm., Vivo	(14)	0.45	0.029	0.023	0.018	0.012	0.020	0.009	0.145	0.042	0.291	-2.831
Granola Berries, Vivo	(15)	0.36	0.030	0.025	0.017	0.012	0.019	0.009	0.145	0.042	0.292	0.246
Outside option	(16)	61.08	0.001	0.001	0.002	0.001	0.003	0.001	0.002	0.001	0.001	0.000

Notes: The first column reports the median market share of each product across all 2,704 markets. For the rest of the table, cell entries j, k—where j indexes rows and k columns—give the percent change in market share of product j with a 1% increase in the price of product k. Each entry represents the median of the elasticities from all markets. Note that the cross-price elasticities within a subcategory are relatively constant. We do not observe product characteristics that vary within subcategories which limits our ability to include preference heterogeneity to recover more flexible substitution patterns.

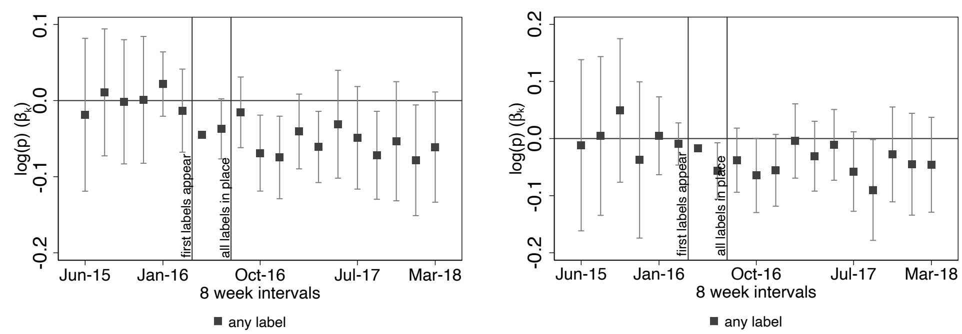
Appendix B: Changes in prices, product assortment, and package size

In this appendix, we study how and whether firms responded to the policy by changing prices, product assortment, or package size.

To quantify the effects of the policy on equilibrium prices, we follow the event study strategy implemented for changes in equilibrium quantities from Equation (1). We estimate the following regression:

$$\log(p_{jst}) \quad = \quad \sum_k \beta_k \cdot L_j \cdot \mathbb{1}\{k=t\} + \delta_{js} + \delta_t + \varepsilon_{jst} \tag{B.1}$$

where all variables and specification details are defined as in Equation (1). Results are presented in Figure B.1, Panel (a). We find that labeled products saw an average decrease of 5.5% in prices relative to unlabeled products. This may be explained by a combination of firms increasing markups on unlabeled products that now face higher demand (and vice versa), and by an increase in marginal costs of unlabeled products due to reformulation. It might also be the case that firms are decreasing prices of labeled products due to their lower demand.



(a) Product-level data

(b) UPC-level data

Figure B.1: Event study for cereal prices

Notes: This figure presents the β_k coefficients of our event study regression for prices from Equation (B.1). Vertical segments delimit the 95% confidence intervals. Panel (a) uses product-level data and is estimated on the sample of 68 ready-to-eat cereals that show up in the pre- and post-policy periods. The sample consists of 27 unlabeled and 41 labeled products. Panel (b) uses UPC-level data and is estimated on a sample of 257 unique UPCs in the cereal market. The sample consists of 86 unlabeled and 135 labeled UPCs.

The previous result must be taken with caution, as prices could change due to a change in the mix of UPCs offered for a given product (e.g., changes in package sizes), and not because the offered price changes. In Figure B.1, Panel (b), we show the same coefficients from Equation (B.1) but aggregate the data at UPC-level. Using this specification, we find that labeled UPCs saw an average decrease of 4.2% in prices relative to unlabeled UPCs.

These results are in contrast to those in Pachali et al. (2022), who conclude that warning labels lead to higher prices of labeled cereals due to changes in product differentiation. The differences seem to be driven by differences in the sample. While we use scanner data from Walmart, they use household panel data from Kantar World-panel Chile. Moreover, of the 94 products in our sample, they focus on 14, of which only three are unlabeled. When repeating the analysis in our data but restricting it to the 14 products in their sample, we find no significant differences in price changes between labeled and unlabeled products.

We then study how product variety changed at Walmart before and after the policy implementation. We measure product variety by looking at the number of different products offered in each supermarket at a given period of time. To this end, we run the following regression:

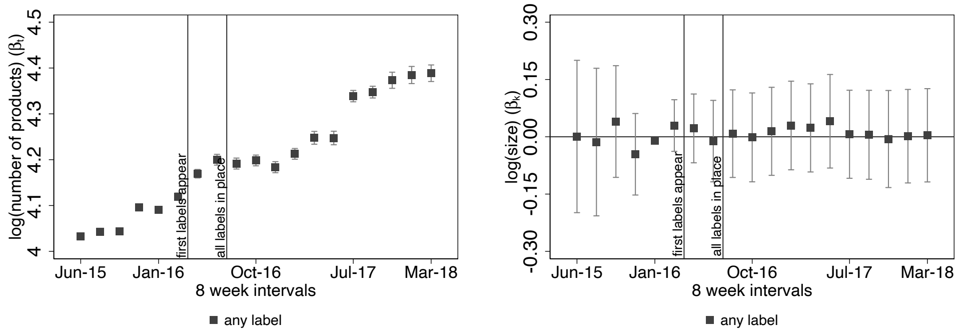
$$\log(N_{st}) \quad = \quad \beta_t + \delta_s + \varepsilon_{st}, \tag{B.2}$$

where N_{st} is the total number of different products offered in store s in period t, and β_t and δ_s are period and store fixed effects, respectively. In Figure B.2, Panel (a), we plot the resulting coefficients β_t. We find that the number of products available increased by around 40% during the whole sample. Nevertheless, it does not seem that the increase in variety is directly related to the policy. No product was discontinued in our sample.

Finally, we look at changes in package size. Previous literature has suggested that policies that increase consumer attention to nutritional information can lead to reductions in package or serving size (Mohr et al., 2012). It is important to notice that in such settings, nutritional content is usually reported on a "per-serving-size" basis. In the context of Chile, the labeling status of products depends on the sugar and caloric concentration per 100 grams of cereal, thus eliminating the incentive to manipulate package or serving size. To study what happened to the average size of the package after the policy was implemented, we run the following regression:

$$\log(\text{size}_{ist}) \quad = \quad \sum_k \beta_k \cdot L_j \cdot \mathbb{1}\{k = t\} + \delta_{js} + \delta_t + \varepsilon_{jst} \tag{B.3}$$

where size_{ist} is the size of the package for product j's UPC i in store s in period t. All other variables and details are defined as in Equation (1), and observations are at the



(a) Average number of products per store (b) Average package size of products

Figure B.2: Changes in product assortment and package size

Notes: This figure presents the β_t and β_k coefficients of the regressions from Equations (B.2) and (B.3). The vertical segments delimit the 95% confidence intervals. Panel (a) uses store-period-level data on a sample of 164 different stores. Panel (b) uses UPC-store-period-level data and a sample of 257 unique UPCs.

UPC level. Results are presented in Figure B.2, Panel (b). We find that once the policy is implemented, there is no significant change in the average size of product packages.

Appendix C: Demand Model Discussion

C.1. *Stockpiling*

We assume static demand. However, cereal is a storable product, which can lead to dynamic incentives that can bias our estimates. Hendel and Nevo (2006a) show that ignoring such dynamics can lead to overestimates of own-price elasticities. We implement several tests for stockpiling behavior proposed by Hendel and Nevo (2006b). We find evidence in favor of stockpiling; however, the effects are much smaller than in Hendel and Nevo (2006b).

Throughout our analysis, we focus on within-consumer predictions and patterns of stockpiling behavior. We construct a dataset in which each observation is a cereal purchase made by a given household. For each observation, we calculate the number of days that passed since the last time the household purchased cereal as well as the number of days until the household's next cereal purchase. We also document whether the product purchased was on sale or not at the time of the purchase.

Assessing whether consumers stockpile in response to price movements would be straightforward if consumers' inventories were observed. For instance, we could test whether end-of-period inventories are higher after sales. However, consumption, and therefore inventories, are unobserved. Hendel and Nevo (2006b) propose a model of stockpiling with different implications that can be tested without requiring us to observe inventories. Specifically, we estimate the following model:

$$y_{it} \quad = \quad \beta sale_{it} + \delta_i + \epsilon_{it},$$

where $sale_{ijt}$ takes the value of one if household i purchases a cereal product in period t that was on sale. Coefficients δ_i control for household fixed effects. We test for the following implications under stockpiling behavior:

1. Duration until the following purchase is longer during a sale.
2. Duration from the previous purchase is shorter for purchases during a sale.
3. Non-sale purchases have a higher probability that the previous purchase was not during a sale.

To test for the first implication, we define the outcome variable as the number of days it took to household i to buy cereal again after their purchase in period t. Under stockpiling, we expect β to be *positive*. In Table C.1, Panel A, we find that $\beta = 0.877$, implying a 2.4% increase in the number of days until the next purchase when the product purchased is on sale. This number is positive but smaller in magnitude than those in Hendel and Nevo (2006b), who find a 10.6% and 9.3% increase in the market for yogurt and soft drinks, respectively.

To test for the second implication, we define the outcome variable as the number of days that passed since the last time household i purchased cereal before buying cereal again in period t. Under stockpiling, we expect β to be *negative*. In Table C.1, column (2), we find that $\beta = -0.420$, implying a 1.1% decrease in the number of days since the last purchase when the product purchased is on sale. This number is negative but smaller in magnitude than those in Hendel and Nevo (2006b), who find a 4.6% and 12.0% decrease in the market for yogurt and soft drinks, respectively.

To test for the third implication, we define the outcome variable to take the value 1 if household i's cereal purchase before buying cereal again in period t was of cereal products that were not on sale. Under stockpiling, we expect β to be *negative*. In Table C.1, column (3), we find that $\beta = -0.0633$, implying a 7.7% decrease in the probability that the last purchase was a non-sale purchase. This number is negative but smaller in magnitude than those in Hendel and Nevo (2006b), who find a 16.7% and 13.5% decrease in the market for yogurt and soft drinks, respectively.

Table C.1: Stockpiling tests

	(1) Days to next purchase	(2) Days since last purchase	(3) Prob of non-sale purchase
$sale_{it}$	0.877***	-0.420***	-0.0633***
	(0.041)	(0.041)	(0.0003)
Mean of dep. var.	37.00	37.00	0.81
Observations	10,580,676	10,580,676	10,580,676

Notes: In this table we present results of different test for stockpiling. In column (1), we test whether the duration until the following purchase is longer during a sale. In column (2), we test whether the duration from the previous purchase is shorter for purchases during a sale. In column (3), we test whether non-sale purchases have a higher probability that the previous purchase was not during a sale. We find evidence in favor of stockpiling; however, the effects are much smaller than found in other settings. Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Our results are in line with O'Connell and Smith (2021), who perform similar tests in the soft-drinks market in the UK and find that the sign of these tests are consistent with stockpiling but very small in magnitude.

C.2. *Salience effects*

In this subsection, we investigate the potential salience effects of food labels in the cereal market. Salience refers to a situation in which an attribute of an item attracts more attention, and subsequently receives more weight when making decisions. In Section 3.1.1, we argue that labels shift consumer demand because they provide consumers with information about the true nutritional content of a product. However, labels may also make the unhealthiness of products more salient to consumers. In other words, labels may induce consumers to pay more attention to the role of sugar and calories in the decision-making process. Hence, if labels were only impacting demand through salience, we should expect the reduction in equilibrium quantities documented in Figure 1(a) to be stronger for those products with higher concentrations of critical nutrients.

To investigate this hypothesis, we follow the same empirical design implemented in Section 3.1.1. We split our sample of labeled products into two groups: products below the median in the caloric concentration distribution (20 products) and products above the median in the caloric concentration distribution (21 products). We use indicator dummies for each of these groups (denoted by Low_j^c and $High_j^c$) and estimate the following equation:

$$\log(q_{jst}) = \sum_k (\beta_k^l \cdot L_j \cdot Low_j^c + \beta_k^h \cdot L_j \cdot High_j^c) \cdot \mathbb{1}\{k = t\} + \gamma \cdot \log(p_{jst}) + \delta_{js} + \delta_t + \varepsilon_{jst}, \tag{C.1}$$

where all variables and specification details are defined as in Equation (1).

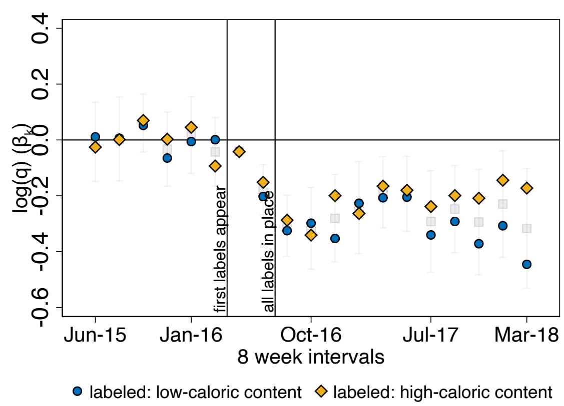


Figure C.1: Changes in equilibrium quantities by caloric concentration

Notes: This figure displays the coefficients from Equation (C.1). Coefficients in blue circles and yellow diamonds denote β_k^l, β_k^h, respectively. Gray squares denote the β_k coefficients from Equation (1) and the vertical lines delimit their 95% confidence intervals. These regressions are run on the sample of 68 ready-to-eat cereals that show up in the pre- and post-periods. The sample contains 27 unlabeled products and 41 labeled ones.

Results from Equation (C.1) are shown in Figure C.1. Coefficients in blue and yellow denote β_k^l and β_k^h estimates, respectively. Coefficients in light gray denote β_k coefficients from Equation (1). Products with low caloric concentration (blue dots) and high caloric concentration (yellow diamonds) saw a similar reduction in equilibrium quantities.[1] If anything, high-calorie products seem to experience lower reductions in demand, as opposed to what we would expect under strong salience effects.

C.3. *Invariant taste*

Equation (4) from the main article does not allow for the experience aspect of the utility, δ_{ijt}, to change when firms reformulate products and change w_{jt}. However, it could be the case that reducing the amount of calories or sugar in products renders them less appealing to consumers due to changes in taste.

In this subsection, we estimate a version of our demand model that allows for w_{jt} to directly affect the experience/taste aspect of consumers' utility function. Similar to the model in the main article, we assume that the utility derived by individual i when purchasing product j can be split into three main components:

$$u_{ijt} = \underbrace{\delta_{ijt}}_{\text{experience/taste}} - \underbrace{\alpha_i p_{jt}}_{\text{price paid}} - \underbrace{w'_{jt}\phi_b}_{\text{health consequences}} . \tag{C.2}$$

The main and most important difference between this model and the model in the main articule relies in the parameterization of the experience/taste aspect of the utility. In this section, we will allow δ_{ijt} to vary with w_{jt}. In particular, we assume that

$$\delta_{ijt} = w'_{jt}\gamma_b + \beta_i r_j + \delta_{jb} + \delta_{T(t)b} + \delta_{S(t)b} + \xi_{jtb} + \epsilon_{ijt}. \tag{C.3}$$

Consumers' decision utility in this model is then given by

$$\mathbb{E}_b[u_{ijt}] = -\alpha_b p_{jt} - \mathbb{E}_b[w_{jt}|L_{jt}]'\phi_b + w'_{jt}\gamma_b + \beta_i r_j + \delta_{jb} + \delta_{T(t)b} + \delta_{S(t)b} + \xi_{jtb} + \epsilon_{ijt}, \tag{C.4}$$

where ϕ_b determines changes in preferences driven by changes in beliefs about the nutritional content of a product and γ_b determines changes in preferences driven by the actual change in nutritional content of the product. Note that preferences driven by baseline beliefs and nutritional content are absorbed by product fixed effects δ_{jb}. Also note that

[1] Splitting products according to sugar concentration is less interesting. Because sugar concentration is highly correlated with beliefs about caloric concentration, results are similar to Figure 1(b). Labeled products with high sugar concentration experienced lower changes in equilibrium quantities than labeled products with low sugar concentration. This, again, rejects important salience effects.

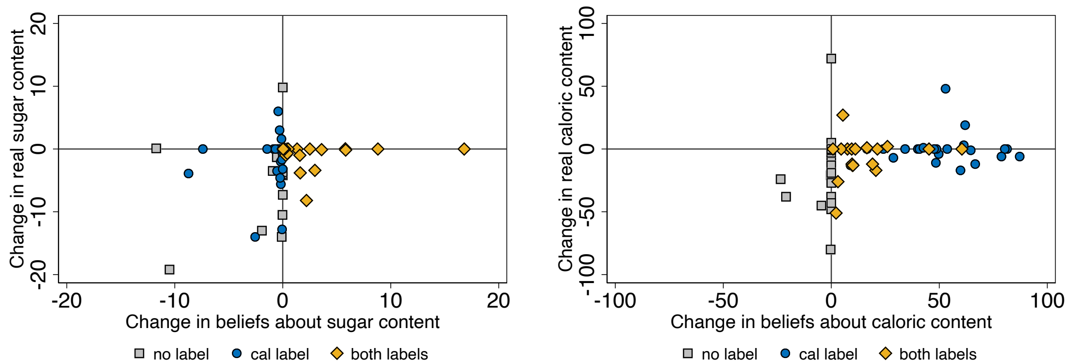
consumers could respond to changes in w_{jt} even if w_{jt} is not observed by them but is correlated with things they do observe but the econometrician doesn't (e.g., taste). This model departs from the one estimated in Section 4 in two ways: First, we allow utility to directly depend on nutritional content w_{jt} through the term $w'_{jt}\gamma_b$. Second, we fix $\Sigma_\phi = \sigma_\alpha = 0$, which allows for more transparent identification of ϕ_b and γ_b. In a model in which consumers dislike a higher concentration of critical nutrients due to the negative health consequences of consuming them—but in which sugar and calories increase the taste of the products—we should expect to find that $\phi_b > 0$ and $\gamma_b > 0$.

There are two important challenges when trying to separately identify ϕ_b and γ_b. First, changes in nutritional content happen around the time of the policy implementation, and therefore changes in $\mathbb{E}_b[w_{jt}|L_{jt}]$ and w_{jt} happen at the same time. Second, changes in $\mathbb{E}_b[w_{jt}|L_{jt}]$ are not directly observed in the data. We infer them by combining the beliefs survey and a Bayesian updating model. If $\Delta\,\mathbb{E}_b[w_{jt}|L_{jt}]$ and Δw_{jt} are correlated and the former is measured with error, γ_b could capture parts of the effects driven by changes in beliefs.

In Figure C.2 we plot the changes in beliefs estimated in Section 4 of the main article vs. the changes in nutritional intake observed in the data for both sugar and calories. For both critical nutrients, there are products for which nutritional content changed but beliefs did not (products that were believed to be low in sugar or calories and that had to reformulate to avoid receiving the label) as well as products for which nutritional content did not change but beliefs did (products that were believed to be low in sugar or calories but did not reformulate and received a label). We exploit changes in demand for both types of products to separately identify ϕ_b and γ_b.

To estimate the model, we fix the nonlinear parameters μ, Σ_β, and ρ at the estimated values of the model from Section 4 in order to keep both models as close as possible. We also add additional instruments for the identification of γ_b by interacting the pre-policy nutritional content with dummies for whether a given product was above or below the threshold and with a dummy for the post-policy period. The intuition behind the instrument is that products above the threshold in the pre-policy period are more likely to reformulate, and products that bunch and are closer to it will reduce their nutritional content less than those that bunch but are further from it.

We present the results in Table C.2. The parameter estimates show that higher concentrations of sugar and calories do not imply higher taste, thus rejecting the hypothesis that reformulated products substantially decreased their taste. This is consistent with the evidence provided in Online Appendix D.2, in which we explain that the reformulation process took place with the explicit goal of not affecting the product's taste. More



(a) Sugar

(b) Calories

Figure C.2: Changes in beliefs vs. changes in real nutritional content

Notes: The figure shows changes in beliefs about nutritional content vs. changes in real nutritional content. To calculate changes in beliefs about nutritional content, we subtract the estimates of $\mathbb{E}_b[w_{jt}|L_{jt}]$ from before and after the policy implementation. We calculate changes in real nutritional content directly from the data. Gray squares are products that did not receive any label, blue circles are products that received a high-in-calorie label, and yellow diamonds are products that received both a high-in-calorie and a high-in-sugar label. Panel (a) shows results for sugar and Panel (b) shows results for calories.

surprisingly, we find that $\gamma_b^c < 0$, which implies that reducing caloric content increases the taste of the product. We believe this finding is driven by measurement error in the change in beliefs shown in Figure C.2. Products that, on average, were believed to be low in calories and reformulated calories to avoid receiving the label should see no changes in beliefs, according to our model. However, some consumers may be learning from the labels regardless, which can induce increases in demand for those products despite reducing their calories.

C.4. *Advertising*

Our model does not account for potential changes in advertising due to the labeling policy. The Chilean Food Act imposed additional marketing restrictions by not allowing firms to advertise labeled products to children under age 14 across different platforms, including websites, social media, magazines, billboards, pamphlets, newspapers, radio, and television. Correa et al. (2020) show that the policy was effective in decreasing advertising of labeled products by documenting a decrease in the share of food advertising that includes labeled products from 41.9% of total food advertising in the pre-policy period to 14.8% in the post-policy period. Since changes in advertising are potentially correlated with changes in beliefs, some of the effects we attribute to changes in beliefs may be driven by changes in advertising. In this subsection, we use data collected by Correa et al. (2020)

Table C.2: Estimated demand parameters with variable taste

Panel A: Preferences for price and healthiness (α_b)				
	low-SES		high-SES	
Price (α_b)	α_l	0.2759***	$\bar{\alpha}_h$	0.2086***
		(0.0200)		(0.0221)

Panel B: Preferences for healthiness and taste (ϕ_b, γ_b)								
	Sugar				Calories			
	low-SES		high-SES		low-SES		high-SES	
Healthiness (ϕ_b)	ϕ_l^s	0.0054**	ϕ_h^s	0.0045	ϕ_l^c	0.0387***	ϕ_h^c	0.0369***
		(0.0028)		(0.0031)		(0.0034)		(0.0042)
Taste (γ_b)	γ_l^s	-0.0033	γ_h^s	0.0010	γ_l^c	-0.0176***	γ_h^c	-0.0221***
		(0.0029)		(0.0036)		(0.0057)		(0.0071)

Notes: This table shows the main results from estimating the model from Equation (C.4). Nutritional content is measured in grams of sugar and kilocalories per gram of cereal and prices in dollars per 100 grams of cereal. Standard errors are reported in parentheses.

and show that all of our estimates are robust to including TV advertising intensity in the utility function.

The data we use comprise all television ads aired on the four main broadcast channels in Chile during a stratified random sample of days in April and May of 2016 (pre-policy) and 2017 (post-policy). Of all ads during the pre-policy period, only 0.5% displayed a product belonging to the breakfast cereal category. Moreover, 9 products appeared in an ad in the pre-policy period and only 6 in the post-policy period. The average number of ads per product on a given day and channel, once we condition for those products that appeared in any ad, is 0.3. This already suggests that the role of TV advertising in the cereal market is likely to be small.

To empirically test whether advertising bans played an important role in consumer choices, we add an additional element to consumers' decision utility:

$$\mathbb{E}_b[u_{ijt}] = -\alpha_i p_{jt} - \mathbb{E}_b[w_{jt}|L_{jt}]'\phi_i + \gamma_b A_{jt} + \beta_i r_j + \delta_{jb} + \delta_{T(t)b} + \delta_{S(t)b} + \xi_{jtb} + \epsilon_{ijt}, \tag{C.5}$$

where A_{jt} is a measure of advertising intensity for product j in market t, and all other variables are the same as in the model from Section 4 in the main article.[2] We measure advertising intensity as the average daily number of ads shown on each TV channel for

[2] We estimate the model following the same methodology as in Section 4, including A_{jt} interacted with consumer type dummies as additional instruments.

each product.[3] Since we only have two snapshots of advertising intensity, we follow the same strategy used for reformulation and changes in beliefs, and assume that all changes happened at the time of the policy implementation. We present the results in Table C.3.

Table C.3: Estimated demand parameters with advertising

Panel A: Preferences for price and healthiness (α_i, ϕ_i)								
	First moments				Second moments			
	low-SES		high-SES		low-SES		high-SES	
Price (α_i)	$\bar{\alpha}_l$	0.2517***	$\bar{\alpha}_h$	0.1864***	σ_{α_l}	0.1504***	σ_{α_h}	0.1114***
		(0.0733)		(0.0597)		(0.0337)		(0.0359)
Sugar (ϕ_i^s)	$\bar{\phi}_l^s$	0.0129***	$\bar{\phi}_h^s$	0.0129**	$\sigma_{\phi_l^s}$	0.0414	$\sigma_{\phi_h^s}$	0.0415
		(0.0043)		(0.0052)		(0.1115)		(0.1120)
Calories (ϕ_i^c)	$\bar{\phi}_l^c$	0.0261***	$\bar{\phi}_h^c$	0.0254***	$\sigma_{\phi_l^c}$	0.0278	$\sigma_{\phi_h^c}$	0.0271
		(0.0075)		(0.0078)		(0.0181)		(0.0171)

Panel B: Individual preferences for different subcategories (Σ_β)									
Plain		Sugary		Chocolate		Granola		Oatmeal	
$\sigma_{\beta_{r_1}}$	0.0577	$\sigma_{\beta_{r_2}}$	0.1991	$\sigma_{\beta_{r_3}}$	0.2077	$\sigma_{\beta_{r_4}}$	0.0350	$\sigma_{\beta_{r_5}}$	0.2828
	(0.1463)		(0.1887)		(0.1355)		(0.1633)		(0.3513)

Panel C: Nest, beliefs, and advertising parameters (ρ, μ, γ_b)							
				low-SES		high-SES	
Nest parameter	ρ	0.9607***	Advertising (γ_b)	γ_l	0.00810	γ_h	0.00813
		(0.0040)			(0.00706)		(0.00807)
Beliefs shifter	μ	-0.1255***					
		(0.0191)					

Notes: This table shows the main results from estimating the model from Equation (C.5). Nutritional content is measured in grams of sugar and kilocalories per gram of cereal and prices in dollars per 100 grams of cereal. Advertising intensity is measured as the average daily number of ads per channel for each product. For random parameters $x_i \in \{\alpha_i, \phi_i, \beta_i\}$, we report their average $\bar{x}$ and standard deviation σ_x. Standard errors are calculated using the delta method and reported in parentheses.

All coefficient magnitudes are almost identical to the main specification in the text. Moreover, the coefficients on γ_b are small in magnitude and not statistically different from zero. Our estimates imply that consumers are willing to pay between \$0.032 and \$0.044 more per 100 grams of cereal for each additional ad shown on every channel, every day.

[3] Our results are robust to other measures of advertising, such as average daily ad minutes per channel and average daily minutes times rating points per channel.

Appendix D: Supply Model Discussion

D.1. *Timing of firms' choices*

In the main article, we assume that firms choose prices and nutritional content simultaneously. In practice, firms are likely to first set the nutritional content of their products in their production facility and then choose prices in the retail stores. Due to strategic incentives, firms may want to deviate from $w_j = \nu_j$ even in the absence of regulation to increase the marginal cost and promote overall higher prices. Whether this incentive exists depends on the specific parameters and shape of the demand function. Here, we show that under a simple oligopolistic model with Bertrand competition, single-product firms, and logit demands, such incentive never arises. Then, we use simulations to show that in the more complicated setting of our framework with random coefficients and multi-product firms, no firm also has an incentive to deviate from $w_j = \nu_j$ in the absence of regulation.

First, note that in our model, demand $s_{jt}(\mathbf{p}, \mathbb{E}_\pi[\mathbf{w}|\mathbf{L}])$ does not directly depend on w_j in the absence of regulation. Therefore, the problem of choosing nutritional content w_j is equivalent to the question of setting marginal cost c_j when marginal cost does not enter in the demand function. In the simultaneous game, it is straightforward to show that, from the first-order conditions, firms set costs at the minimum possible value (see Section 5 of the main article). We show next that in a sequential model with single-product firms and logit demand, in which firms set marginal cost first and then choose prices, it is also an equilibrium for all firms to choose the minimum cost.

Let the profit function of a single-product firm be given by $\pi_j(\mathbf{p}, c_j) = (p_j - c_j)s_j(\mathbf{p})$, where $s_j(\mathbf{p}) = \frac{exp(-\alpha p_j + \delta_j)}{1+\sum_k exp(-\alpha p_k + \delta_k)}$. In the first stage of the sequential model, firms choose $c_j \geq \underline{c}_j$. In the second stage, after marginal costs are realized, firms choose p_j.

First, note that under logit demand, $\pi_j(\mathbf{p}, c_j)$ has increasing differences in (p_j, p_{-j}), which means that the second-stage game in the sequential model is a supermodular game. Also, note that $\pi_j(\mathbf{p}, c_j)$ has increasing differences in (p_j, c_j), which implies that larger choices of c_j in the first stage will translate into larger choices of p_j in the second stage.

Let $\mathbf{p}^*$ be the vector of equilibrium prices in the second stage when all firms play $c_j = \underline{c}_j$ in the first stage. We want to show that no firm j has incentives to deviate and choose $c_j > \underline{c}_j$ in the first stage.

Suppose that j deviates and chooses $c'_j > \underline{c}_j$ in the first stage. Let p'_j be the price specified by j's strategy following such a deviation, and $\mathbf{p}'$ the equilibrium price vector after the deviation. Because $\pi_j(\mathbf{p}, c_j)$ has increasing differences in (p_j, c_j), we know that $p'_j \geq p^*_j$. Moreover, because the second-stage game in the sequential model is a supermodular game, we will also have that $\mathbf{p}' \geq \mathbf{p}^*$ (i.e., all firms will set larger prices in the second stage after the deviation).

From the first-order conditions of firm k, we have that $s_k(\mathbf{p}') \geq s_k(\mathbf{p}^*)$. It is also straightforward from the logit demand formula that $s_0(\mathbf{p}') \geq s_0(\mathbf{p}^*)$, where $s_0(\cdot)$ is the market share of the outside option. Because market shares add up to one, we have then that $s_j(\mathbf{p}') \leq s_j(\mathbf{p}^*)$. Finally, with logit demand, lower market shares imply lower markups. Thus, we have that $\pi_j(\mathbf{p}', c_j') \leq \pi_j(\mathbf{p}^*, \underline{c}_j)$, which proves that firm j has no incentive to deviate.

We test this result in the context of our estimates using the simulations from the counterfactual analysis of Section 6. For each simulation, we ask each firm whether they would be willing to deviate from $w_j = \nu_j$ in a potential first stage. We find that no firm would increase their profits by implementing such deviation.

Comparing the simultaneous and sequential games when a labeling policy is in place is more complicated due to the potential presence of multiple equilibria. In our simulations, we find that whether a firm decides to bunch or not is mostly driven by Λ_j, the cost of decreasing a product's nutritional content. Products with a low value of Λ_j tend to always reformulate, while products with a large value of Λ_j never reformulate. Because the decision to bunch is discrete, a firm's optimal response is constant under a large range of strategies p_{-j}. This means that in our setting, the equilibrium tends to be unique and identical in both the simultaneous and sequential games.

D.2. *Reformulation process*

In the main article, we assume that reformulation does not change the taste of products. This assumption simplifies the firm's problem of choosing w_{jt} in the absence of regulation, which we use to estimate ν_j from the first-order conditions. IThis assumption is driven by industry participants' descriptions of how reformulation was accomplished which we describe below. We also assume that reformulation changes marginal cost and do not model it as a fixed cost. This is consistent with how reformulation operated in the cereal market, where the techniques used were already developed in other countries and widely used in the diabetic food industry.

There are two potential ways firms may reformulate their products. In one way, firms may choose to sacrifice taste for healthiness by removing some of the critical nutrients from their products. In the other way, firms may choose to replace critical nutrients with alternative, potentially more expensive, ingredients without compromising taste, mouthfeel, shelf life, and other attributes to ensure that consumers will continue to buy their products.

We conducted interviews with consumer product managers at the two largest ready-to-eat cereal producers in Chile and asked them about their reformulation process. They explained that when products are reformulated, it is an explicit goal of the company to produce products that are indistinguishable from the previous version. When making modifications to products, they follow different steps to ensure their goals are met. First, they hire a group of "taste experts" who work closely with the firm during the reformulation process and check that attribute standards are met. Then, they implement randomized blind tests to corroborate that consumers cannot distinguish between the old and new versions of the product. Only if a product successfully passes the different tests will firms release the new version of the product to the market.

Reformulating cereal products presents different challenges. One of the main roles of sugar is to deliver sweetness. Artificial and natural high-intensity sweeteners are alternatives to sugars (e.g., sucralose acesulfame-K, saccharin steviol glycosides). Firms usually also use taste enhancers to amplify the sweetness intensity of sweeteners like sucralose or stevia. Another key role of sugar in the production process is to provide volume and structure to cereals which artificial sweeteners do not. Without sugar, cereals crumble. Polyols, which are widely used in the diabetic food industry, act as bulking agents and provide thickness and structure to products. They are less sweet than sucrose and deliver a clean, non-lingering sweet taste very close to the profile of sucrose. Combinations of polyols with intense sweeteners and/or sweetness enhancers allow a higher level of sweetness intensity while maintaining the important physicochemical properties of sugars (Lê et al., 2016). Replacing sugar with these ingredients results in a more expensive product to produce, which raises the cost of cereal ingredients by more than 20%, according to the product managers.

We collected data on the specific ingredients of 17 of the 20 products that were reformulated in our sample. We found that after the policy is implemented, 47% start using maltitol (a type of polyols), 29% sucralose, and 35% stevia.

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