

# On the Design of Food Labeling Policies<sup>a</sup>

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*Abstract:* We study a regulation in Chile that mandates front-of-package warning labels on products whose sugar or caloric concentration exceeds certain thresholds. We find that after the introduction of the regulation, consumers reduced their overall sugar and caloric intake by 9% and 6%, respectively. This change is explained by consumers buying healthier products and firms reformulating their products. On the demand side, labels induce consumers to substitute *within* categories rather than *between* categories. On the supply side, we document bunching at regulatory thresholds, with substantial heterogeneity across categories. We provide insights to inform the design of effective food labeling policies.

*JEL Codes:* D12, D22, I12, I18, L11, L81

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## 1. INTRODUCTION

The average American adult weighs nearly 23 pounds more today than in 1975 (NCHS, 2018). This dramatic rise in obesity is not specific to the United States: Over the same period, obesity in the world has tripled, and today roughly 40% of the world’s adult population is considered to be either obese or overweight (WHO, 2018). In response to this health pandemic, governments around the world are grappling with how to design policies that effectively improve diet quality.

An increasingly popular policy is to provide simplified information about products’ healthiness to consumers through front-of-package (FOP) warning labels. These labels are simple symbols that clearly signal to consumers when a product is considered unhealthy based on whether targeted critical nutrients—such as sugar and calories—exceed certain concentration thresholds. Chile was a pioneer country in implementing government-mandated FOP warning labels in the Chilean Food Act in 2016. Since then, more than 25 countries have approved or are considering similar regulations.

In this article, we review the Chilean experience and provide guidelines for the effective design of FOP warning-label policies. We investigate the impact of the regulation by analyzing Walmart’s scanner data, which covers all purchases made in Chile’s largest food retailer. We combine these data with product’s nutrition facts tables before and after the policy to construct an individual-level measure of nutritional intake. We start by documenting a sharp overall decrease in sugar and caloric intake of 9% and 6% per dollar spent, respectively, immediately after the policy was phased in. We present these findings in Figure 1.

The reduction in sugar and caloric intake—which persists for the 2-year post-policy window in our data—is explained by a combination of demand- and supply-side responses. Consumers reacted to the regulation by making healthier choices, even when the nutritional content of products is kept constant over time (dashed curves). Firms responded by reducing the concentration of critical nutrients in their products, thus offering a healthier bundle of products (the difference between solid and dashed curves).<sup>1</sup>

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<sup>1</sup>In Appendix A, Figure A.1, we show figures that divide nutritional intake by the volume of food purchased instead of by dollars spent. Overall, the findings and key takeaways are similar to the analysis above.

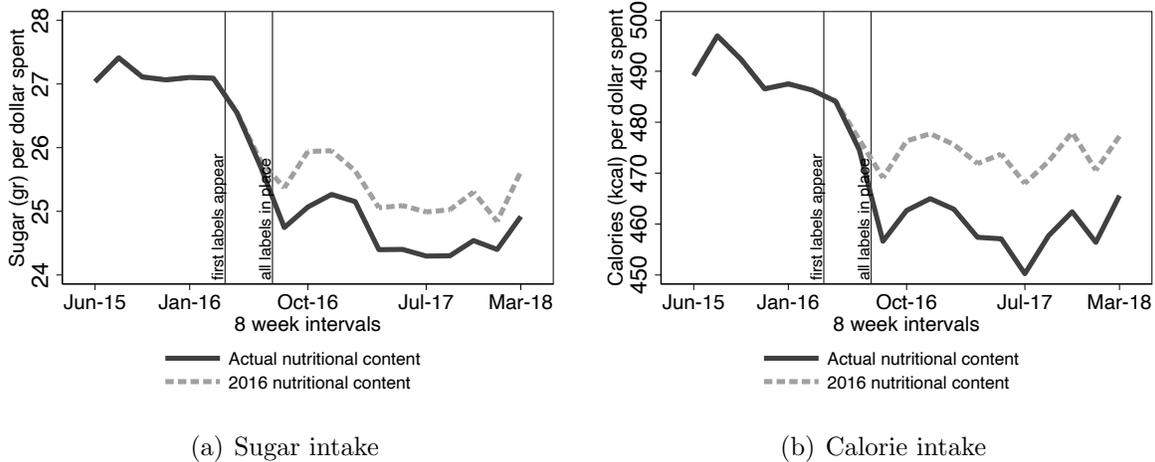


Figure 1: Nutritional intake per dollar spent before and after the policy

**Notes:** We produce this figure using a panel of Walmart consumers and computing their sugar and caloric intake during every 8-week period. After the labeling policy was introduced, total sugar intake decreased from 27.3 to 24.9 grams of sugar per dollar, and total caloric intake decreased from 488 to 457 kcal per dollar. The solid curve represents the total amount of sugar or calories purchased for every dollar spent in every 8-week period. The dashed curve is constructed in the same way as the solid curve, but fixing products’ nutritional content at their 2016 values. The left vertical line corresponds to when the first labels appeared, and the right vertical line corresponds to when the Food Act became mandatory. We have two snapshots of nutritional information data: one from early 2016, before the policy was introduced, and one from 2018, after the policy was introduced. We assume that all changes in nutritional content occurred around the date of policy implementation (June 2016), and thus use these two snapshots for all pre-policy and post-policy nutritional values, respectively, in our calculations.

We decompose the demand-side effects on *between-* and *within-*category substitution. First, we study whether the food labeling policy has the potential to shift consumer demand between categories (e.g., substituting ready-to-eat cereal for fruits). To do so, we compare categories with different shares of labeled products and examine whether categories with a low share of labeled products increased their revenue relative to categories with a high share of labeled products. We find that the extent to which consumers substituted between categories due to the presence of labels is negligible and cannot explain the patterns we document in Figure 1.

Next, we document important *within-*category substitution across labeled and unlabeled products in several product categories. We compare the quantities sold of labeled and unlabeled products before and after the introduction of the policy. We focus on categories for which there is enough variation in the share of labeled products and for which labeled and unlabeled products followed similar trends before the implementation

of the policy. We document substantial heterogeneity in these substitution effects across different categories.

To understand the source of this heterogeneity, we implement a survey in which we elicit consumers' beliefs about the nutritional content of soft drinks and cereal. These categories present the smallest and largest substitution effects, respectively. We find that beliefs are very accurate for soft drinks but not for cereal. These results are consistent with the idea that food labels are more effective in shifting demand in categories in which labels are more informative.

On the supply side, firms might respond to labeling policies by reformulating their products and avoiding labels. To empirically assess these responses, we compare the distribution of nutritional content before and after the policy's implementation. We document a significant amount of bunching at the regulatory threshold in several product categories, with important heterogeneity across product categories. For instance, whereas virtually all products above the regulatory thresholds were reformulated in the yogurt category, only 5% of ex ante labeled cookies changed their nutritional composition.

Product reformulation is more likely when the demand effects of labels are larger, when the threshold is close to the original nutritional content, and when reformulation costs are lower. For example, in categories such as yogurt or juice, firms can reformulate their products by substituting sugar with other low-cost sweeteners that mimic the products' taste. On the other hand, in cereal or cookies, sugar serves as a bulking agent, and replacing it with low-cost sweeteners may cause them to crumble. Our results are consistent with this pattern, whereby categories with low reformulation costs present a larger share of products that bunch.

Our findings are important for policy design. First, the lack of between-category substitution implies that policymakers need to set regulatory thresholds to maximize the effects within specific categories. Second, the threshold for each nutrient should be set such that it targets categories that represent a large share of consumers' bundles in terms of the overall intake of that nutrient. Third, these categories need to have both healthy and unhealthy products that are close substitutes, and consumers must be misinformed about the healthiness status of those products. Fourth, the optimal threshold should also consider the extent to which reformulation is feasible at a low cost in the targeted

categories.

### 1.1. *Contributions to the literature*

In a recent study, [Barahona et al. \(2023\)](#) develop and estimate an equilibrium model to study the Chilean Food Act that allows both price adjustments and product reformulation. The study shows that the regulation was effective in reducing the consumption of unhealthy nutrients in the cereal category. This article builds on this previous research in three ways. First, we evaluate the policy’s impact on overall nutritional intake. Second, we estimate the label’s effect across several product categories, which allows us to validate the model’s predictions outside the cereal category. Third, we leverage the heterogeneous substitution effects of labels and heterogeneity in product reformulation across categories to gain insights into optimizing label design for all consumption categories.

Several others papers have also studied the Chilean Food Act. [Taillie et al. \(2020\)](#) document a significant decline in purchases of labeled beverages following the policy’s implementation. [Reyes et al. \(2020\)](#) and [Quintiliano Scarpelli et al. \(2020\)](#) find a reduction in critical nutrient concentration of multiple products within 1 and 3 years of the policy’s implementation, respectively. [Araya et al. \(2022\)](#) take advantage of the staggered introduction of labeled products to store inventories and find that—in the very short run—labels decrease demand in the breakfast cereal category, but not for chocolates or cookies. Two other papers focus on supply-side responses to the policy in the cereal market. [Pachali et al. \(2022\)](#) study price adjustments and conclude that the 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. We document important heterogeneity across categories in both demand- and supply-side responses and discuss how these differential effects matter for policy design.

More broadly, this paper adds to the literature that investigates the effect of food labeling regulations on the demand for food. Most of this work has focused on specific food categories such as microwave popcorn ([Kiesel and Villas-Boas, 2013](#)); sugar-sweetened beverages ([Taillie et al., 2020](#)); cheese and yogurt ([Allais et al., 2015](#)); and ready-to-eat

breakfast cereal (Zhu et al., 2015; Pachali et al., 2022; Alé-Chilet and Moshary, 2022; Barahona et al., 2023). Our paper contributes to these studies by providing evidence of and quantifying the effects of national food labeling regulations on multiple categories. It also extends the literature that examines firms’ responses to food labeling policies by reformulating products (Quintiliano Scarpelli et al., 2020; Reyes et al., 2020; Alé-Chilet and Moshary, 2022; Barahona et al., 2023). By comparing firm responses across categories, we show that reformulation is more prevalent in categories in which there are accessible substitutes of critical nutrients that can mimic the products’ taste.

Finally, our paper advances the debate on mandatory information disclosure and its potentially heterogeneous effect across categories and population groups (Cawley, 2015; Araya et al., 2022). We show that food labeling policies can help to improve nutritional intake for consumers who do not respond to the labels via the product-reformulation channel. However, their effectiveness varies by product category and must be combined with complementary policies such as sugar taxes.

The remainder of the paper is organized as follows. Section 2 describes the setting and the data. In Section 3, we present empirical evidence of how labels impact overall nutritional intake through demand- and supply-side responses. We discuss policy implications and conclude in Section 4.

## 2. SETTING AND DATA

In recent years, many countries have introduced FOP labels to help consumers make healthier food choices. Unlike nutrition facts tables, FOP labels simplify nutritional information, which makes it easier to use and interpret in a context in which shoppers make quick purchasing decisions (Temple, 2020). A recent development is warning labels that indicate whether a food product has a relatively high content of a critical nutrient, such as sugar, sodium, fat, or calories. Relative to other FOP labels, warning labels are simple binary symbols that clearly signal to consumers when a product has a high concentration of a given nutrient. Perhaps due to their simplicity, warning labels have become popular in the last few years. Following Chile’s implementation in 2016, more than 25 countries, including Argentina, Brazil, Canada, Israel, and Mexico, have either implemented or are

discussing the implementation of country-wide mandatory food labeling policies.<sup>2</sup>

Mandatory warning labels can be justified from both a demand- and supply-side perspective. In terms of consumer behavior, labels might help mitigate biases that drive consumers to over-purchase unhealthy products beyond their true preferences, such as lack of self-control, inattention to potentially harmful health effects, and poorly calibrated beliefs over products' nutritional content (Bernheim and Taubinsky, 2018; Allcott et al., 2019; Barahona et al., 2023).

Food labels can also incentivize firms to produce healthier products. In the absence of mandatory labels, firms do not have incentives to invest in reducing the concentration of critical nutrients in their products.<sup>3</sup> If consumers increase the demand for healthier products in response to labels, firms can benefit from reducing the concentration of regulated nutrients to avoid getting a label. In equilibrium, regulated markets with labels can induce consumers to make better nutritional decisions and firms to offer a healthier bundle of products (Barahona et al., 2023).

### 2.1. *The Chilean Food Act*

Chile was the first country to introduce a nationwide mandatory FOP warning-label policy.<sup>4</sup> In response to high rates of obesity, the most prevalent chronic disease in the country, in 2016 Congress passed Law 20.606 (hereafter, the Food Act), which introduced FOP warning labels to inform consumers about products' healthiness and help guide purchasing decisions.<sup>5</sup> The rationale was that nutritional information available in the

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<sup>2</sup>Table A.1 presents the list of countries, including the critical nutrients targeted in the regulation.

<sup>3</sup>Although suppliers of healthy products have incentives to solve these inattention and informational problems in a well-functioning market, several frictions make it unlikely that the market itself will self-regulate and thus provide ground for government intervention. Dranove and Jin (2010) discuss several conditions that are required for markets to unravel.

<sup>4</sup>Chile was the first country to approve mandatory national FOP warning labels for food high in calories, added sugars, saturated fats, and sodium and to implement the warning labels for all processed food products. Before 2016, several countries had implemented voluntary FOP labels. For example, Sweden, Denmark, Norway, Lithuania, and Iceland used the Keyhole logo; The Netherlands, Belgium, and Poland used the Choices logo; Korea and the United Kingdom used traffic-light labels; and Singapore used the Healthier Choice Symbol. Finland implemented a mandatory warning label in 1993 but only for some products high in salt. Thailand introduced a mandatory GDA label in 2007 but only for five categories of snacks. Also, Ecuador and Iran implemented mandatory traffic-light labeling for all processed products in 2014 and 2015, respectively.

<sup>5</sup>The Food Act also included regulations to ban selling labeled products in schools and a ban on advertising labeled products aimed at children younger than 14 years of age.

form of a fact table on the back of the product was too complex and “did not allow [consumers] to make an informed decision” ([Historia de la Ley 20.606, 2011](#), p. 170).

The Chilean Food Act mandated that products with calories, added sugar, saturated fats, and sodium higher than a given threshold must include a FOP warning label for each nutrient threshold surpassed. Figure 2 shows what Chilean FOP warning labels look like and how they are displayed on actual products. The thresholds were established uniformly for all food products, depending on whether the product is a solid or a liquid. To define the thresholds, the legislators chose the 90th percentile of the distribution of the concentration of critical nutrients from non-processed food products according to the USDA. The introduction of the thresholds was gradual and implemented in three stages. Stages 1, 2, and 3 took place in June 2016, 2018, and 2019 respectively. Threshold values are presented in Appendix A, Table A.2.<sup>6</sup>



Figure 2: FOP warning labels on selected products

**Notes:** The figure presents both the FOP warning labels implemented in Chile and how these are displayed on various food packages. The labels say, from left to right, “High in sugar,” “High in saturated fat,” “High in sodium,” and “High in calories.” Products can have from zero to four labels. Table A.2 presents the threshold values that determine the assignment of each label.

<sup>6</sup>The Food Act has a relevant exception that limits its scope to regulating only processed and packaged foods. This means that even if a product exceeds a certain threshold, it will not require a label if it does not contain added sugars, sodium, saturated fats, honey, or syrup.

## 2.2. Data

The main outcome measures used in the analysis come from scanner-level data from Walmart, which we expand using nutritional information and a survey that captures consumers' beliefs about product healthiness.

2.2.1. *Walmart data:* We use data from Walmart-Chile, the largest food retailer in Chile, which is responsible for over 40% of supermarket sales. The data cover all transactions in Walmart stores between May 2015 and March 2018, and identifies products by a Universal Product Code (UPC). For each transaction, we have access to information such as a product's price, revenue, product name, brand name, and discounts.<sup>7</sup>

We use Walmart's loyalty program to connect transactions with individual shoppers over time. We focus on regular Walmart customers who visited a store at least once every 8 weeks during the study period, leading to a total of roughly 524,000 individuals. We have access to information on these customers, such as their gender, age, and household income. The average customer in our study is 48 years old, and 69% are women. Before the policy was introduced, the median customer shopped at Walmart 24 times, at three different Walmart locations, and traveled about 3 kilometers to get to the nearest store.<sup>8</sup>

2.2.2. *Nutritional Information:* The 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 we collected and digitized ourselves. INTA collected nutritional information for a sample of products in January 2016 at UPC level. This included the nutrition facts table, whether the product is a liquid or a solid, and the size of the package.

To collect nutritional information for the post-policy period, we developed a camera phone app that could capture images of nutrition facts tables. We then used this app to digitize the nutritional content of all available products in the three largest Walmart stores in Chile. Our dataset includes 90% of Walmart's revenue from packaged food

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<sup>7</sup>The data comprise over 9 billion transactions by over 5 million consumers for over 20,000 different food products.

<sup>8</sup>We count as a visit anytime a customer spends at least \$20 on food products.

products. We collected this information in March 2018, two years after the first stage of the labeling law was implemented in June 2016. To include information on non-packaged products, such as fresh produce or meat—which don’t have nutrition facts tables—we consulted publicly available data from the USDA’s FoodData Central. We used these data to complete any missing information across all food categories.

2.2.3. *Consumer beliefs:* We conducted a survey of 1,500 consumers to elicit beliefs about the nutritional characteristics of packaged food products. We asked participants to provide an estimate of the sugar and caloric content of certain cereal and soft drink products. We conducted the survey in Argentina in August 2019, when there was no food labeling policy in place.<sup>9</sup>

### 3. EMPIRICAL EVIDENCE

In this section, we provide evidence of demand- and supply-side responses to food labels. We investigate the degree to which labels prompt consumers to substitute products both within and between categories, the importance of the accuracy of consumers’ beliefs for the effectiveness of food labels, and the extent to which products have been reformulated in order to avoid being labeled.

#### 3.1. *Demand-side responses*

*Between-category substitution:* We start by examining whether consumers shift their consumption of food products across food categories as a response to food labels. To do so, we define broader groups of products that contain multiple categories in which we could expect substitution to occur. For instance, we check whether there was substitution between categories for product categories that are likely to be eaten at breakfast: eggs, yogurt, bread, fruits, jams, and breakfast cereal. Then, within each broad group, we compare revenues before and after the policy for categories with a high and a low share of labeled products.

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<sup>9</sup>Although we would have preferred to conduct the survey in Chile before the policy’s implementation, we used Argentina as a proxy due to its similar population and food market, but lack of exposure to any labeling policy.

In Figure 3, we plot changes in the share of revenue over time of the food categories that fall into the breakfast and drinks food groups. In each group, categories are ordered from top to bottom according to the share of labeled products they contain (weighted by pre-policy revenue). The darker the area’s color, the larger the share of labeled products. For instance, in breakfast products, 0% of egg products are labeled, while in cereals—the category with the highest share of labeled products in this group—62% of the products are labeled.

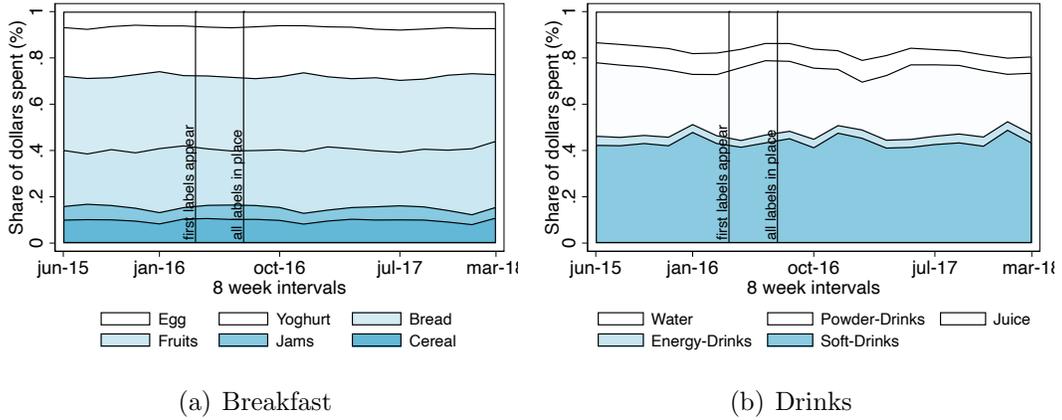


Figure 3: Share of dollars spent across categories

**Notes:** The figure shows the evolution of the share of dollars spent in each category within broader groups of products. Colors represent the share of labeled products within each category. White areas are categories in which no product received a label, and dark-blue areas (e.g., snacks) are categories in which all products received at least one label. We show no differential changes in dollars spent between low-in-labels and high-in-labels categories.

Figure 3 suggests there is little to no evidence that consumers are shifting consumption from highly labeled categories, such as breakfast cereals or soft drinks, to low-labeled categories, such as eggs or juices. For instance, in Panel (a), the share of breakfast spending on cereals averages 9.9% in both the pre- and post-policy period.<sup>10</sup>

To formalize these results, we pool all food categories together (not only breakfast and drinks) and run the following regression:

$$\log(r_{cst}) = \beta_t \cdot L_c + d_{cs} + \delta_t + \varepsilon_{cst}, \tag{1}$$

<sup>10</sup>In Appendix A Figure A.2, we show that this finding extends to several other food groups, such as carbs, meats, desserts, and snacks.

where  $r_{cst}$  denotes the total revenue from products in category  $c$  sold in store  $s$  in period  $t$ , and  $L_c$  is the (weighted) share of products in category  $c$  that have at least one label. Finally,  $\delta_t$  denotes period fixed effects and  $d_{cs}$  refers to category-store fixed effects. We normalize the  $\beta_t$  coefficient corresponding to the first period post-adoption to zero. Observations are weighted by category-store pre-policy revenues, and standard errors are clustered at the category level.

Figure 4 displays the results from estimating Equation (1). In both the pre- and post-policy period, the difference in coefficients is small, and none is significantly different from zero.<sup>11</sup> Regression results are consistent with the results for breakfast products and drinks presented in Figure 3. This evidence suggests that the extent to which consumers substituted toward other categories due to the presence of labels is negligible and cannot explain the patterns we document in Figure 1.

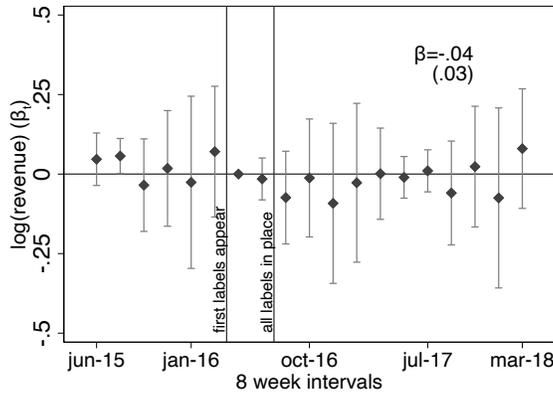


Figure 4: Changes in total spending per capita across categories

**Notes:** The figure presents the  $\beta_t$  coefficients from Equation (1). Vertical lines delimit the 95% confidence intervals. These regressions are run on a sample of 69 categories. The average share of labeled products in each category is 0.3, with a minimum of 0 and a maximum of 1.

*Within-category substitution:* Next, we examine the effects of food labels within each food category, where products are more likely to be close substitutes. For our analysis, we limit our attention to eight categories and subcategories that meet the following criteria: (a)

<sup>11</sup>Note that the variance of the estimates increases in January and February. Since we are pooling many different products together, seasonality affects them differently. However, as long as the seasonality of different categories is not correlated with the shares of products labeled, this should not bias our estimates. To control for seasonality, we need to compare coefficients belonging to the same period of the year as the normalized coefficient. When we proceed this way, coefficients are more precise and still not statistically different from zero.

products are sufficiently similar such that consumers would consider substituting from one to another as a result of the regulation, (b) there is sufficient variation in terms of the share of products that received a label, and (c) unlabeled and labeled products within the category follow similar pre-trends in the absence of the policy. We select eight categories that represent 5.7% of the pre-policy revenue of all food products and 11.9% of the pre-policy revenue of all labeled products. In Appendix B, we explain in more detail the selection process for these categories and sample coverage.

We define a product as the union of UPCs that share the same product name and brand. For example, we assign all *Diet Coke* the same product ID regardless of their can or bottle size. We assign labels to a product based on its 2018 nutritional content. We collapse our original data into product-store-period data bins (in which a period is defined as 8 consecutive calendar weeks) and estimate the following regression for each category:

$$\log(q_{jst}) = \beta \cdot L_j + \gamma \cdot \log(p_{jst}) + \delta_{js} + \delta_t + \varepsilon_{jst}, \quad (2)$$

where  $q_{jst}$  denotes the grams (ml) of product  $j$  sold in store  $s$  in period  $t$ ,  $p_{jst}$  refers to the product’s price per 100 grams (ml), and  $L_j$  is an indicator variable that takes the value of one if the product has one or more labels. Finally,  $\delta_{js}$  refers to product-store fixed effects and  $\delta_t$  to period fixed effects. We normalize the  $\beta_t$  coefficients so that their average value over the pre-policy period is 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.<sup>12</sup>

In Figure 5, we plot the estimated changes in demand for each of the categories. We find a significant impact of the policy for all eight categories. These results confirm that consumers substituted from labeled to unlabeled products within all of these product categories and that the effect holds in the medium run. Overall these findings suggest that the policy is effective in shifting consumption in many product categories and thus com-

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<sup>12</sup>Given our context, in which consumers substitute from one product to another, it is natural that the no-interference assumption—which is standard in the impact evaluation literature—does not hold. In the extreme case of one-to-one substitution, a  $\beta$  of 10% would reflect a 5% decrease in labeled products and a 5% increase in unlabeled products. As a result, our coefficients should be interpreted as the impact on the relative change in the equilibrium quantities of labeled versus unlabeled products sold.

plements the policy impact for breakfast cereal documented by [Barahona et al. \(2023\)](#).<sup>13</sup> Interestingly, the effects are highly heterogeneous by product category, ranging from 26% in the case of cereals to 10% in the case of soft drinks. Next, we explore a mechanism that can help make sense of the dispersion in observed effects.

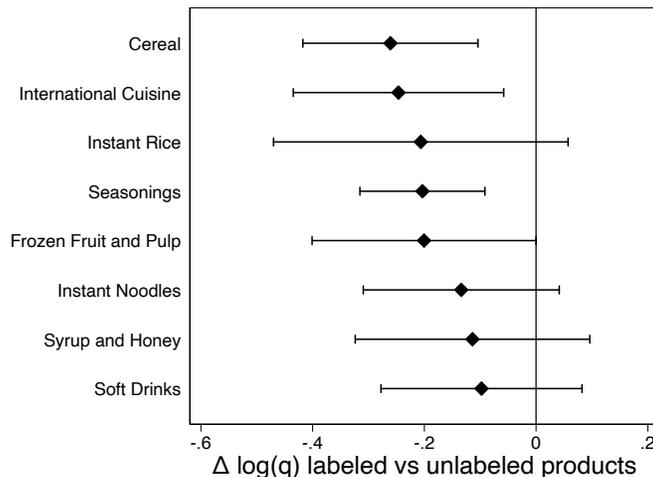


Figure 5: Changes in demand for selected categories

**Notes:** This shows the changes in equilibrium quantities between labeled and unlabeled products from estimating Equation (2) for different product categories. The set of products in this analysis represents 11.9% of the pre-policy revenue of labeled products in the sample. We provide more details on sample selection in Appendix B.

*The importance of prior beliefs:* In related work, [Barahona et al. \(2023\)](#) show that the effect on cereals is mostly explained by substitution away from products that consumers believed to be healthy but which ended up with a label. In other words, at the product level, labels are more effective if they provide new information to consumers. To investigate how information and beliefs affect the extent of *within*-category substitution, we use the beliefs survey described in Subsection 2.2.3 and compare the effects of the policy on cereal and soft drinks.

The pre-policy concentration of sugar in soft drinks follows a bimodal distribution driven by diet and non-diet drinks, which highly correlates with consumers’ beliefs about sugar concentration in these products. The correlation between the average value of

<sup>13</sup>In Appendix A Figure A.3, we present nonparametric results. Pre-period coefficients are small and not significantly different from zero in all categories. After the introduction of the labels, we observe a noticeable drop in demand for labeled products relative to that for unlabeled products. This effect persists throughout our observational time window.

respondents’ beliefs about the sugar concentration of each product and the product’s observed pre-policy sugar concentration in the soft drinks category is 0.94. In cereal, however, consumers have mistaken beliefs about the caloric content of products. The correlation between the average value of respondents’ beliefs about the caloric concentration of each product and the product’s observed pre-policy caloric concentration is 0.23. We present the relationship between consumer beliefs and pre-policy nutritional content in Appendix A, Figure A.4.

The accuracy of beliefs about sugar content implies that labels came as no surprise in this category, which means that the effect of the policy should be smaller in soft drinks than in cereal. To test for this, we estimate the following regression for each category:

$$\log(q_{jst}) = \sum_k \beta_k \cdot L_j \cdot \mathbb{1}\{k = t\} + \gamma \cdot \log(p_{jst}) + \delta_{js} + \delta_t + \varepsilon_{jst}, \quad (3)$$

where all variables and specification details are defined as in Equation (2).

Figure 6 displays the results of estimating Equation (3) for soft drinks and cereal. Pre-period coefficients are small and not significantly different from zero in both categories. After the introduction of the labels, we observe a noticeable drop in the demand for labeled products relative to that for unlabeled products in the cereal market but not in the soft drinks market.<sup>14</sup>

The main takeaway is that labels have a larger *within*-category effect when they provide useful information to consumers. This is consistent with the evidence provided by Araya et al. (2022), who study the short-term effects of the same regulation for breakfast cereals, chocolates, and cookies. They exploit the staggered rollout of labels across different stores before the law went into effect, which allows them to study the effect of labels in categories in which all products would have received a label after full deployment of the law. They find a null effect of food labels in chocolates and cookies, in which labels are likely to offer no new information to consumers.

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<sup>14</sup>There is a small and non-significant decrease in demand for labeled products in the soft-drink market after September 2017, which is when Coca-Cola Company reformulated two products—Regular Fanta and Regular Sprite—to remove their high-in-sugar label.

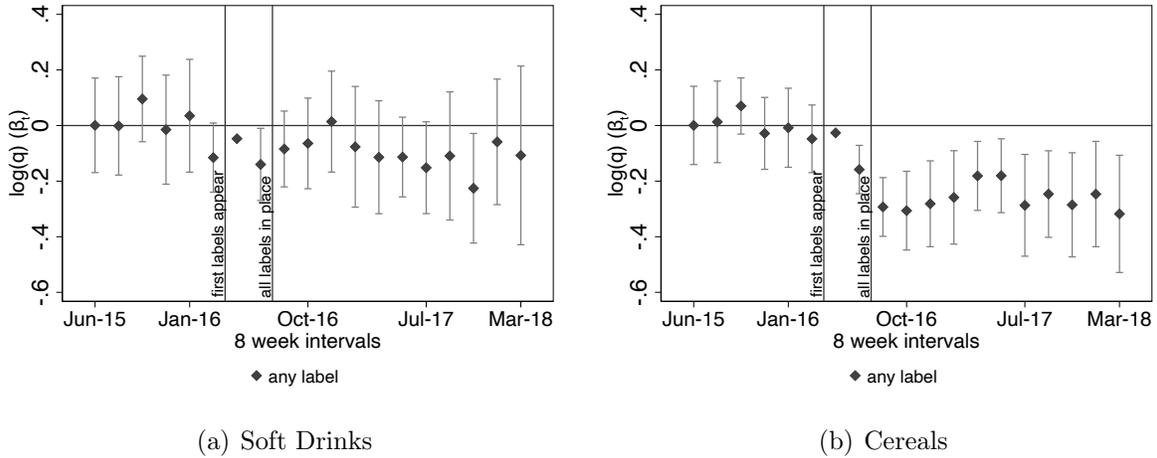


Figure 6: Dynamic changes in demand for soft drinks and cereals

**Notes:** This figure presents regression coefficient estimates from Equation 3. Panel (a) presents the  $\beta_k$  coefficients of the regression on the sample of 37 soft drinks that show up in the pre-and post-policy periods. The sample consists of 27 unlabeled and 10 labeled products for a total of 94,391 observations. Panel (b) displays the  $\beta_k$  coefficients of the regression 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.

### 3.2. Supply-side responses

Finally, we examine supply-side responses to the regulation. We look at the extent to which firms reformulated their products in different categories due to the introduction of food labels. We focus on reformulation in sugar and restrict our attention to categories in which the distribution of sugar concentration is neither entirely to the left of the regulation threshold nor too far to the right, such that it would not be feasible to modify the nutritional content up to threshold levels. This gives us a total of 13 categories that represent 15.5% of the pre-policy revenue of all food products and 53.6% of the pre-policy revenue of products to the right of the threshold for which we collected nutritional content data. We discuss further details of the selection of categories and sample coverage in Appendix C.

To assess behavioral responses on the supply side, we compare the distribution of nutritional content before and after the policy was implemented and explore bunching at regulatory thresholds. Figure 7 plots the distribution of sugar concentration in 2016 (pre) and 2018 (post) for products in the juice and cereal categories. The size of the bars represents the pre-policy revenue of the products included in that bar. Each subfigure

also includes three vertical lines that indicate the thresholds of the policy in each of the three stages.

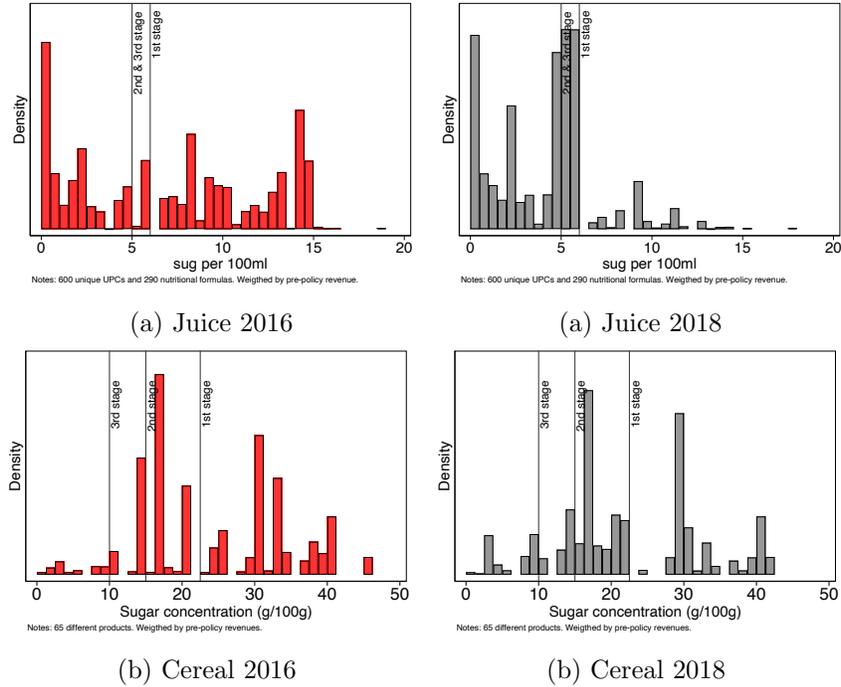


Figure 7: Distribution of sugar content pre- and post-policy in selected categories

**Notes:** This figure plots the distribution of sugar concentration for juice and cereal before and after policy implementation. Observations are weighted by pre-policy revenue.

Before the introduction of food labels, we do not observe any noticeable pattern of bunching at any of the thresholds in either the juice or cereal category. However, in 2018 we find some evidence of bunching in both categories. In juice, we find that whereas in 2016 more than half of the products had a sugar concentration per 100 ml above the first-stage threshold, the distribution shifted to the left, and most products avoided first-stage labels. In cereal, we also find that some products were reformulated in order to be on the left side of the threshold. Nevertheless, reformulation occurred to a much lesser extent than in juice.

In Figure 8, we summarize the findings for all categories by plotting the (weighted by pre-policy revenue) share of the products in each category that surpassed the sugar threshold in the pre-policy period and were reformulated to be to the left of the threshold in the post-policy period. We show histograms for each category in Appendix A, Figures A.5 and A.6.

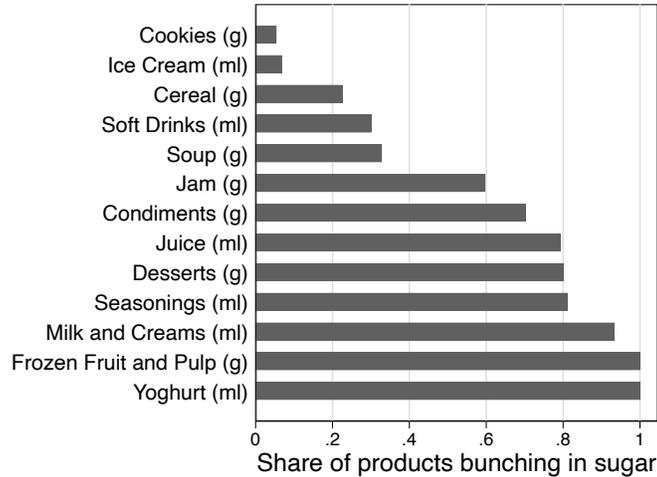


Figure 8: Share of products bunching in sugar

**Notes:** This figure summarizes the findings for bunching from Appendix A, Figures A.5 and A.6. It shows the pre-policy revenue-weighted share of products to the right of the threshold in sugar in the pre-policy period that reduced the concentration of sugar to be to the left of the regulatory threshold in the post-policy period. The products used represent 54% of the pre-policy revenue of all products to the right of the policy threshold in the pre-policy period. We provide more details on sample selection in Appendix C.

We find that while in some categories, 100% of the products were reformulated to cross the regulatory threshold, in other categories, less than 10% were reformulated. Three important features of a product category can affect the extent to which products are reformulated. First, firm responses depend on the expected impact of labels on product demand. In categories with close substitutes and in which labels can provide more information, the returns to reformulation are higher. Second, reformulation is a function of the distance between the products' current nutritional content and the regulatory threshold. Third, firms are more likely to reformulate products when they are able to do so without substantially affecting their quality (e.g., taste). For example, in categories such as yogurt or juice, firms can reformulate their products by substituting sugar with other low-cost sweeteners that mimic the products' taste. On the other hand, sugar serves as a bulking agent in cereal or cookies, and replacing it with low-cost sweeteners may cause them to crumble. Our results are consistent with this pattern, whereby categories with liquid products present a larger share of products that bunch.

## 4. DISCUSSION

The Chilean Food Act suggests that FOP warning labels have the potential to reduce the overall intake of calories and sugar. We use access to rich micro-data—the universe of Walmart transactions in Chile between 2015 and 2018—and perform several empirical exercises to unpack the mechanisms through which labels affect consumer and firm behavior to inform policy design. We find that labels are ineffective in shifting consumption across product categories. In other words, we do not find evidence of substitution from unhealthy to healthy categories. Instead, most of the policy effects arise from substitution within a product category. We also find that labels are substantially more effective in product categories in which beliefs about product healthiness are poorly calibrated. Finally, we find that labels have the potential to promote product reformulation across several product categories and that these responses are highly heterogeneous.

These results are consistent with the predictions of the model of supply and demand for nutrients in [Barahona et al. \(2023\)](#). On the demand side, labels are most effective when they correct mistaken beliefs about product healthiness and when consumers are willing to substitute labeled and unlabeled products (i.e., whether labeled and unlabeled products are close substitutes). On the supply side, the model suggests that firms are more likely to reformulate their products and avoid being labeled when it is economically feasible to maintain taste consistency at a low cost.

Our findings provide insights to inform the design of effective food labeling policies. Policymakers seeking to implement labels need to decide where to set label thresholds to harness demand- and supply-side responses effectively. First, the lack of between-category substitution implies that food labels should be designed to focus on effects within specific categories. For instance, labels should not be designed to maximize substitution from cereal to fruit but instead from unhealthy to healthy cereal. Second, policymakers should target categories that (i) represent a large share of consumers’ intake of critical nutrients, (ii) have both healthy and unhealthy products that are close substitutes, and (iii) in which consumers are misinformed about the health status of the products therein. Third, thresholds must be set to maximize substitutability within targeted categories and product reformulation, and should therefore consider the extent to which taste consistency can be

preserved without significant increases in production costs.

It is important to bear in mind that the policy we examine in this study applied a uniform threshold for all solids and a uniform threshold for all liquids for each targeted nutrient. To maximize the potential of the policy design by taking advantage of the heterogeneous demand- and supply-side responses across categories, policymakers may consider implementing an alternative policy that incorporates category-specific thresholds. Understanding whether and how category-specific thresholds can enhance the effectiveness of the policy is an important area for future research.

Finally, our results also shed light on the importance of combining alternative policies to tackle obesity. In categories such as chocolates and candy, in which all products receive labels and are known to be high in critical nutrients, food labels are less effective for improving diet quality. Also, other market imperfections, such as lack of self-control or time inconsistency, may induce consumers to not always choose food products that are best for them (Sadoff et al., 2020; Samek, 2019). In those cases, a better policy tool may be to implement sugar taxes (Barahona et al., 2023). Consequently, because labels and sugar taxes counteract different externalities, they should be seen as complementary policies rather than substitutes.

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# Online Appendix for: On the Design of Food Labeling Policies

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March 28, 2023

## APPENDIX A: ADDITIONAL FIGURES

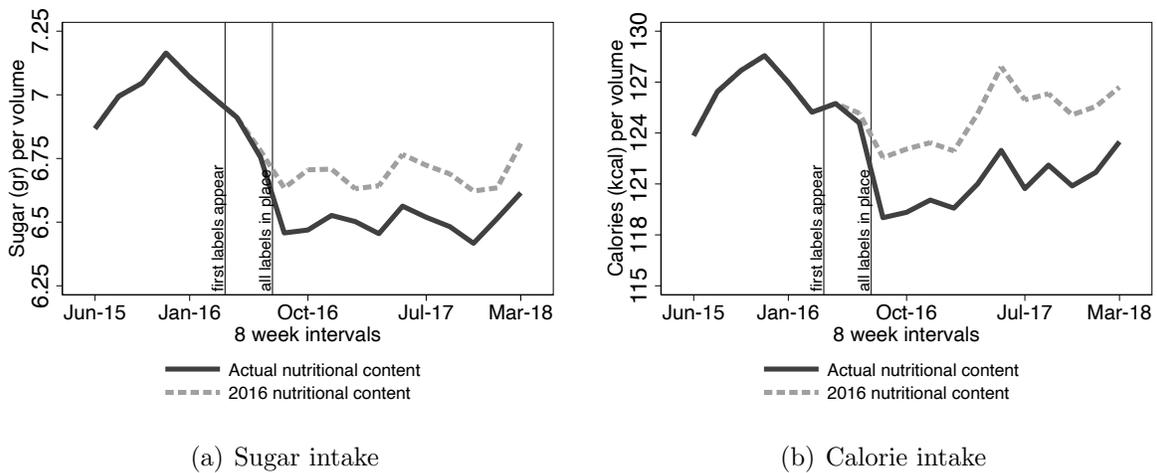


Figure A.1: Sugar intake per grams and milliliters consumed before and after the policy

**Notes:** This figure shows the changes in nutritional intake per volume/mass of food products purchased at Walmart. For volume, we calculate the total amount of kilograms and total liters of products purchased at Walmart. We then divide the total intake of sugar by the total volume/mass of products. Measures of volume and mass of products are subject to measurement error from potential coding error in package sizes.

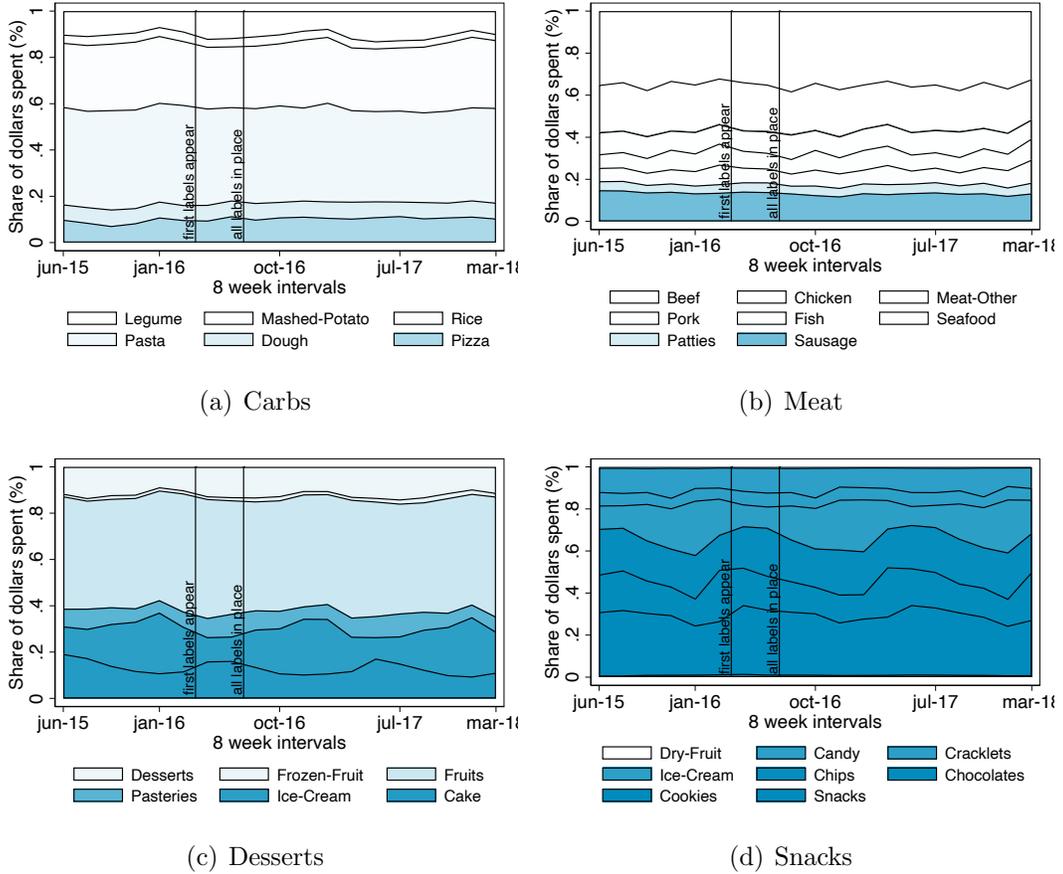
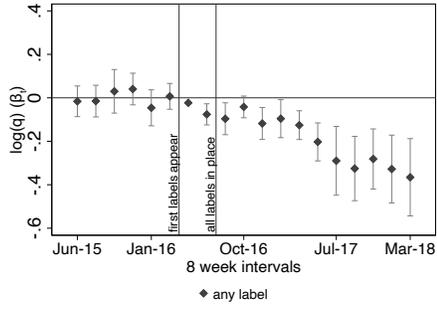
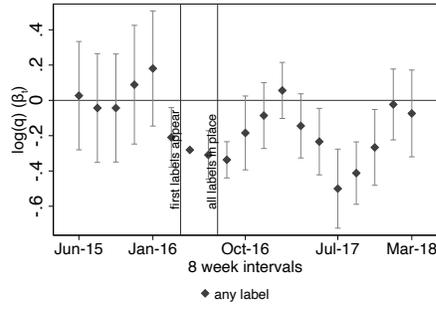


Figure A.2: Share of dollars spent across different categories

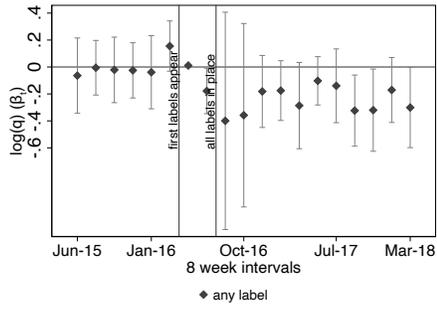
**Notes:** This figure shows the evolution of the share of dollars spent in each category within broader groups of products. Colors represent the share of labeled products within each category. White areas are categories in which no product received a label, dark-blue areas (e.g. snacks) are categories in which all products received at least one label. We show that there are no differential changes of dollars spent between low-in-labels and high-in-labels categories.



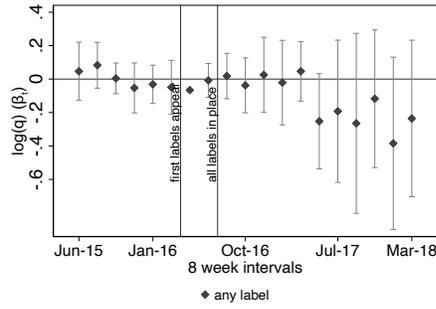
(a) Seasonings



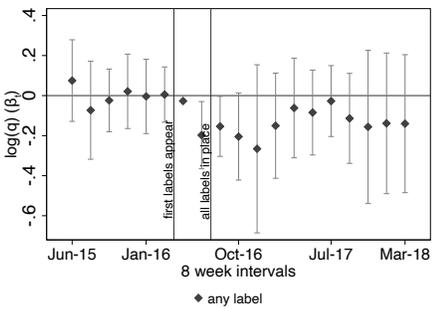
(b) Frozen Fruit and Pulp



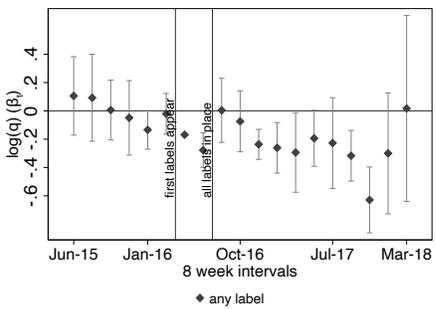
(c) International Cuisine



(d) Syrup and Honey



(e) Instant Noodles



(f) Instant Rice

Figure A.3: Estimates by category

**Notes:** This figure presents regression coefficient estimates. Each panel presents the  $\beta$  coefficients from Equation (2) for selected categories.

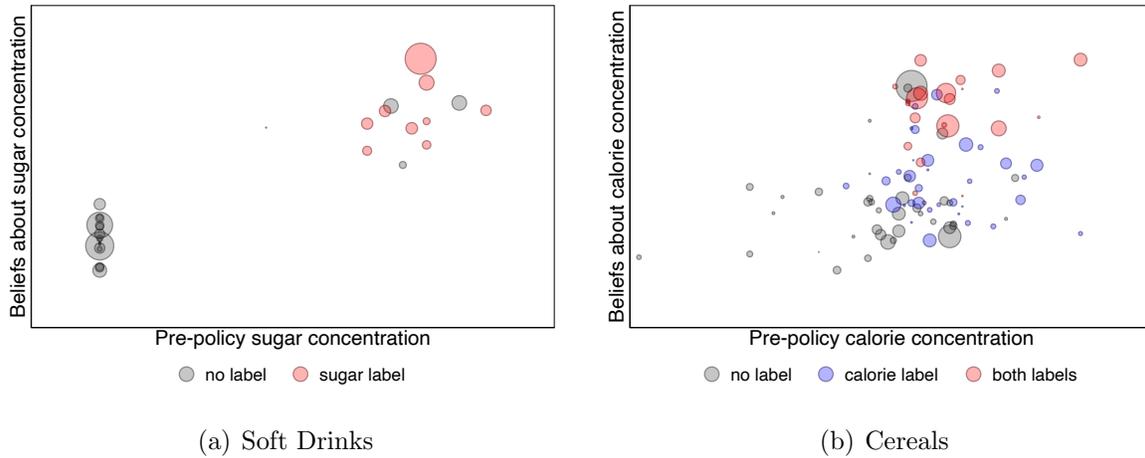


Figure A.4: Correlation between beliefs about nutritional content and true nutritional content

**Notes:** This figure shows the first moments of beliefs about each product's nutritional content vs. its real nutritional content. Each circle corresponds to a different cereal, and its size represents the total revenue from that product in our sample period. Panel (a) focuses on the sugar concentration of soft drinks as measured by g sugar/g product and panel (b) on the caloric concentration of cereals, as measured by kcal/g product. Since we focus on the relative distance between survey responses for different products, we do not provide numerical labels for the x- and y-axes.

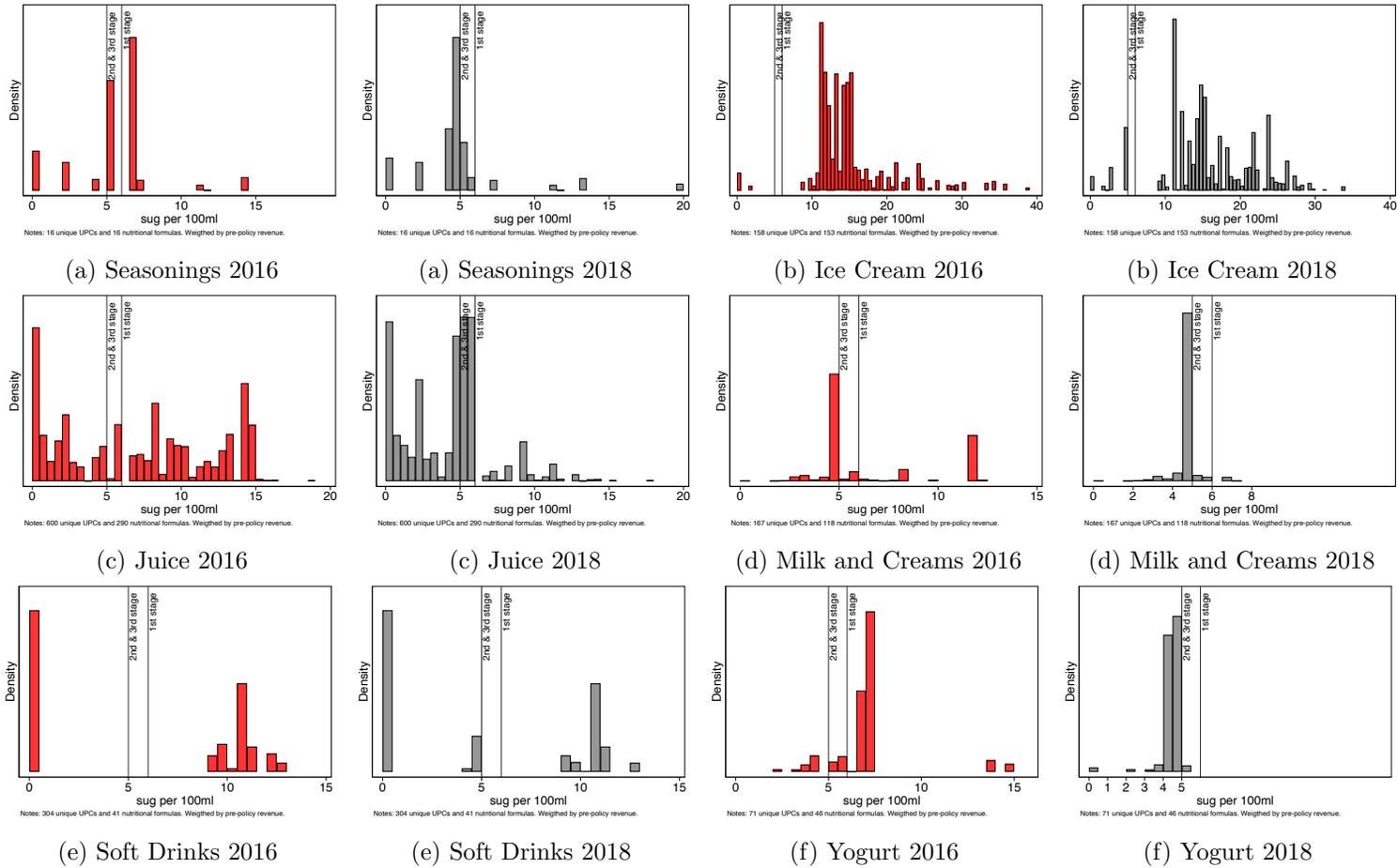


Figure A.5: Distribution of sugar content pre- and post-policy for liquids in selected categories

**Notes:** This figure plots the distribution of sugar concentration for liquid products in different categories before and after the policy implementation. Observations are weighted by pre-policy revenue.

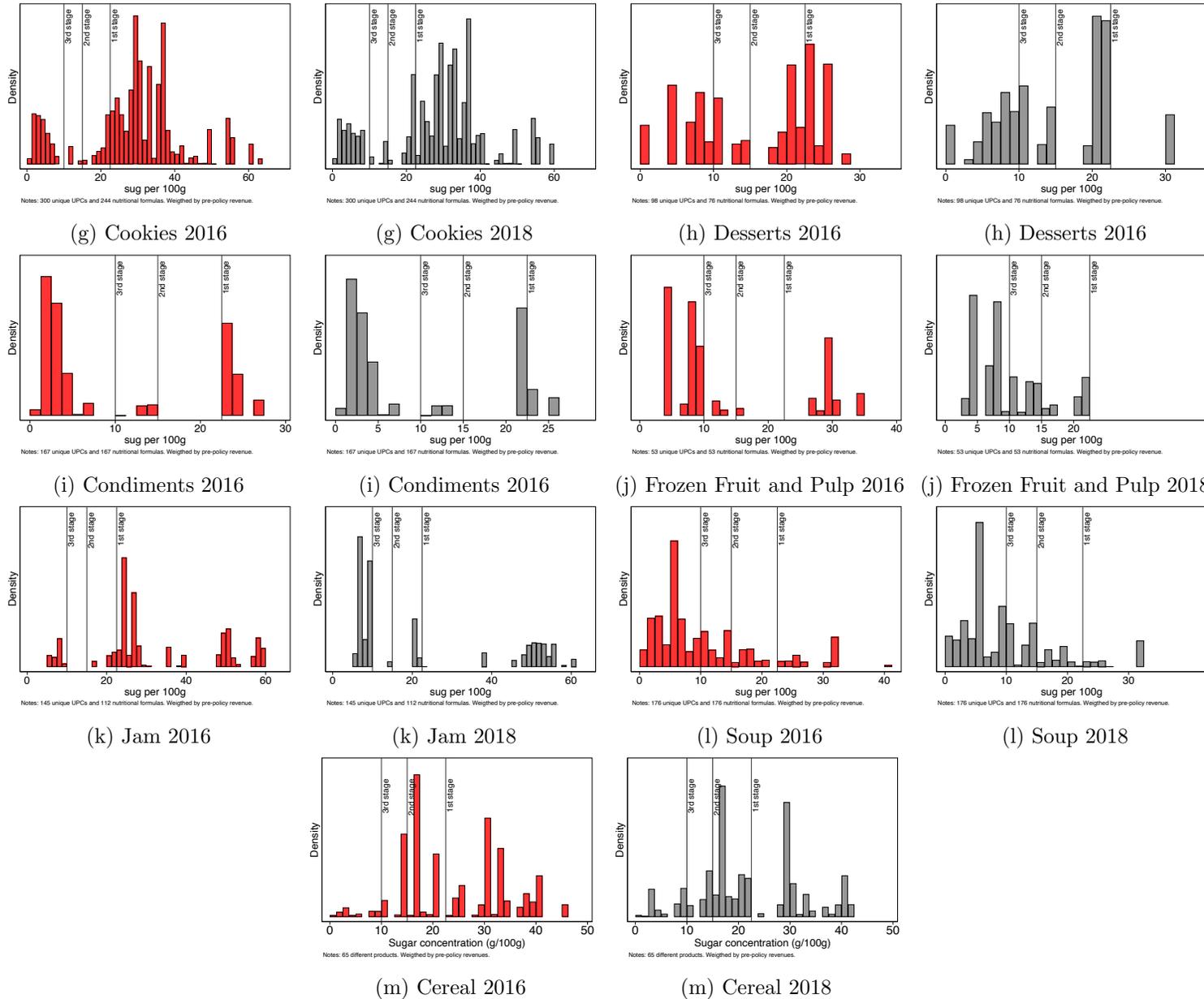


Figure A.6: Distribution of sugar content pre- and post-policy for solids in selected categories

**Notes:** This figure plots the distribution of sugar concentration for solid products in different categories before and after the policy implementation. Observations are weighted by pre-policy revenue.

Table A.1: FOP warning-label policies

Country	Status	Year	Critical nutrients			
			Sugar	Sodium	Fat	Calories
Chile	Implemented	2016	✓	✓	✓	✓
Peru	Implemented	2019	✓	✓	✓	
Israel	Implemented	2020	✓	✓	✓	
Mexico	Implemented	2020	✓	✓	✓	✓
Uruguay	Implemented	2021	✓	✓	✓	
Argentina	Implemented	2022	✓	✓	✓	✓
Brazil	Implemented	2022	✓	✓	✓	
Colombia	Approved	2021	✓	✓	✓	
Venezuela	Approved	2021	✓	✓	✓	
Canada	Approved	2022	✓	✓	✓	
Antigua and Barbuda	In discussion	-	✓	✓	✓	
Bahamas	In discussion	-	✓	✓	✓	
Barbados	In discussion	-	✓	✓	✓	
Costa Rica	In discussion	-	✓	✓	✓	✓
Dominica	In discussion	-	✓	✓	✓	
El Salvador	In discussion	-	✓	✓	✓	✓
Guatemala	In discussion	-	✓	✓	✓	
Guyana	In discussion	-	✓	✓	✓	
Haiti	In discussion	-	✓	✓	✓	
India	In discussion	-	✓	✓	✓	✓
Jamaica	In discussion	-	✓	✓	✓	
Panama	In discussion	-	✓	✓	✓	✓
Paraguay	In discussion	-	✓	✓	✓	✓
Saint Kitts and Nevis	In discussion	-	✓	✓	✓	
Saint Lucia	In discussion	-	✓	✓	✓	
Suriname	In discussion	-	✓	✓	✓	
Trinidad and Tobago	In discussion	-	✓	✓	✓	

**Notes:** The table shows the introduction and discussion of mandatory FOP warning-label policies around the world. The table includes countries with laws or government resolutions implemented, approved but not implemented, or under discussion. Countries with discussions of the topic that do not have a specific government plan or law proposal to establish mandatory FOP warning labels are not included. For countries with approved or implemented policies, “Year” indicates the date the policy was approved or the first implementation stage began. Some of these policies distinguish between total fat, saturated fat, and trans fat; we group all of them together for expositional purposes.

Table A.2: Chilean Food Act thresholds

	Solids			Liquids		
	Stage 1	Stage 2	Stage 3	Stage 1	Stage 2	Stage 3
Energy (kcal/100g)	350	300	275	100	80	70
Sodium (mg/100g)	800	500	400	100	100	100
Sugar (g/100g)	22.5	15	10	6	5	5
Saturated fat (g/100g)	6	5	4	3	3	3

**Notes:** The table shows the level of calories, sodium, sugar, and fat at which a product would need to be labeled. The policy was implemented in three stages, with each stage setting stricter thresholds. Stages 1, 2, and 3 took place in June 2016, June 2018, and June 2019.

## APPENDIX B: SAMPLE SELECTION IN OUR WITHIN-CATEGORY SUBSTITUTION ANALYSIS

In this appendix we discuss the sample selection process for the categories in our analysis of within-category substitution. We also provide basic descriptive statistics regarding sample coverage.

### B.1. *Selection of Categories*

For the purpose of estimating the impact of labels on consumer demand, we first need to define the set of products contained in a given category. The ideal definition of a category for this exercise meets three criteria: (a) products are sufficiently similar, such that consumers would consider substituting from one to another as a result of the regulation; (b) there is sufficient variation in terms of the share of products that receive a label; and (c) for the purpose of estimating a differences-in-differences model, we would need unlabeled and labeled products within a category to follow similar pre-trends in the absence of the policy.

Examining the categories that meet these conditions in our data is not straightforward. First, the product categories in our data are defined by Walmart for administrative and internal processes, and in many cases, they include products that are not necessarily substitutes. Second, about 35% of total revenue comes from products that belong to a category with significant variation in exposure to labels (as defined by having less than 90% of labeled and unlabeled products). Third, most products within Walmart's categories do not follow parallel trends. To address these issues, we selected and combined certain categories, and within those, we restricted our analysis to products that have the potential to function as close substitutes. We also visually inspected and kept those in which labeled and unlabeled products followed similar pre-trends.

### B.2. *Sample Coverage*

In Table B.1, we show the share of the revenue covered by the categories included in our demand-side analysis. Column (1) displays the share of total revenue represented by each category provided by Walmart. This column contains the universe of food products

purchased by individuals from our consumer panel and adds up to 100%. We group a set of categories for which most products are either below or above the policy threshold in the post-policy period and label them “Mostly unlabeled” and “Mostly labeled.” Together, these two groups represent close to 63% of the revenue and include categories such as fruit, meat, salads, candy, and chocolate. Another 30% of total revenue corresponds to other categories in which labeled and unlabeled products did not follow similar pre-trends. Some products in these categories include pastry, bakery products, cold cuts, and biscuits. Our selected categories cover the remaining 5.7% of total revenue.

Table B.1: Selected categories used to study the impact of food labels on consumer demand

	Market share	Share labeled	Market share within labeled products
	(1)	(2)	(3)
<b>Included</b>	5.7	47.7	11.9
<i>Cereal</i>	1.4	62.7	3.6
<i>Frozen Fruit and Pulp</i>	0.1	11.2	0.1
<i>Instant Noodles</i>	0.1	47.3	0.1
<i>International Cuisine: Mexican food</i>	0.1	27.6	0.1
<i>Instant Rice</i>	0.1	27.1	0.1
<i>Seasonings</i>	0.5	57.5	1.2
<i>Soft Drinks</i>	3.3	42.4	6.5
<i>Syrup and Honey</i>	0.1	42.4	0.2
<b>Not Included</b>	94.3	21.2	88.1
<i>Mostly unlabeled</i>	57.4	1.2	1.6
<i>Mostly labeled</i>	6.3	99.2	25.8
<i>Others</i>	30.6	46.9	60.7
<b>Total</b>	100	22.8	100

**Notes:** Column (1) presents the share of total revenue for each category provided by Walmart. This column contains the universe of food products purchased by individuals from our consumer panel and adds up to 100%. Column (2) presents the share of labeled products within each of the categories. Column (3) presents the share of total revenue for labeled products.

Column (2) reports the share of products, weighted by revenue, that received a warning label within a given category. Column (3) reports the share of total revenue for products that received a label. When focusing on labeled products, our working sample comprises

around 12% of the pre-policy revenue of labeled products in the total sample.

## APPENDIX C: SAMPLE SELECTION IN OUR PRODUCT REFORMULATION ANALYSIS

In this appendix we discuss the sample selection process for the categories in our analysis of product reformulation. We also provide basic descriptive statistics regarding sample coverage.

### C.1. *Selection of Categories*

Organizing the categories for this exercise requires different criteria from those used to study demand substitution in Appendix B. We focus on categories in which the distribution of sugar and calories is not entirely to the left of the regulatory threshold. Naturally, unlabeled products do not face any incentives to change their nutritional content. We also dropped categories with products that were too far to the right and for which it was not feasible to modify the nutritional content up to the threshold level.

### C.2. *Sample Coverage*

In Table C.1, we show the share of revenue covered by the categories included in the supply-side analysis. Column (1) reports the share of total revenue for each category provided by Walmart. This column contains the universe of food products purchased by individuals from our consumer panel and adds up to 100%. We group a set of categories for which most products lie either below or above the policy threshold in the pre-policy period and label them “Mostly below” and “Mostly above.” Together, these two groups represent close to 67% of revenue and include categories such as fruit, meat, salads, candy, and chocolate. Another 17.5% of total revenue is for categories with products that are exempted from the regulation (e.g., nuts) or products for which we are missing the pre-policy nutritional content. Our selected categories cover the remaining 15.5% of total revenue.

Column (2) reports the share of products, weighted by revenue, that are above the sugar threshold in the pre-policy period within a given category. Column (3) reports the share of total revenue for all products that are above the sugar threshold in the pre-policy period. When focusing on products with the potential to bunch, our working sample comprises around 54% of the pre-policy revenue for them.

Table C.1: Selected categories used to study the impact of food labels on product reformulation

	Market share	Share above the sugar threshold before the policy	Market share within products above the sugar threshold
	(1)	(2)	(3)
<b>Included</b>	15.5	63.2	53.6
<i>Cereal (g)</i>	1.4	43.5	3.1
<i>Cookies (g)</i>	2.1	77.3	10.7
<i>Desserts (g)</i>	0.6	31.2	1.3
<i>Condiments (g)</i>	0.4	30.9	0.9
<i>Seasonings (ml)</i>	0.1	49.0	0.1
<i>Frozen Fruit and Pulp (g)</i>	0.1	28.4	0.2
<i>Ice Cream (ml)</i>	0.9	98.2	6.0
<i>Jam (g)</i>	0.4	83.2	2.2
<i>Juice (ml)</i>	2.6	54.0	9.4
<i>Milk and Creams (ml)</i>	2.5	92.0	5.4
<i>Soft drinks (ml)</i>	3.3	53.7	11.5
<i>Soup (g)</i>	0.6	11.4	0.2
<i>Yogurt (ml)</i>	0.5	83.0	2.6
<b>Not Included</b>	84.5	10.0	46.4
<i>Mostly below</i>	63.8	0.3	1.0.1
<i>Mostly above</i>	3.2	98.0	17.2
<i>Others</i>	17.5	29.3	28.1
<b>Total</b>	100	18.28	100

**Notes:** Column (1) presents the share of total revenue for each category provided by Walmart. This column contains the universe of food products purchased by individuals from our consumer panel and adds up to 100%. Column (2) presents the share of labeled products within each of the categories. Column (3) presents the share of total revenue for labeled products.