Equilibrium Effects of Food Labeling Policies*

Nano Barahona† Cristóbal Otero⋆ Sebastián Otero§ Joshua Kim‡
(Job Market Paper)

November 6, 2020

[Link to the latest version]

Abstract: Warning labels on unhealthy food products are an increasingly common policy tool to combat obesity. Although informing consumers usually improves their welfare, supply-side responses can either offset or amplify the positive effects of food labels. This paper studies the *equilibrium effects* of a regulation in Chile that mandates the use of warning labels on products whose sugar or calorie concentration exceeds certain thresholds. Using scanner data from Walmart, we find an overall decrease in sugar and calorie intake of 9% and 7% after the policy. To reveal mechanisms, we zoom in on the breakfast cereal market. On the demand side, we show that consumers substitute from labeled to unlabeled products. This effect is mostly driven by products which, according to survey-based evidence, consumers mistakenly believed to be healthy. On the supply side, we find substantial reformulation of products and bunching just below the regulatory thresholds. We develop and estimate a model of supply and demand for food and nutrients. Consumers care about products' price, taste, and nutritional content but have poorly calibrated beliefs about nutrition. Firms choose products' prices and nutritional content to maximize profits. We find that food labels increase consumer surplus by 3.6% of total expenditure. These effects are enhanced by firms' responses. We then use the model to study alternative policy designs. Under optimal policy thresholds, food labels cause gains in average consumer surplus similar to those of optimal sugar taxes but benefit the poor relatively more.

*First version: Sep, 2020. We would like to thank Matthew Gentzkow, Liran Einav, Rebecca Diamond, and Pascaline Dupas for their invaluable mentorship and advice. We thank Hunt Allcott, Claudia Allende, Rodrigo Carril, José Ignacio Cuesta, Pierre Dubois, Andrés Elberg, Ben Handel, Caroline Hoxby, Enrique Ide, Gastón Illanes, Carlos Noton, Ariel Pakes, Anna Popova, Tobias Salz, Dmitry Taubinsky, and seminar participants at Stanford University, UC Berkeley, and Ponitificia Universidad Catolica de Chile for valuable comments and suggestions. We also thank Camila Corvalán and Marcela Reyes for very useful conversations on institutional details, Christine Von Dessauer and Roberto Cases for excellent research assistance, and Alejandro Guin-Po and Fernanda Mediano for their contribution to the data collection process. We gratefully acknowledge financial support from the Stanford King Center on Global Development, the Stanford Center for Computational Social Sciences, Microsoft Research, the Stanford Institute for Economic Policy Research (SIEPR), and the Mark A. Israel Dissertation Fellowship. Finally, we thank Walmart-Chile and Instituto de Nutrición y Tecnología de los Alimentos (INTA) for sharing the data for the project, and the Stanford Center of Population Health Sciences (PHS) for providing a secure environment to store and analyze the data. All remaining errors are our own. †Stanford University. Email: `hbaraho@stanford.edu`. ⋆University of California, Berkeley. Email: `cotero@berkeley.edu`. §Stanford University. Email: `sotero@stanford.edu`. ‡Facebook. Email: `joshkim@fb.com`.

1. Introduction

Obesity rates in the world have tripled over the last half century. Today, the World Health Organization estimates that roughly 40% of the world's adult population is either obese or overweight (WHO, 2018).[1] One increasingly popular policy tool governments are using to help promote healthier diets and combat obesity are front-of-package labels (FoPLs), which are visual warnings placed prominently on the front of packaged food products. Unlike nutritional fact tables, which provide detailed information on the back of food products, FoPLs are simple symbols that clearly signal to consumers when a particular product is considered unhealthy. Since 2016, over 30 countries have either implemented or are in the process of implementing country-wide mandatory FoPL regulations (Reyes et al., 2019).

Several features of FoPLs make them popular. First, providing information to consumers is widely perceived as innocuous, in the sense that it can only improve consumer welfare.[2] 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 FoPLs, however, argue that they are ineffective in shaping consumers' decisions towards a healthier diet and impose an unnecessary burden on firms.[3]

Most of this discussion focuses on consumers' responses to labels. However, firms' responses to large-scale implementations of FoPLs 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 all together, the impacts of large-scale FoPL regulations are ambiguous.

In this paper, we study how the introduction of a national FoPL regulation affects consumers' purchases, firms' pricing and production decisions, total nutritional intake, and overall welfare. We combine reduced-form analyses with a structural model of supply and demand for food and nutrients to quantify the impact of the Chilean Food Act of 2016, the first mandatory nationwide FoPL regulation to be implemented in the world. The regulation mandates food manufacturers to put warning labels on all of their packaged food products that surpass a threshold concentration of sugar, calories, sodium, or saturated fat.[4]

[1] In the United States, where 72% of the population is considered either overweight or obese, obesity is estimated to account for 10%-27% of medical costs (Finkelstein et al., 2009) and 18% of total deaths (Masters et al., 2013).

[2] The notion that more public information is better goes back to J. S. Mill, who argued that exchange of information would create a beneficial marketplace of ideas. Contemporary proponents of transparency contend that provision of information improves consumer choice (TFEU, 2016).

[3] Industry participants, for example, think that FoPLs are confusing and invasive and that the problem of obesity should be approached through consumer education (Jacobs, 2018).

[4] The Chilean Food Act has gained a lot of international attention and has been described as "*the world's most ambitious attempt to remake a country's food culture, and could be a model for how to turn the tide on a global obesity epidemic*" (Jacobs, 2018).

To study how the regulation affected consumer choice, we use scanner data on all purchases made in Walmart, the largest food retailer in Chile, from 2015 to 2018. The data contain information on prices and quantities, alongside consumer demographics, such as gender, age, and income. To shed light on mechanisms, we surveyed 1,500 consumers and elicited their beliefs about the nutritional content of products. Finally, we scanned nutritional facts tables for over 6,000 products before and after the policy and used these to study strategic reformulation decisions by firms. We thus have a rich window into consumer demand and beliefs, as well as firm behavior.

We start by documenting a sharp overall decrease in sugar and calorie intake of 8.8% and 6.5%, respectively, immediately after the policy was phased in. This reduction, which persists for the two-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, and firms responded by reducing the concentration of critical nutrients in their products.

To unpack the drivers behind both demand- and supply-side responses, 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 where the information content of the labels may be particularly high due to consumers' nutritional content misperceptions. These features allow us to credibly estimate the substitution patterns from labeled to unlabeled products and provide strong incentives to firms to respond to the policy. Three key findings arise from our reduced-form analysis.[5]

First, we show that consumers substituted from labeled to unlabeled products. We find that after the policy was implemented, consumer purchases of labeled products dropped by 26% relative to unlabeled ones.

Second, we present evidence suggesting that the decrease in the demand for labeled products is primarily driven by updates in consumer beliefs. Using the results from our consumer beliefs survey, we find that products which consumers already knew had high sugar or calorie concentration only experienced a small and temporary drop in demand. However, products which consumers previously believed to be low in sugar and calories but received a warning label under the FoPL 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 show that suppliers responded to the regulation by reformulating their products and changing prices. To avoid receiving labels, many firms modified the nutritional content of their products to lie just below the regulatory thresholds. This bunching results in a healthier bundle of products with an average reduction of sugar and calorie concentration of 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.

[5] We extend our analysis to other product categories and show that our findings are not unique to the cereal market.

Motivated by these findings, 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 surplus. On the demand side, consumers care about the price, taste, and healthiness of food 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 each product, allowing them to make better-informed purchasing decisions. On the supply side, firms strategically choose products' prices and nutritional content to maximize profits. Food labels create a sharp discontinuity in demand at the policy threshold, inducing firms to reformulate their products to avoid receiving a label. However, reducing the concentration of critical nutrients is costly, and may cause firms to raise prices.

Our model highlights two ways by which incomplete information creates inefficiency in the economy. First, consumers may make mistakes when choosing which products to buy. Second, firms do not have incentives to produce healthier products if they cannot credibly inform consumers about product healthiness. Thus, information interventions may reduce inefficiencies by improving consumer choice and incentivizing suppliers to produce healthier goods.

We identify the demand side of the model by taking advantage of the panel structure of our data. By adding product, time, and store fixed effects, we take advantage of high frequency variation in residual prices to recover price elasticities. To estimate preferences over perceived healthiness, we combine the timing of the policy with data on consumer beliefs elicited in our survey.[6] According to the model, labels induce a shift in consumers' beliefs about nutritional content. Products for which labels are more surprising (according to the survey responses) experience larger changes in demand in the data. Our results suggest that consumers are willing to pay an additional 11% to reduce the sugar or calorie concentration of cereal by 1 standard deviation (i.e. half of the difference in sugar content between *Honey Nut Cheerios* and *Original Cheerios*) if taste is kept constant.

To estimate the supply side, we use the firm's first-order conditions with respect to both price and nutritional content and exploit the variation in distance between products' pre-policy nutritional content and the policy threshold. While all products benefit from not receiving labels, those closer to the threshold can do so by reformulating at a lower cost. Our estimates imply that the average increase in marginal cost for products bunching in any nutrient is 6.2% of the average price of cereal products.

We use our model to estimate the impact of the Chilean Food Act on nutritional intake and consumer surplus in the cereal market. To analyze how equilibrium forces change the effectiveness of FoPL 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 any supply-side responses. We find that, compared to a counterfactual where no policy

[6] Ideally, we would have elicited consumer beliefs in Chile prior to the policy implementation. Since this was not possible, we mimicked this exercise by conducting the survey in Argentina, a country with a similar population and food market to Chile but which has not been exposed to any food labeling policy.

is in place, the regulation reduces sugar and calorie intake in the cereal market by 5.7% and 1.7%, respectively, resulting in average gains in consumer surplus equivalent to 3% of total cereal expenditure.[7] The gains in consumer surplus are driven by a combination of a healthier diet (+), fewer dollars spent (+), and an increase in consumption of less tasty products (−). Consumers substitute from high-in-sugar products to low-in-sugar products that tend to be cheaper and, according to our estimates, less tasty (e.g. oatmeal).

Second, we allow firms to optimally set prices in response to the policy but not to change the nutritional content of their products. Under this counterfactual, we find that prices of unlabeled products go up while those of labeled products go down. Overall, prices increase by 0.15% on average and gains in consumer surplus relative to the no intervention counterfactual are 15% lower than in the absence of supply-side responses.

Third, we also allow firms to optimally reformulate their products to avoid receiving labels. By doing so, we recover the full effect of the policy. We find that, relative to the counterfactual with no supply-side responses, this full equilibrium counterfactual amplifies the benefits from a healthier diet by 142% but reduces the benefits from spending fewer dollars by 75%. On one hand, high-in-taste products become healthier due to reformulation. On the other hand, producing those products is now more costly, increasing the average price of cereal by 2%. Overall, gains in consumer surplus under this counterfactual are 18% 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 surplus 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 19.4% and increase consumer surplus gains by 7.5% relative to the outcome under the threshold that maximizes information.

Finally, we compare FoPL regulations to other popular policy instruments, such as sugar taxes. We find that sugar taxes, when optimally implemented, have the potential to increase consumer surplus at rates equivalent to those of food labels. Nevertheless, taxes disproportionally increase the price of unhealthy products that are more prominently consumed by poorer households. We show that even though taxes achieve equivalent gains in consumer surplus, food labels present distributional advantages that benefit poor individuals relatively more.[8]

This paper contributes to several strands of literature. It adds to a large literature that studies consumer choice in settings of imperfect information (Hastings and Weinstein, 2008; Abaluck and

[7] We calculate average gains in consumer surplus across all regular Walmart customers in our panel, most of whom buy cereal at some point. The average expenditure on cereal in our sample is $25 a year.

[8] Our results relate to the theoretical framework in Farhi and Gabaix (2020), who discuss the trade-off between taxes and nudges under distributive concerns: food labels can correct potentially progressive biases while avoiding the potentially regressive financial incidence of taxes.

Gruber, 2011; Woodward and Hall, 2012; Handel and Kolstad, 2015; Allcott and Knittel, 2019). Moreover, it adds to the literature examining how providing nutritional information to consumers helps shape consumer demand. This includes a consideration of the effects of advertising (Ippolito and Mathios, 1990, 1995; Dubois et al., 2017), nutritional information on menus (Elbel et al., 2009; Wisdom et al., 2010; Bollinger et al., 2011; Finkelstein et al., 2011), and FoPL regulations (Sacks et al., 2009; Kiesel and Villas-Boas, 2013; Zhu et al., 2015). Our project contributes to these studies by providing evidence of the equilibrium effects of national information policies. The importance of product reformulation was recently emphasized by Griffith et al. (2017) and Lim et al. (2020), who show that firms improved the nutritional quality of their products after the implementation of voluntary reformulation targets in the U.K. and voluntary FoPLs in the U.S., respectively.

Other concurrent and independent work has also studied the impact of 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. (2020) estimate the impact of labels on the demand for products in different categories taking advantage of the staggered introduction of labeled products across stores. They find that warning labels decrease purchase probabilities on breakfast cereal, but not on chocolates or cookies. Two other studies have focused their attention on supply-side responses to the Chilean Food Act. Both studies focus on the breakfast cereal market. Pachali et al. (2020) study price adjustments after the introduction of FoPLs and conclude that prices of labeled products increased due to increased product differentiation. Closest to our work, Alé-Chilet and Moshary (2020) provide evidence of bunching just below the regulatory thresholds. They estimate a demand model and use it to predict consumers' purchases in the absence of reformulation. They conclude that reformulation reinforces the policy's effects by lowering the calorie content of cereal purchases.

Our paper–which uses new retailer data from more than 500,000 customers and over 160 stores–is consistent with most of the above results and extends some of them to other categories. It also goes further on several dimensions. First, we develop an equilibrium framework that allows both price adjustments and product reformulation. This is key to assess the overall role of equilibrium responses to food labeling policies. Second, we show that beliefs over nutritional content are a key driver of consumer behavior and explicitly incorporate them into our model. This allows us to provide a welfare evaluation of the Chilean Food Act. Third, we use our model to answer additional policy-relevant questions, such as the design of optimal policy thresholds and the comparison of FoPLs to sugar taxes.

Our work also relates to a 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; Ito and Sallee, 2018; Houde, 2018), and to a literature in industrial organization that estimates demand models under endogenous product characteristics (Ackerberg and Crawford, 2009; Draganska et al., 2009; Fan, 2013; Wollmann, 2018). We use an equilibrium model to show that mandatory disclosure policies in the food industry

can improve consumer choice and induce firms to improve the quality of their products.

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 role of advertisement on junk food consumption. Allcott et al. (2019a), Aguilar et al. (2019), and Dubois et al. (2020) study optimal taxes for sugar-sweetened beverages and calorie-dense food products. Our paper provides evidence of an additional policy instrument and shows that it can be an effective tool to improve diet quality and combat obesity.

The remainder of this 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 Section 4, we introduce a model of demand and supply for food and nutrients. In Section 5, we estimate the model. We present our main counterfactual exercises in Section 6. We discuss some policy implications in Section 7 and conclude in Section 8.

2. Setting and data

2.1. *The Chilean Food Act*

Obesity is the most prevalent chronic disease in Chile. In 2016, 45% of Chilean children and 74% of Chilean adults were overweight or obese (OECD, 2019). Concerned by the growing obesity problem, in 2015 the Chilean legislature passed Law 20.606 (hereafter, the Food Act) to improve nutritional choices. The Food Act imposed new regulations on how food manufacturers could package and advertise food products. An important part of the Food Act was a FoPL system, prominently displaying to consumers which products were considered *unhealthy*.[9] The Food Act sought to help consumers' decision-making by providing easy-to-process information about the healthiness of food products. The rationale for the Act was that nutritional information available at the time–in the form of fact tables on the back of the products–was too complex and "did not allow [consumers] to make an informed decision" (Historia de la Ley 20.606, 2011, p. 170). Figure 1 shows what Chilean FoPLs look like and how they are displayed on actual products.

The Food Act established threshold values for sugar, calories, sodium, and saturated fat concentration and mandated suppliers to place a warning label on the front of their packaged product for each nutrient threshold surpassed. The thresholds were implemented in three stages, with each stage setting stricter threshold values than the last. Stages 1, 2, and 3 took place in June of 2016, 2018, and 2019 respectively.[10] The threshold values for the first stage of implementation are presented in

[9]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.

[10]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. It received substantial pushback from industry stakeholders who initially tried to unsuccessfully modify or override the rule through lobbying and advertising campaigns. The thresholds were established based on

Figure 1: FoPLs on selected products

Notes: The figure presents both the FoPLs 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 1 presents the threshold values that determine the assignment of each label.

Table 1. The thresholds are uniform for all food products, and vary only depending on whether the product is a solid or a liquid.[11]

Table 1: Law 20.606 thresholds for Stage 1

	Solids	Liquids
Sugar (g/100g[ml])	22.5	6
Energy (kcal/100g[ml])	350	100
Sodium (mg/100g[ml])	800	100
Saturated fat (g/100g[ml])	6	3

Notes: The table shows the level of sugar, calories, sodium, or saturated fat at which products receive each label after the implementation of Stage 1. For solids, the thresholds are calculated as a function of grams of product (e.g. kcal/100g). For liquids, the formula uses millilitres in the denominator (e.g. kcal/100ml).

Since implementing the Chilean Food Act, numerous countries have shown interest in implementing similar FoPL regulations. By 2017, 29 countries had consulted with the Chilean Ministry of Health to adopt similar legislation (MINSAL, 2019). By 2020, Mexico, Peru, Israel and Uruguay had passed similar legislation, and others such as Brazil, Canada and India had already started the legislative process of similar bills.

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 lobby.

[11]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 350kcal/100g, they did not receive a label.

2.2. *Data*

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 contains all transactions that occur in any Walmart store in Chile between May 2015 and March 2018. Every transaction identifies products at the UPC (Universal Product Code) level and contains information about price, revenue, product name, brand name, and discounts.[12] We can also track buyers enrolled in Walmart's loyalty program and link them to individual characteristics, such as gender, age, and household income. We supplement this data with additional information about product and store characteristics, also provided by Walmart.

Since our data only covers 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 only.[13] Our final sample consists of 524,000 consumers that visited Walmart store at least once every 8 weeks during the study period. The average age of customers in our panel is 48 years old and 69% of them are women. In the first year of data, from May of 2015 to May of 2016, the median customer shops at Walmart 24 times, at three different Walmart locations, and travels 3 kilometers to get to her closest store.[14] In the same period, the median customer buys cereal 6 times and spends a total of $15 on cereal (the average expenditure on cereal in the same period is $25 per customer).

2.2.2. *Nutritional Information*: The nutritional data for packaged products comes 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. For non-packaged products, we use publicly available data provided by the United States Department of Agriculture (USDA). For our main analysis, that focuses on the cereal market (Sections 3.2 onwards), we only use INTA data and our hand-collected data. Together these comprise information on 94 cereal products, which represent 94% of total cereal revenue.

Pre-policy: Anticipating the implementation of the Food Act, INTA collected nutritional information for a sample of products in January 2016 at the UPC-level. This included the nutritional facts tables, whether the product is a liquid or a solid, the size of the package, and whether the product would receive a front-of-package warning label once the policy was in place.

Post-policy: To supplement INTA's nutritional data, we hand-collected nutritional information as follows: we developed a camera phone app that took pictures of nutritional facts tables and linked them to the Walmart scanner-level data. A team of enumerators visited the three largest Walmart stores in Chile and used the app to digitize the nutritional content of all available products. Our dataset covers 90% of Walmart's revenue from food packaged products. We collected this information in March 2018, two years after the first stage of the law was implemented in June 2016. We provide

[12] The data comprises over 9 billion transactions by over 5 million consumers of over 20,000 different food products.
[13] We also drop all purchases coming from non-natural persons or consumers below 18 years old.
[14] We count as a visit anytime that a customer spends at least $20 on food products.

additional description of the fieldwork in Appendix B.1.

USDA: For products sold without nutritional facts tables, such as fresh produce or meat, we rely on FoodData Central data that is publicly available from the USDA. We use this data to complete missing data for categories of food other than cereal in our aggregate analysis in Section 3.1. We provide details about the data and matching procedure in Appendix B.2.

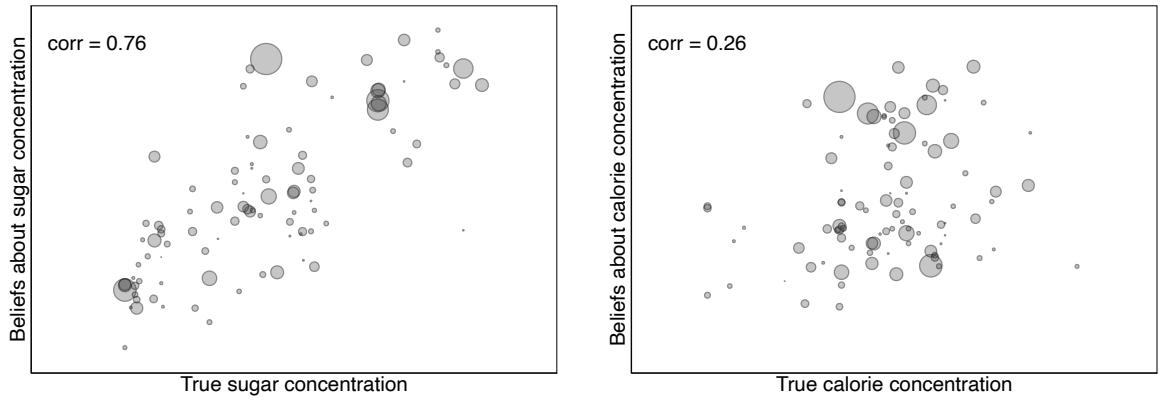
2.2.3. *Consumer beliefs*: We conducted a survey to elicit consumers' beliefs about the nutritional characteristics of a set of cereal and soft-drink products in the absence of FoPLs. We implemented the survey in Argentina using Qualtrics in August 2019 and surveyed a total of 1,500 individuals. Ideally, we would have elicited consumer beliefs in Chile prior to the policy implementation. Since this was not possible, we mimicked this exercise by conducting the survey in Argentina, a country with a similar population and food market to Chile but which has not been exposed to any food labeling policy. We asked consumers to provide their best estimate of the sugar and calorie concentration of a set 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 provide a detailed description of the survey in Appendix B.3.

Importantly, we rely on the survey data for information on the *relative levels* of believed nutritional content of different cereals (using the distance between the first moments of beliefs about nutritional content of different products) but not on the *absolute levels* of believed nutritional content of each product. This is because before implementing the survey at-scale, we tested three different survey designs, varying the reference products shown to respondents.[15] 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 three survey designs.

The main findings from the survey are summarized in Figure 2. 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 calorie concentration of cereal were less aligned with reality–the correlation between the actual and predicted calorie concentration is only 0.26. This result is explained by consumers mistakenly thinking there is a high correlation between calorie and sugar concentration (the correlation between beliefs about calorie and sugar concentration is 0.94) whereas in the data they only exhibit a moderate correlation of 0.29.[16]

[15] To guide consumers' responses, we provided them with the true nutritional content of referential non-cereal products, such as apples, whole meal bread, Oreo cookies, and peanuts.

[16] In Appendix C, we provide figures illustrating these correlations. We also show that beliefs are highly correlated between respondents of different socioeconomic status groups and age, and summarize the results for soft-drinks products.



(a) Sugar

(b) Calories

Figure 2: Correlation between beliefs about nutritional content and true nutritional content

Notes: The Figure shows the first moments of beliefs about each cereal product's nutritional content vs their 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 sugar concentration as measured by g sugar/g product, and panel (b) on calorie concentration 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 axis.

3. Descriptive evidence

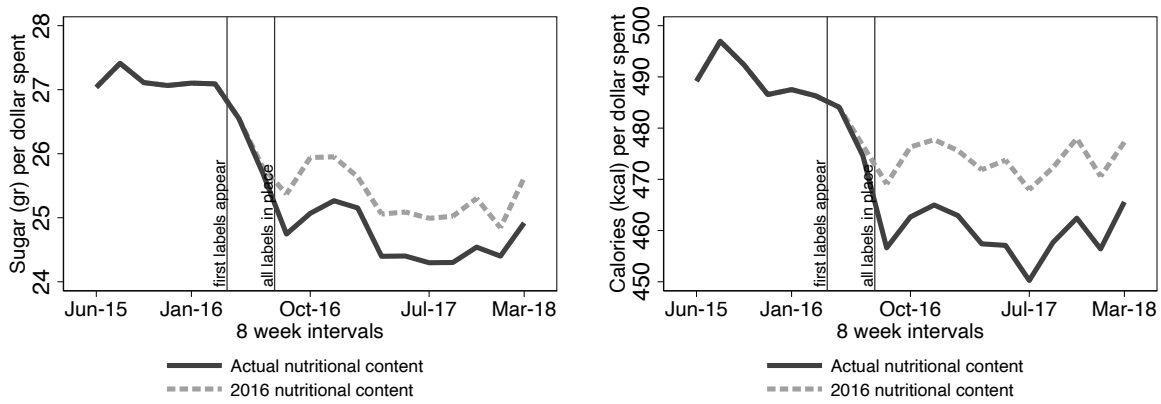
In this section, we provide descriptive evidence of the impact of the FoPL policy on nutritional intake, consumer choice, and firm behavior. We start by measuring sugar and calorie intake from all food products purchased by consumers in our sample before and after the policy. We then focus our analysis on the breakfast cereal market and unpack the different economic forces at play by looking more closely at consumer and firm behavior.

3.1. *Changes in overall nutritional intake*

Figure 3 depicts the change in total nutritional intake per dollar spent in Walmart stores over the course of the policy for all consumers in our data.[17] Panels (a) and (b) plot changes in sugar and calorie intake. Each plot includes two vertical lines, corresponding to the moment when the first labels were introduced in some supermarkets, and the moment when the Food Act made it mandatory for every product to comply with the FoPL policy in every store. Each plot also includes two curves representing the total amount of sugar or calories purchased for every dollar spent in each eight-week period. Of these, the dark solid curve uses actual nutritional content in any given period, and the light dashed curve fixes products' nutritional contents at their pre-policy levels.

Figure 3 shows that after the FoPL policy was introduced total sugar intake decreased from 27.3 to 24.9 grams of sugar per dollar, and total calorie intake decreased from 488 to 457 kcal per dollar.

[17] In Appendix A, Figure A.1, we present similar figures dividing by volume of food purchased instead of by dollars spent.



(a) Sugar intake

(b) Calorie intake

Figure 3: Nutritional intake per dollar spent before and after the policy

Notes: This figure compares nutritional intake per dollar spent before and after the policy. The solid curve represents the total amount of sugar or calories purchased for every dollar spent in each eight-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 the moment when the first labels appeared in some supermarkets. The right vertical line corresponds to the moment when the Food Act made it mandatory for every product to comply with the FoPL policy in every store. While we have scanner-level data on prices and quantities for every eight-week interval, we only have two snapshots of nutritional information data: one from early 2016 before the FoPL 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. In Appendix A, Figure A.1, we present similar figures dividing by volume of food purchased instead of by dollars spent.

This reduction can be decomposed into two parts. First, consumers shift towards buying healthier bundles of products after the policy, even when the nutritional content of individual products is kept constant (dashed curves). Second, the bundles of products bought post-policy are healthier than they would be if the nutritional content of individual products did not change (difference between solid and dashed curves).

Three important channels may potentially explain the change in nutritional intake observed in Figure 3. First, consumers may be substituting between product categories, from those high in critical nutrients to those low in critical nutrients (e.g., from breakfast cereal to bread or fruit). Second, consumers may be substituting within product categories (e.g., from labeled cereal to unlabeled cereal). Third, suppliers may be reformulating their products to make them healthier and avoid incurring labels.

To study whether consumers are substituting between product categories, we compare total revenue before and after the policy between categories where substitution is likely to happen. For example, we group all categories that are likely to be consumed at breakfast, and look for a shift in revenue from high-in-labels categories to low-in-labels ones. We present our results in Appendix D, where we find no evidence that between-category substitution explains much of the change in nutritional intake observed.

In the remainder of this section, we examine the impact of the FoPL policy on within-category substitution and product reformulation in the market for breakfast cereal. 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. This allows us to estimate substitution from labeled to unlabeled products. Since the nutritional policy thresholds are uniform across product categories, some categories such as ice cream or chocolate have warning labels on all their products. In other categories, such as pasta or rice, none of the products received a warning 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.[18] We provide evidence of the effects of the policy for other product categories in Appendix E and show that our findings are not unique to the breakfast cereal market.

3.2. *Changes in demand: breakfast cereal*

For our analysis, we define a product as the union of UPCs which 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 corresponding to 14 different producers. Out of the 94 products, 55 received a high-in-calories label and 21 of them received an additional high-in-sugar label. No cereal products received a high-in-sodium or high-in-fat label in our sample period. For that reason, our main analysis focuses specifically on calorie and sugar intake. We assign labels to a product based on its 2018 nutritional content.

Our first main result is that demand for labeled products experienced a sharp drop relative to that for unlabeled products shortly after the policy implementation. Figure 4 plots the log of total grams of cereal purchased from labeled and unlabeled products. We see an increase in the equilibrium quantities of unlabeled products relative to labeled ones after the labels are introduced. Overall, the raw data suggest that the policy shifted consumption towards unlabeled products and that these effects persisted over time. We do not find substantial differences in the total quantities of cereal purchased between the pre- and post-policy period, suggesting that most of the decrease in demand for labeled products was compensated by an increase in demand for unlabeled cereal and not for products outside the cereal category.

3.2.1. *Event study*: We quantify the effects of the policy on demand by using an event-study design. We collapse our original data into product-store-period data bins (where a period is defined as eight

[18] We show this to be the case with our beliefs survey in Appendix C.

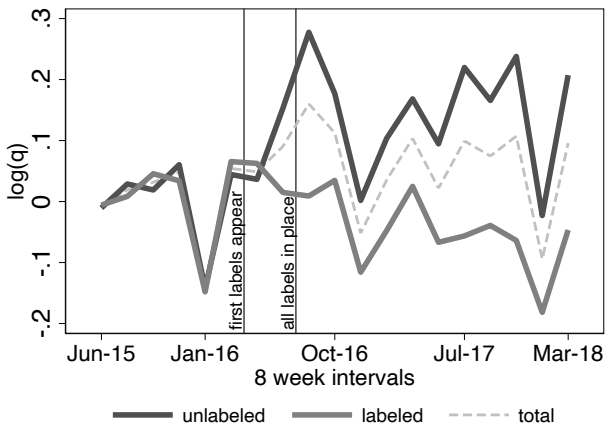


Figure 4: Log-quantities of labeled and unlabeled ready-to-eat-cereal

Notes: This figure compares the normalized log-quantities of labeled and unlabeled products sold over time. One observation is the log total grams of cereal purchased across labeled and unlabeled products over eight consecutive weeks. The y-axis is normalized such that the average value for the two groups is zero in the pre-period. The dashed and the solid lines denote the labeled and unlabeled products, respectively. In Appendix A, Figure A.2 we show the same figure but plotting revenue instead of quantities to capture potential price effects.

consecutive calendar weeks) and estimate the following regression:

$$\log(q_{jst}) \quad = \quad \beta_t \cdot L_j + \gamma \cdot \log(p_{jst}) + \delta_{js} + \delta_t + \varepsilon_{jst} \tag{1}$$

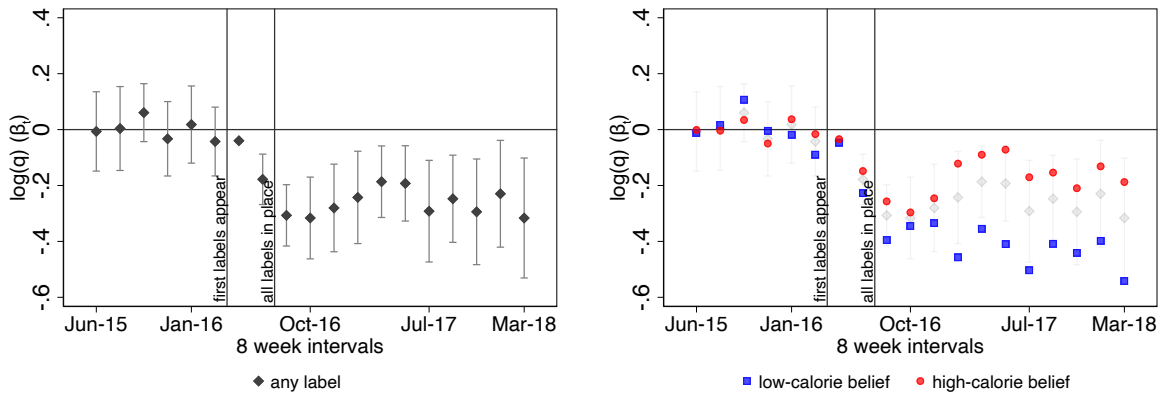
where q_{jst} denotes the grams of product j sold in store s in period t, p_{jst} refers to the product's price per 100 grams of cereal, and L_j is an indicator variable that takes the value of one if the product has one or more labels.[19] Finally, δ_{js} refers to product-store fixed-effects and δ_t to period fixed-effects. We normalize the β_t 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.

Given our context, in which consumers substitute from one product to another, it is natural that the no interference assumption–standard in the impact evaluation literature–does not hold. In the extreme case of one-to-one substitution, a β 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 equilibrium quantities of labeled versus unlabeled products sold.

Figure 5(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, however, 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: in the very first period after the labels

[19] In Appendix A, Figure A.3 we present alternative specifications in which we (a) do not control for prices, (b) drop all oatmeal products (exempt from the regulation), and (c) drop all reformulated products that crossed the policy threshold in the post-policy period. Our results are robust across all specifications.

were implemented, labeled products experienced a 26% reduction in sales, compared to an estimated 27% in the last period of our sample. This suggests that labels shifted consumer purchases away from labeled products, with the effect lasting throughout the entire period covered by our sample.



(a) Changes in equilibrium quantities of cereal sold

(b) Changes in equilibrium quantities of cereal sold by prior beliefs about caloric content

Figure 5: Event study

Notes: This figure presents the coefficients of our event study regressions. Panel (a) presents the β_t coefficients from Equation (1). Panel (b) displays the coefficients from Equation (2). Coefficients in blue squares, red circles and grey diamonds denote β_t^l, β_t^h and β_t 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.

3.2.2. *The role of beliefs*: To investigate how information and beliefs shape consumer choices, we use our beliefs survey discussed in Section 2.2.3. Recall from Figure 2 that consumers have miscalibrated beliefs about the caloric content of cereal. We use the elicited beliefs about calorie concentration to test for heterogeneity in the impact of labels. If labels provide useful information to 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 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:

$$\log(q_{jst}) \quad = \quad \beta_t^l \cdot L_j \cdot Low_j + \beta_t^h \cdot L_j \cdot High_j + \gamma \cdot \log(p_{jst}) + \delta_{js} + \delta_t + \varepsilon_{jst} \tag{2}$$

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

Results from Equation (2) are shown in Figure 5(b). Coefficients in blue squares and red circles denote β_t^l and β_t^h estimates, respectively. Coefficients in light grey diamonds denote β_t coefficients from Equation (1). Products that consumers believed to be high-calorie (red circles) saw an initial

drop in demand which faded six months after the policy implementation.[20] In contrast, products consumers thought were relatively healthy but actually received a label (blue squares) saw a persistent decrease in demand of around 40%.[21] These empirical findings suggest that labels are especially effective for products about which consumers are more misinformed.[22,23]

3.3. *Changes in supply: breakfast cereal*

In this subsection we study firms' responses to the FoPL policy. We first look at product reformulation and then at changes in equilibrium prices.

3.3.1. *Product reformulation*: To study whether firms responded to the labeling policy, we compare the distribution of nutritional content before and after the policy is implemented. Figure 6(a) plots the distribution of calorie concentration in 2016 for products in our sample. Each bar corresponds to one product, with the size of the bar representing its pre-policy revenue. We see that most products lie between 350 and 400 kcal per 100 grams. Figure 6(b) plots the distribution of calorie concentration in 2018, after the law was implemented. We see that a number of products reduced the concentration of calories to lie just below the policy threshold. In 2016, 55 cereal products lay above the threshold. In 2018, 13 of those products reduced the concentration of calories to lie below the threshold, with eight of them bunching at the threshold of 350 kcal per 100 grams. This suggests that firms chose to respond strategically to the labeling policy, bunching at the threshold to avoid receiving a label.

We observe a similar pattern when we look at sugar concentration in Figures 6(c) and 6(d). In 2016, 27 regulated products were above the threshold. In 2018, nine of these reduced their sugar content to lie below the threshold, and six reduced it to between 20 and 22.5 grams of sugar per 100 grams of cereal.

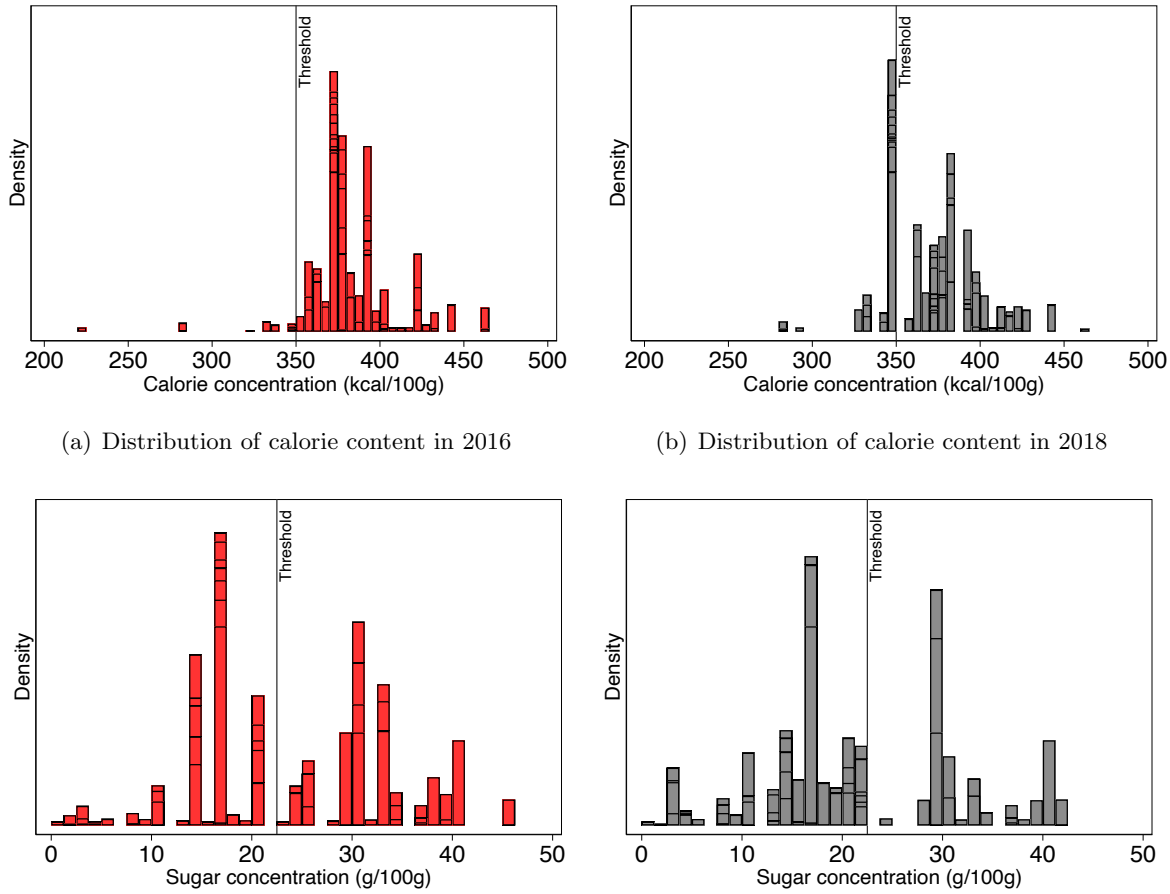
This bunching results in a net reduction in the calorie and sugar concentration of cereal products offered in the market. The weighted average of the calorie concentration of products decreased from 383.6 to 372.8 kcal per 100 grams, while the weighted average of the sugar concentration of products decreased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

[20] The initial drop in high-calorie belief products can be explained by *novelty effects*, due to which consumers avoided all labeled products in response to an increased interest in the new regulation.

[21] 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.

[22] The information mechanism is also mentioned in Araya et al. (2020), who find no significant effects of labels on categories where labels do not provide useful information.

[23] There are two other potential mechanisms that can explain these findings: (i) The composition of consumers that purchase low- and high-calorie belief products might be different, and different consumers may have different policy responses. We reject this possibility in Appendix F.1. (ii) High-calorie belief products might not have close unlabelled substitutes. In Section 5, we test different substitution patterns through several nested-logit structures and reject specifications with a pattern consistent with this hypothesis.



(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 6: Distribution of cereal calorie 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. 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. We include them in Appendix A, Figure A.4. In Appendix A, Figure A.5, we present complementary information regarding the movement of products in the nutritional space.

3.3.2. *Changes in prices*: 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:

$$\log(p_{jst}) \quad = \quad \beta_t \cdot L_j + \delta_{js} + \delta_t + \varepsilon_{jst} \tag{3}$$

where all variables and specification details are defined as in Equation (1). Results are presented in Figure 7. 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.[24]

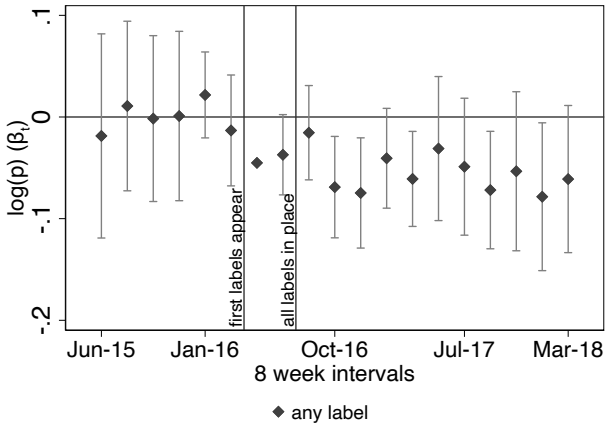


Figure 7: Event study for cereal prices

Notes: This figure presents the β_t coefficients of our event study regression for prices from equation (3). The vertical segments delimit the 95% confidence intervals. We run 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.

4. A model of demand and supply for food and nutrients

Three key facts emerge from the motiving evidence presented above. First, consumers decrease 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. In this section, we develop a model of supply and demand for food products that can explain these facts. Using the structure from our model, we can answer a number of policy-relevant questions such as what the total effect of the policy was in terms of consumer surplus and per-capita nutritional intake, where the optimal threshold should be set, and how warning labels compare to alternative policies such as sugar taxes.

4.1. *Demand*

Our model consists of a continuum of risk neutral consumers, indexed by $i \in \mathcal{I}$. Each consumer visits a store in a given period to purchase products belonging to certain product categories. We refer to each store-period combination as a "market" and index it by t. Given the lack of between-category substitution discussed in Section 3, we assume that decisions are independent across categories. Without loss of generality, we present the model for a single product category (i.e. cereal).

There are J products in the category indexed by $j \in \mathcal{J}$ and one outside good (i.e. a product from another category, or the option to buy no product). Each product j is produced by a firm $f \in \mathcal{F}$ and characterized by $(\bar{\delta}_j, p_{jt}, w_{jt})$, where $\bar{\delta}_j$ is an attribute that can be interpreted as the taste of the

[24] In Appendix A, Figure A.6, we show that results hold when we drop reformulated products.

product, p_{jt} is its price in market t, and w_{jt} is its vector of nutritional content.[25]

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

$$u_{ijt} = \underbrace{\delta_{ijt}}_{\text{experience/taste}} - \underbrace{\alpha_i p_{jt}}_{\text{price paid}} - \underbrace{w_{jt}\phi_i}_{\text{health consequences}} \tag{4}$$

where δ_{ijt} corresponds to the part 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 all product characteristics, including taste $\bar{\delta}_j$, and other individual- and product-level demand shocks (e.g. hunger relief, food craving, social status).

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 α_i governs the price elasticity.

Finally, $w_{jt}\phi_i$ corresponds to the long-term health consequences of consuming unhealthy products.[26] We assume that consumers do not know the true nutritional content, w_{jt}, but have beliefs π_{ji} about it. Based on her beliefs, consumer i chooses the product that maximizes her expected utility:

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

where $\mathbb{E}_{\pi_{ji}}$ denotes the expectation operator over prior beliefs π_{ji}, and $L_{jt} \in \{\text{pre-policy}, \text{no}, \text{yes}\}$ denotes the label status of product j in market t. We assume that, in the short run, changes in beliefs only come from the information provided by L_{jt}. Utility derived from consuming the outside good is normalized to 0.

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

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

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 shopping in market t, which we normalize to have mass one. The market share of product j in market t is given by $s_{jt} = \int_{i \in \Theta_{jt}} di$.

4.2. *Supply*

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. sacralose,

[25] Note that the attribute $\bar{\delta}_j$ does not need to be single-dimensional. It corresponds to the set of objetive characteristics (e.g. sweetness, crunchiness, color, smell, volume) that defines a product and makes it different from others. We discuss the assumption that $\bar{\delta}_j$ is time invariant in Section 4.2 below.

[26] Note that ϕ_i does not need to be the same for consumers and for the social planner. So far, we are mostly interested in modeling consumer behavior. In Section 6, where 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.

polyols).[27] 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 further assume that the taste of a product, $\bar{\delta}_j$, is invariant to reformulation. That is, when firms reformulate their products, they choose inputs to always achieve the same taste. This is consistent with industry participants' descriptions of the way that reformulation took place.[28] Since taste $\bar{\delta}_j$ is invariant, firms need to choose w_{jt} and m_{jt} such that:

$$\delta_j(w_{jt}, m_{jt}) = \bar{\delta}_j \tag{7}$$

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

$$\tilde{c}_{jt}(w_{jt}, m_{jt}) \quad = \quad p_w w_{jt} + p_m m_{jt} + \vartheta_{jt} \tag{8}$$

From Equations (7) and (8) we can redefine the marginal cost of producing product j as:

$$c_{jt}(w_{jt}) = p_w w_{jt} + p_m m_j(w_{jt}, \bar{\delta}_j) + \vartheta_{jt} \tag{9}$$

where $m_j(w_{jt}, \bar{\delta}_j)$ is the inverse function of $\delta_j(w_{jt}, m_{jt})$ in Equation (7), 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*, as the former is a sweetened version of the latter.

Departing from the bliss point is possible but costly. As discussed in Appendix G, in the breakfast cereal market, after the FoPL policy was introduced, firms substituted sugar for artificial alternatives such as sucralose and polyols. This reformulation results in a more expensive product, captured in our model by the functional form of $c_{jt}(w_{jt})$.[29]

The firm's profit maximization problem is given by:

$$\max_{\{p_{jt}, w_{jt}\}_{j \in \mathcal{J}_{ft}}} \quad \sum_{j \in \mathcal{J}_{ft}} (p_{jt} - c_{jt}(w_{jt})) \cdot s_{jt}(\mathbf{p_t}, \mathbb{E}_\pi[\mathbf{w_t}|\mathbf{L_t}]) \tag{10}$$

[27] Note that firms might substitute critical nutrients, w_{jt}, for other inputs, m_{jt}, that might also have adverse health consequences in real life. 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.

[28] 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 (we explain the process of reformulation in detail in Appendix G). Coming up with a formula that changes taste, and therefore creates a new product, may not be feasible for firms in the short run as it comes with high fixed costs (e.g. branding strategies, advertising).

[29] We impose two functional form assumptions on $c_{jt}(w_{jt})$. First, it has a minimum at ν_j. Second, its Hessian is semidefinite positive. Both assumptions hold under a broad set of functions $\delta_j(w, m)$, including Cobb-Douglas.

where s_{jt} is the market share of product j in market t, that depends on the vector of all prices $\mathbf{p_t}$ and all individuals' expectations about 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:

$$w^*_{jt} = \nu_j \tag{11}$$

$$p^*_{jt} = c_{jt}(w^*_{jt}) + \Delta^{-1}_{(j,\cdot)}\mathbf{s_t} \tag{12}$$

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

$$\Delta_{(j,k)} = \begin{cases} \frac{-\partial s_k}{\partial p_j} & \text{if } k \in \mathcal{J}_{ft} \\ 0 & \text{otherwise} \end{cases} \tag{13}$$

and $\Delta^{-1}_{(j,\cdot)}$ is the jth column of the inverse of Δ. Equation (11) states that firms will choose the nutritional content of product j to be equal to its bliss point.[30] Equation (12) 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 in Figure 6.

4.3. *Discussion*

Our setting highlights two sources of inefficiency in the economy. First, consumers have incomplete information about nutritional content and so may make mistakes when choosing which product to buy. Second, firms do not have incentives to produce healthier products if they cannot credibly inform consumers about the healthiness of their products. Thus, government intervention may reduce inefficiencies by improving consumer information and incentivizing suppliers to produce healthier goods. The model accommodates several key reduced-form facts discussed in Section 3, with particular emphasis on the role of beliefs and the importance of bunching and supplier decisions. In this subsection, we discuss additional results implied by the model as well as its potential limitations.

4.3.1. *Theoretical results*: In Appendix H we work over a simplified toy model with only two products. Three main conclusions arise from that model: (i) From consumers' ex-ante perspective and in the absence of supply-side responses, consumer surplus under a labeling policy is greater or equal to that under no policy. (ii) From consumers' ex-ante perspective, total intake of critical nutrients can

[30] Note that 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.

either decrease or increase under a food labeling policy, even in the absence of supplier responses. (iii) Once we allow for equilibrium effects, changes in consumer surplus become ambiguous. These results highlight the importance of taking the model to the data to test the effectiveness of food labeling policies.

4.3.2. *Limitations*: The model abstracts from reality in different ways that we discuss below.

Static demand: We assume static demand. Researchers in both marketing and economics have documented consumer inertia in brand choice (Frank, 1962; Dubé et al., 2010). Our model allows for inertia caused by spurious state dependence, captured by individual-level unobserved persistent shocks inside the experience part of the utility function δ_{ijt}. The model does not allow, however, for structural state dependence, where past purchases directly influence consumers' present choices. Structural state dependence can increase the effectiveness of FoPLs by breaking consumers' habits of unhealthy eating. We study the extent to which we see consumer inertia in our data and discuss its consequences in Appendix I.1.

Salience effects: Labels could affect demand not only through information but also through salience effects. Labels may make the unhealthiness of products salient to consumers, that is, they can increase the weight that consumers give to calorie and sugar content when making decisions. If salience were an important mechanism, labeled products with higher concentration of critical nutrients would have experienced larger reductions in demand. We study potential salience effects in Appendix I.2, and show that labeled products with higher calorie concentration did not experience a relatively larger decrease in demand, as salience effects would predict. Instead, the empirical evidence suggests that information plays a more relevant role in affecting demand. We also discuss how our model accommodates the possibility that labels affect the salience of believed nutritional content instead.

Advertising: Our model does not account for potential changes in advertising due to the labeling policy. In Appendix I.3, we use data on TV advertising for cereal products in Chile in 2016 and 2017 from Correa et al. (2020) and show that our results are robust to including advertising in the utility function.

Invariant taste: We assume that taste is invariant to reformulation. This assumption simplifies the firm's problem of choosing w_{jt}. As explained in Appendix G, this assumption is consistent with industry participants' descriptions of the way that reformulation took place. Moreover, in Appendix J.1, we estimate a version of the demand model where we allow δ_{ijt}, the part of utility that comes from the experience of consuming product j, to vary with changes in w_{jt} by exploiting variation in the data induced by product reformulation. We find coefficients very close to zero, reinforcing our assumption that taste does not change with reformulation.

Stable beliefs: We assume that changes in beliefs only happen through the information provided by L_{jt}. This means that, in the absence of the policy, firms can change products' nutritional content without affecting consumers' beliefs about them. This may not be true in the long run, as consumers

can eventually learn products' new nutritional contents and update their beliefs. From the survey, we do not find that beliefs are more accurate for products that consumers know better or that have been available in the market for a longer period. In the absence of FoPLs, informing consumers about changes in nutritional content is costly and needs to be done through expensive and credible marketing campaigns.

Fixed vs. variable reformulation cost: We do not model reformulation as a fixed cost. Instead, we assume that reformulation is costly because it increases products' marginal costs. This is consistent with the way that reformulation happened in the cereal market. The techniques used in cereal were already developed in other countries and widely used in the diabetic food industry. As discussed in Appendix G, replacing sugar by alternative inputs increased ingredients' costs of cereal by more than 20%, with little cost in research and development, according to the product managers of two large firms.

No entry and exit of products: Our model does not allow for endogenous entry and exit of products. In our sample period, we do not see any cereal product entering or exiting the national market. However, we acknowledge that food labels can induce entry or exit of products in the long run or under different policy thresholds. Studying the entry (and exit) of new products to the market is out of the scope of this paper and we abstract from it. Food labels can also induce entry and exit of products at the store level, which for simplicity, we abstract from and take as given.

5. Estimation

In this section, we estimate the model described in Section 4 for the breakfast cereal market. We estimate demand and supply separately.

5.1. *Demand estimation*

5.1.1. *Parametrization*: We make several additional assumptions before taking the model to the data. First, we split consumers into two bins defined by being above or below median household income in our sample. We refer to them as low- and high-SES consumers, and denote them by their type $b \in \{l, h\}$.[31] We make this distinction to study the distributional consequences of food labels and sugar taxes in Section 6.

Second, since no cereal received a label for sodium or saturated fat, we focus on nutritional intake of sugar and calories only. Specifically, w_{jt} is a two-dimensional vector consisting of the concentration of sugar (in grams per 100 grams of cereal) and calories (in kcal per 100 grams of cereal) in a given product.

Third, we parameterize δ_{ijt} into three components: (a) product, period, and store fixed effects specific to each consumer type (δ_{jb},$\delta_{T(t)b}$,$\delta_{S(t)b}$), (b) a product-market-type specific idiosyncratic

[31]The median income in our sample corresponds to the 70th percentile of the national income distribution of the Census. We provide more information about baseline characteristics of low- and high-SES consumers in Appendix F.2.

demand shock, ξ_{jtb}, and (c) an individual error term independently distributed across consumers, ϵ_{ijt}, such that

$$\delta_{ijt} = \delta_{jb} + \delta_{T(t)b} + \delta_{S(t)b} + \xi_{jtb} + \epsilon_{ijt} \tag{14}$$

where ϵ_{ijt} jointly follows a generalized extreme value distribution that follows the distributional assumptions of the nested logit model. We define two nests. One nest includes the inside goods and the other nest, the outside good. We denote the intra-nest correlation by ρ. We also assume that within consumer type, all individuals have the same valuation over the price, α_b, and health consequences of consuming a given product, ϕ_b.[32]

Fourth, we make the following assumptions about the structure of consumer beliefs. (i) We assume that all consumers within the same type b have the same prior beliefs π_{jb}, which follow a multivariate normal distribution with mean μ_{jb} and variance Σ_{jb}. We allow both moments of the beliefs distribution to vary across products. Additionally, due to data constraints, we assume that the non-diagonal elements of Σ_{jb} are zero. This implies that sugar labels do not change beliefs about calories and vice versa.

(ii) We assume that consumers form their beliefs by using the observed labels (or lack thereof) and applying Bayes rule, not taking into account strategic product reformulation by firms.[33]

(iii) 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 nutritional content of two different products, but that their absolute levels may be wrong. We allow for the first moment of beliefs be determined by $\mu_{jb} = \tilde{\mu}_{jb} + \mu$, where $\tilde{\mu}_{jb}$ is the average response about 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 nutritional content of all products among all consumers by a constant amount.[34] The rationale behind this assumption is that, in contrast to the absolute levels of consumer responses, consumer rankings and relative distances between responses showed to be robust to different survey designs. Assuming this is isomorphic to having consumers that have beliefs about which cereals have relatively more or less sugar and calories, but do not necessarily know the exact quantities in them. We also use the survey to estimate the

[32] We run several robustness checks on these parametric assumptions in Appendix J. First, in Appendix J.1, we estimate a model that includes a term w_{jt} in Equation (14) to test whether taste depends on nutritional content. Second, in Appendix J.2, we estimate a random coefficient nested logit (RCNL) model with unobserved individual heterogeneity in ϕ_i. Third, in Appendix J.3, we vary the structure of nests to have chocolate, flakes, granola, oats, and sugary cereal in different nests. Fourth, in Appendix J.4, we allow for flexible fixed effects at the product-store level. Results are robust to all different specifications.

[33] We make this assumption for several 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. In the Appendix J.5, we make the opposite extreme assumption that consumers overestimate the amount of bunching when updating their beliefs. We show our results are robust to that assumption. The fully rational Bayesian equilibrium lies between these two models.

[34] 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 one standard deviation is equivalent to a change in nutritional content of one standard deviation if nutritional content was observed.

second moments of beliefs, Σ_{jb}.[35] We provide further details on the consumer beliefs survey and the estimation of Σ_{jb} in Appendix C.

Since ϵ_{ijt} is drawn from a generalized extreme value distribution, we can invert the demand system and arrive at the following estimating equation:

$$\log(s_{jtb}) - \log(s_{0tb}) \quad = \quad -\alpha_b p_{jt} - \mathbb{E}_b[w_{jt}|L_{jt}]\phi_b + \rho \log(s_{j|g,tb}) + \delta_{jb} + \delta_{T(t)b} + \delta_{S(t)b} + \xi_{jtb} \quad (15)$$

where s_{jtb} and s_{0tb} are the share of consumers from bin b in market t buying product j and the outside good, respectively, and $s_{j|g,tb}$ is the market share of product j within all the inside goods offered in market t. The parameters we wish to recover are α_b, ϕ_b, μ, ρ, and all the fixed effects.[36]

5.1.2. *Identification*: Identification in our model relies on the rich panel structure of our data. By having δ_{jb} in equation (15), we absorb all observed and unobserved product characteristics that do not vary in time and might be correlated with p_{jt} or $\mathbb{E}_b[w_{jt}|L_{jt}]$. We also include $\delta_{T(t)b}$ and $\delta_{S(t)b}$ to account for differences in aggregate demand for cereal across time and stores, flexibly by consumer type.

Our identification assumption is given by the following moment condition:

$$\mathbb{E}[\Delta\xi_{jtb}|\Delta p_{jt}, \nu_j, \pi_{jb}, r_j] \quad = \quad 0$$

where $r_j \in \{chocolate, flakes, granola, oats, sugary\}$ is the subcategory to which product j belongs. Intuitively, this identification assumption imposes that demand shocks do not differentially vary for products with different bliss-points, about which consumers have different beliefs, and that belong to different subcategories across time and stores. Moreover, changes in demand shocks are also not correlated with changes in prices.

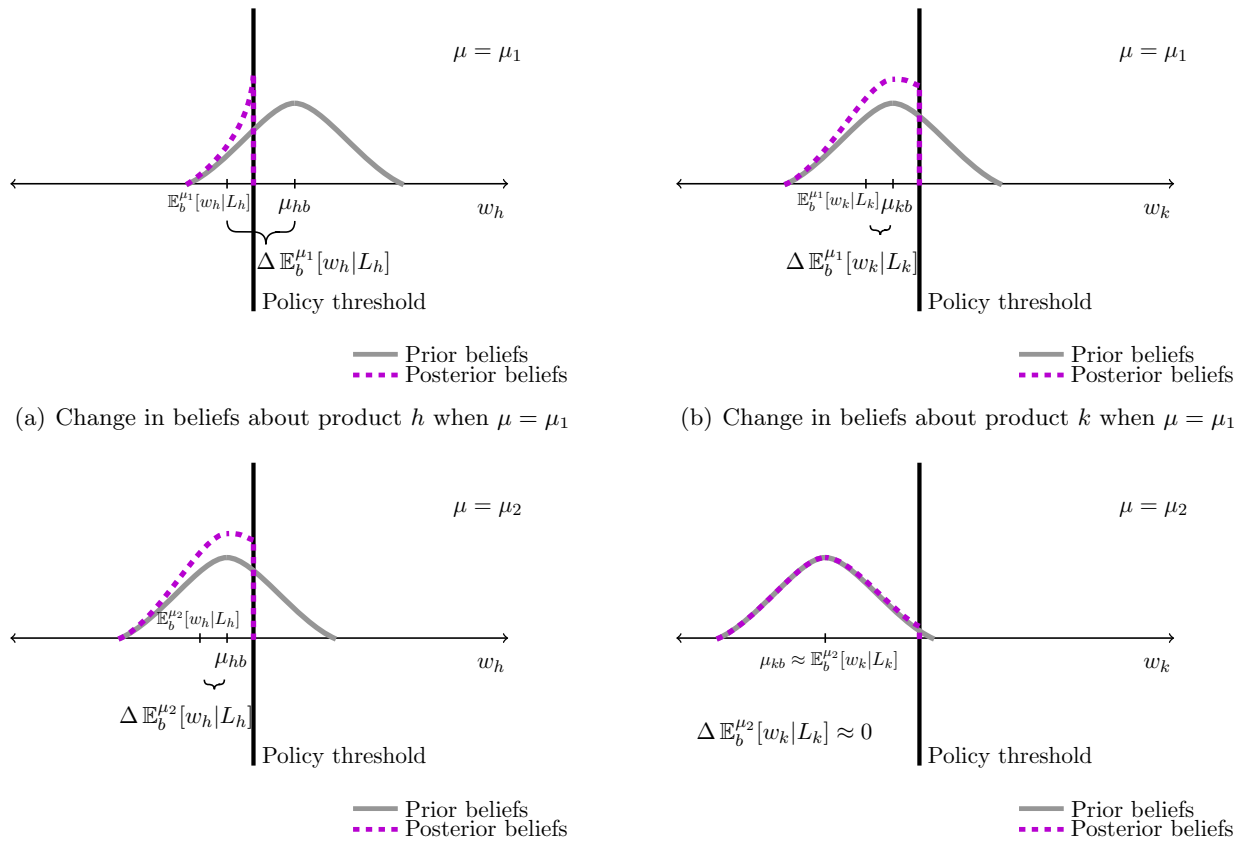
To identify α_b, the preferences over the price attribute, we exploit the residual variation in prices after controlling for all fixed effects. Our identification assumption requires that prices p_{jt} are not correlated with the structural demand shocks ξ_{jtb} once we control for all fixed effects. This assumption would be violated if Walmart could predict the idiosyncratic demand shock for a given product, at a given store, during a given period, and set prices accordingly. Even though it is likely that Walmart sets higher prices for generally more popular products, or that it can predict that demand for cereal products is generally lower during summer break, it is hard for them to respond to very specific and high-frequency demand shocks at the product-market level. Recent research highlights managerial inertia and brand-image concerns as agency frictions and behavioral factors that complicate high-frequency price optimization (DellaVigna and Gentzkow, 2019).[37]

[35] Σ_{jb} could potentially be flexibly identified from the Walmart data. However, due to lack of power, we impose the diagonal assumption and recover it from the survey. In Appendix J.6, we show that our relevant elasticities are robust to different choices of Σ_{jb}.

[36] The value of μ determines the shape of $\mathbb{E}_b[w_{jt}|L_{jt}]$ in equation (15)

[37] In Appendix J.7, we show that, once we control for all fixed effects, prices do not correlate with market-specific

The identification of ϕ_b, the preferences over the perceived health consequences of consuming sugar and calories, and μ, the parameter that shifts the value of consumer beliefs elicited in the survey, is more difficult. First, note that if $\mathbb{E}_b[w_{jt}|L_{jt}]$ were observed in the data, we could identify ϕ_b following the standard assumptions of a difference-in-differences. Unfortunately, we do not observe $\mathbb{E}_b[w_{jt}|L_{jt}]$ directly in the data. However, $\mathbb{E}_b[w_{jt}|L_{jt}]$ is a parametric function that depends only on the parameter μ. This adds enough structure to jointly identify ϕ_b and μ using Walmart data. Figures 8 and 9 provide the intuition behind our identification strategy. To explain this, 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 different parameter values, $\mu = \mu_1$ and $\mu = \mu_2$ (with $\mu_1 > \mu_2$).



(a) Change in beliefs about product h when $\mu = \mu_1$

(b) Change in beliefs about product k when $\mu = \mu_1$

(c) Change in beliefs about product h when $\mu = \mu_2$

(d) Change in beliefs about product k when $\mu = \mu_2$

Figure 8: Model-implied change in beliefs about about sugar and calorie concentration, w, for products h and k at different values of μ

Notes: The figure shows the distribution of prior and posterior beliefs about sugar and calorie concentration, w, for products h and k conditional on not receiving a label. In panels (a) and (b), we plot beliefs when $\mu = \mu_1$, and in panel (c) and (d), when $\mu = \mu_2$.

conditions such as the number of people shopping at Walmart in a given market. We also estimate our model using three alternative approaches that rely on instrumental variables. The first one uses sugar prices as exogenous cost-shifters, the second one uses prices from neighboring stores as instruments, and the third one uses high-frequency product discounts as instruments. The first two approaches exploit low-frequency variation in prices and recover long-run elasticities. The third approach exploits high-frequency variation in prices and recovers short-run elasticities. Our baseline estimates lie between the long- and short-run elasticities from the other approaches.

In Figure 8, 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 $\Sigma_h = \Sigma_k$. In panels (a) and (b), we plot beliefs when $\mu = \mu_1$, and in panel (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 by $\Delta\,\mathbb{E}^{\mu}[w_j|L_j]$, where $j = \{h, k\}$, the absolute change in the expected value of w_j induced by the labeling policy at parameter value μ. 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 non-linear 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 9 to illustrate how the non-linearity of $\Delta\,\mathbb{E}^{\mu}[w_j|L_j]$ with respect to $\tilde{\mu}_{jb}$ and μ helps us to identify these parameters. The figure shows the change in expected utility from consuming product j as a function of $\tilde{\mu}_{jb}$. The dashed line corresponds to $\mu = \mu_1$ and the solid 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.

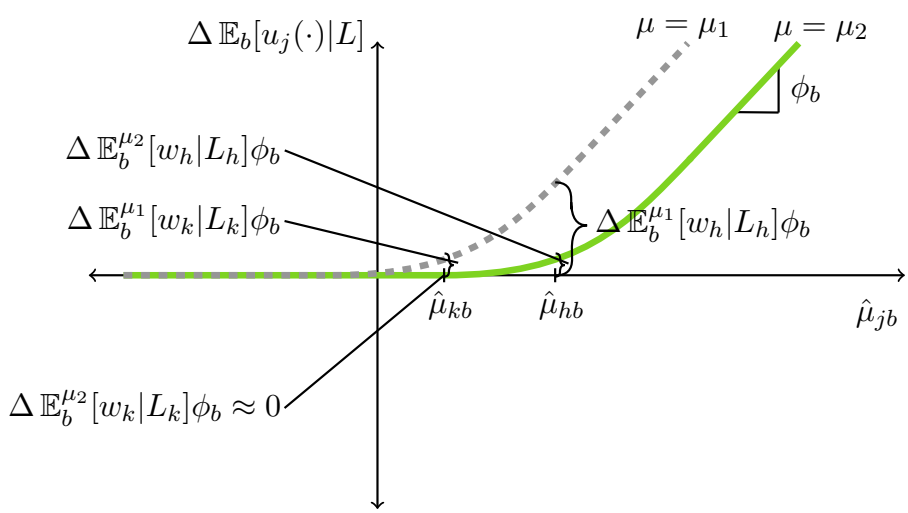


Figure 9: Model-implied change in expected utility for product h and k at different values of μ

Notes: The figure shows the change in expected utility from consuming product j as a function of $\tilde{\mu}_{jb}$ for different values of μ. The dashed line conveys this relationship for $\mu = \mu_1$, and the solid line for $\mu = \mu_2$.

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 curve in Figure 9. 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.[38]

Finally, we identify ρ, the intra-nest correlation of the logit error, using variation in the within-product market shares, denoted by $s_{j|g,tb}$. Given the structure of the model, $s_{j|g,tb}$ will be mechanically correlated with ξ_{jtb}. To deal with this endogeneity problem, we follow Miller and Weinberg (2017) and instrument $s_{j|g,tb}$ with the number of products available in a given market, which we take as given.

5.1.3. *Estimation*: We estimate the model using the generalized method of moments (GMM). The estimating moment conditions are given by $\mathbb{E}[\hat{\xi}_{jtb} \otimes Z_{jtb}] = 0$, where $\hat{\xi}_{jtb}$ is the model residual from Equation (15), and Z_{jtb} is given by:

$$Z_{jtb} = \left[\begin{array}{cccccc} p_{jt} \times d_b & \hat{L}_{jt} \times d_{\tilde{\mu}} \times d_b & N_t & d_{jb} & d_{S(t)b} & d_{T(t)b} \end{array} \right]$$

where $p_{jt} \times d_b$ is the price of product j in market t interacted with consumer-type dummies; $\hat{L}_{jt} \times d_{\tilde{\mu}} \times d_b$ is an instrument for label status, which we describe below, interacted with bins that group products according to $\tilde{\mu}_{jb}$, and consumer-type dummies; N_t is the number of products available in market t; and d_{jb}, $d_{T(t)b}$, and $d_{S(t)b}$ are matrices of indicator variables for product-type, period-type, and store-type fixed effects.

Each set of instruments helps us to identify different parameters and the estimating moment conditions are consistent with our identification assumption. As explained in Section 5.1.2, variation in prices helps us to identify α_b. We interact prices with consumer type to separately estimate α_l and α_h.

The set of instruments given by $\hat{L}_{jt} \times d_{\tilde{\mu}} \times d_b$ estimate ϕ_b and μ. As illustrated in Figure 9, 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 $\mathbb{E}[\hat{L}_{jt} \times d_{\tilde{\mu}} \times d_b \times \hat{\xi}_{jtb}]$, we impose conditions over $\hat{\xi}_{jtb}$ that prevent the patterns in Figure 9 from being explained by differential demand shocks. Without the 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 to happen, thus identifying ϕ_b and μ.

Because firms are strategically bunching to avoid receiving labels, label status may indeed be correlated with ξ_{jtb}. To avoid confounding correlations in our moment conditions, we use a predictor of the label status as an instrument for it. The predictor uses the subcategories r_j and the pre-policy nutritional content (equal to ν_j from the firms' first order conditions) as inputs, and estimates a

[38]The same intuition follows for labeled products, except that products to the left of the kink will be the ones with larger changes in expected utility, and that expected utility decreases instead of increasing after the policy implementation.

random-forest model to avoid overfitting. Distance to 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 label status and, from our identification assumption, is uncorrelated with ξ_{jtb} once we control for all fixed effects.

Finally, N_t, the number of products available in market t, and d_{jb}, $d_{T(t)b}$, and $d_{S(t)b}$, the matrices of indicator variables for the fixed effects, provide the moments to estimate ρ and the respective values of the fixed effects.

5.1.4. *Results*: Our estimated demand parameters are presented in Table 2. Our estimates imply an average own-price elasticity of -3.66, with a higher absolute elasticity among low SES households (-3.77 vs. -3.55). These elasticities imply median markups–defined as the ratio of price minus marginal cost to price–of 27% in the pre-policy period. These results are similar to those of Nevo (2001), who estimate demand for cereal in the US market and find elasticities between -2.3 and -4.25, and median markups of 34%. Our estimates are also comparable to accounting estimates provided by the Chilean antitrust agency, who estimate markups of 45% for the largest cereal brand in Chile (FNE, 2014).

Table 2: Estimated demand parameters

α_l	0.0548^{***}	ϕ_l^s	0.02801^{***}	ϕ_l^c	0.01350^{***}
	(0.0142)		(0.01087)		(0.00431)
α_h	0.0503^{***}	ϕ_h^s	0.02570^{**}	ϕ_h^c	0.01213^{***}
	(0.0156)		(0.01029)		(0.00383)
ρ	0.9919^{***}				
	(0.0046)				

Notes: Nutritional content is measured in grams of sugar and kilocalories per each gram of cereal respectively. Prices are measured in dollars per 100gr of cereal. Standard errors are clustered at the market level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

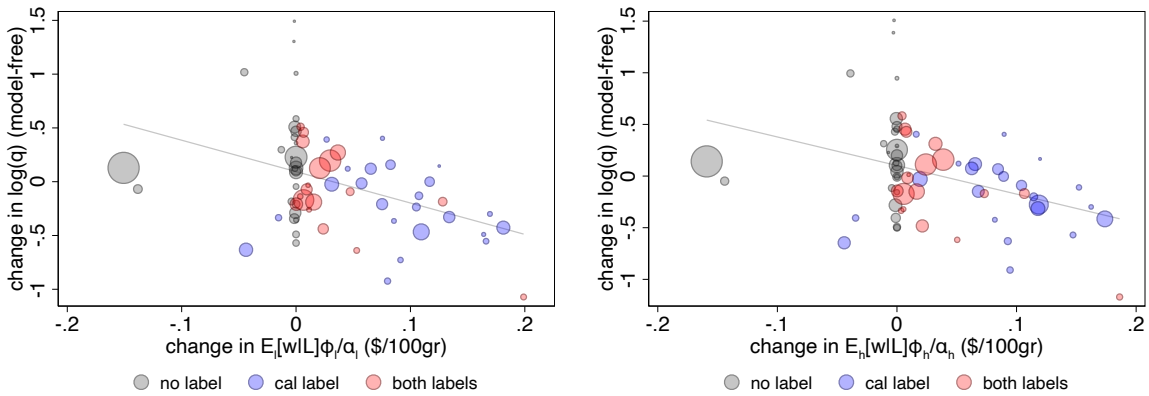
The estimates for ϕ_b indicate that consumers are willing to pay 11% of the average price of cereal (i.e. \$3.2 a year) to reduce the sugar or calorie concentration of products by 1 standard deviation (12gr of sugar and 25kcal per 100gr of cereal, respectively), while keeping the taste constant. For example, *Original Cheerios* contain 5gr of sugar per 100gr, while *Honey Nut Cheerios* contain 32.5gr of sugar per 100gr. According to our model, consumers would be willing to pay \$0.77 more for a 550gr family size box of *Honey Nut Cheerios* if they contained the sugar content of *Original Cheerios* but kept their own taste (\$0.77 for 550gr corresponds to 22% of its average price in our data).

Finally, we find an intra-nest correlation of $\rho = 0.9919$, suggesting that there is little substitution from inside goods to the outside good. This is consistent with the reduced-form evidence presented in Appendix D, where we show there is little evidence of between-category substitution.

5.1.5. *Model fit*: To visualize how our model interacts with the raw data, in Figure 10, we compare the model-based prediction of changes in believed product healthiness with reduced-form estimates of changes in equilibrium quantities. On the horizontal axis, we plot the model-based estimate of the change in expected utility for type b consumers from consuming product j after the labels are implemented, given by $\frac{1}{\hat{\alpha}_b}\Delta\hat{E}_b[w_{jt}|L_{jt}]\hat{\phi}_b$. On the vertical axis, we plot the coefficient from a reduced-form regression that captures the average log-change in equilibrium quantities of cereal purchased by type b consumers. Specifically, we estimate and plot β_{jb} from the following regression:

$$\log(q_{bjst}) \quad = \quad \beta_{jb} \cdot \text{Post}_t + \gamma_b \cdot p_{jst} + \delta_{jsb} + \delta_{tb} + \varepsilon_{jstb} \tag{16}$$

where q_{bjst} denotes the grams of product j purchased by type b consumers in store s in period t, Post_t is a dummy variable that takes the value of one after the date of policy implementation, and β_{jb} are coefficients specific to each product. p_{jst} refers to the price per 100 grams, δ_{jsb} denotes product-store-type fixed effects, and δ_{tb} denotes period-type fixed effects. Weights and standard errors are implemented as in Equation (1). We run the regression separately for low- and high-SES households.



(a) low SES households

(b) high SES households

Figure 10: Model based-prediction of changes in expected utility due to changes in beliefs vs reduced-form estimates of changes in equilibrium quantities

Notes: The figure compares model-implied changes in beliefs about the healthiness of products agains reduced-form estimates for changes in quantities. In the horizontal axis we plot the change in beliefs between before and after the policy implementation. On the vertical axis, we plot the coefficient from a reduced-form regression that captures the average log-change log-change of quantities of cereal purchased by consumers of type b estimated in equation (16).

We find that products for which consumers updated their beliefs about product healthiness downwards (i.e. $\frac{1}{\hat{\alpha}_b}\Delta\hat{E}_b[w_{jt}|L_{jt}]\hat{\phi}_b > 0$) experienced a decrease in demand relative to those products for which consumers updated their beliefs about product healthiness upwards or not at all. This is consistent with the evidence shown in Section 3, Figure 5(b).

5.2. *Supply estimation*

5.2.1. *Parametrization*: To model supply, we need to recover two key sets of parameters: the marginal cost of producing each product, and how this marginal cost varies when firms change the nutritional content of their products. Recall from Section 4.2 that marginal costs are constant in quantity and are minimized when the nutritional content of a given product is equal to its bliss point (i.e. $\nabla c_{jt}(\nu_j) = 0$). For each product, we approximate the marginal cost function by a second order Taylor polynomial around the bliss point, such that:

$$c_{jt}(w) = \bar{c}_{jt} + (w - \nu_j)'\Lambda_j(w - \nu_j) \tag{17}$$

where $\Lambda_j = \begin{bmatrix} \lambda_j^c & 0 \\ 0 & \lambda_j^s \end{bmatrix}$ with $\lambda_j^n = \kappa^n + \zeta_j^n > 0$ for $n \in \{s, c\}$ and all products j. We assume that κ^n is constant across products and that ζ_j^n is drawn from a lognormal distribution with parameters $\left(\mu_\zeta^n, \sigma_\zeta^n\right)$. This parametric restriction implies that the decision regarding optimal calorie concentration is independent of that regarding optimal sugar concentration. Moreover, we assume that the costs of reducing sugar and calorie concentration are not correlated. These assumptions are consistent with the data, where we find no correlation between calorie and sugar content, nor high correlation between changes in these induced by reformulation.[39]

5.2.2. *Estimation*: We can recover $c_{jt}(w_{jt}^*)$ and ν_j from the firm's first order conditions (Equations (11) and (12)).[40] We then estimate κ^n, μ_ζ^n and σ_ζ^n by exploiting variation in the decisions of firms to bunch.

Using our demand estimates from Section 5.1, we solve for the equilibrium at the current parameters and labels.[41] We then ask, for each product, what would be the value of λ_j^n that would make firm $f(j)$ indifferent between choosing the bliss point level ν_j^n or having product j bunching at the threshold, keeping all other products' nutritional content decisions fixed.[42] We denote the indifference value by $\tilde{\lambda}_j^n$. If, in the data, we observe that product j is not bunching in nutrient n, we can infer that $\lambda_j^n > \tilde{\lambda}_j^n$, otherwise, $\lambda_j^n \leq \tilde{\lambda}_j^n$.

We estimate κ^n, μ_ζ^n, and σ_ζ^n for $n \in \{s, c\}$, a total of six parameters, using a maximum likelihood

[39] The correlation between the levels of sugar and calorie concentration is 0.27 in the pre-policy period and 0.19 in the post-policy period. The correlation between changes in sugar and calorie concentration among products that reformulated to cross the policy threshold is 0.08.

[40] The parameter ν_j can be inferred from the nutritional content of products before the labeling policy implementation, while $c_{jt}(w_{jt}^*)$ comes from the derivative of the profit function with respect to prices, evaluated at the optimum.

[41] Note that to solve for the equilibrium, we only need the to know demand, and the values of $c_{jt}(w_{jt}^*)$ and w^*. We estimated demand in Section 5.1, $c_{jt}(w_{jt}^*)$ is estimated from the first order conditions, and w^* is observed in the data.

[42] We allow firms to optimally choose prices and solve for two equilibria. One where firm $f(j)$ chooses $w_{jt} = \nu_j$ and one where firm where firm $f(j)$ chooses to bunch in product j. We then find the value of λ_j^n that makes firm $f(j)$ indifferent between the two equilibria.

estimator that solves:

$$\max_{(\kappa^n,\mu_\zeta^n,\sigma_\zeta^n)} \sum_n \sum_j \left[B_j^n \log\left(Pr(\lambda_j^n \leq \tilde{\lambda}_j^n)\right) + (1-B_j^n)\log\left(Pr(\lambda_j^n > \tilde{\lambda}_j^n)\right)\right]$$

where B_j^n is a dummy variable indicating whether product j is bunching in nutrient n. Once we estimate κ^n, μ_ζ^n, and σ_ζ^n, we calculate $\bar{c}_{jt}$ by solving $c_{jt}(w_{jt}) = \bar{c}_{jt} + \mathbb{E}_\zeta[(w_{jt}-\nu_j)'\Lambda_j(w_{jt}-\nu_j)|B_j]$.

5.2.3. *Results*: Our estimated supply parameters are presented in Table 3. To interpret these parameters, we calculate $\mathbb{E}[\lambda_j^n|B_j^n = 1]$, the expected value of λ_j^n conditional on product j bunching in nutrient n. We find an average value of $0.19527\frac{¢}{(gr/100gr)^2}$ in the case of sugar and of $0.02719\frac{¢}{(kcal/100gr)^2}$ in the case of calories. The average reduction in sugar concentration among products bunching in sugar is 8.2 gr/100gr, while the average reduction in calorie concentration among products bunching in calories is 23.8 kcal/100gr. Putting everything together, our model finds that the average expected increase in marginal cost for products bunching in any nutrient is 3.9¢ per 100gr, equivalent to 6.2% of the average price of cereal.

Table 3: Estimated supply parameters

κ^s	0.005	μ_ζ^s	-1.219***	σ_ζ^s	1.464***
	(0.011)		(0.369)		(0.343)
κ^c	0.373***	μ_ζ^c	1.398***	σ_ζ^c	2.919***
	(0.157)		(0.165)		(0.273)

Notes: Nutritional content is measured in 10gr of sugar and 100kcal per 100gr of cereal respectively. Standard errors are presented in parenthesis. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

5.2.4. *Model fit*: The change in marginal cost estimated above is estimated by combining the amount of bunching observed in the data with equilibrium conditions consistent with the model. To assess the accuracy of our estimates, we run a semi-parametric 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 it to the change in marginal cost implied by our estimated supply parameters. To do this, we estimate the following equation:

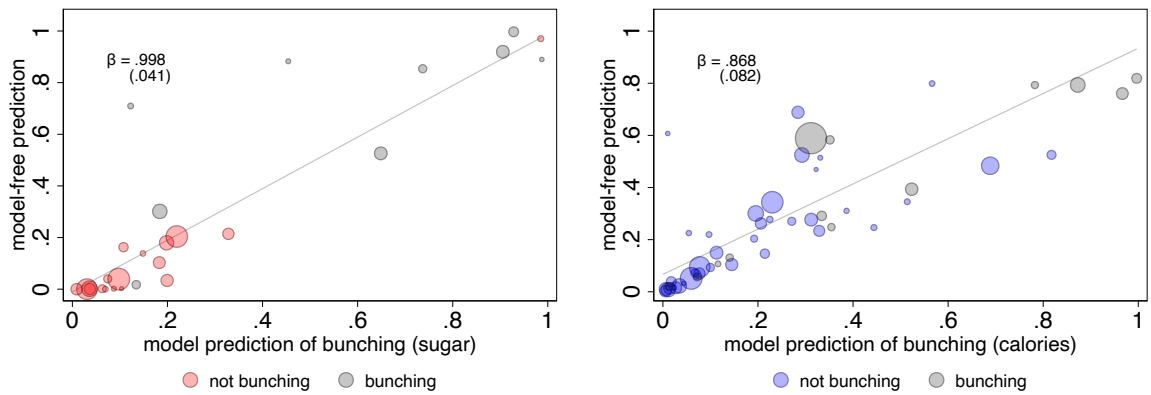
$$c_{jt}(w_{jt}^*) = \beta \cdot B_j \cdot Post_t + \delta_{js} + \delta_t + \varepsilon_{jt}$$

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. This alternative method suggests an average change in marginal cost of 3.0¢ per 100gr, similar to the 3.9¢ per 100gr estimated with the parametric model-based approach above.

We also compare the model-based predicted probability of each product bunching in a given nutrient, with a reduced-form prediction based only on pre-policy nutritional content values and the first moment of consumers' prior beliefs. We use a logistic regression model of the form:

$$P(B_j = 1) = \frac{e^{f(\nu_j, \mu_{jb})}}{1 + e^{f(\nu_j, \mu_{jb})}}$$

where $f(\cdot)$ is a second order polynomial. We present the model-based and reduced-form predictions for sugar and calories in Figure 11.



(a) bunching in sugar

(b) bunching in calories

Figure 11: Predicted probability of nutritional bunching for products to the right of the regulatory threshold in the pre-policy period

Notes: The figure compares the model-based predicted probability of each product bunching in a given nutrient to a reduced-form prediction based only on pre-policy nutritional content values and the first moment of consumers' prior beliefs.

6. Counterfactuals

In this section, we use our model to evaluate the effects of FoPL 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 to sugar taxes–the most prominent alternative policy instrument. Finally, we discuss the distributional consequences of both policies. We provide details about the simulation method in Appendix K.

6.1. *Equilibrium effects of food labels*

We estimate the effects of the Chilean Food Act on consumer choices, firms' production and pricing decisions, overall nutritional intake, and consumer surplus. To disentangle the role of demand and supply on changes in nutritional intake and consumer surplus, we run several counterfactuals summarized in Table 4. The benchmark counterfactual, denoted by (0), *no intervention*, corresponds to

the case where there is no policy at place. To isolate demand forces, we compare the no intervention benchmark to a situation in which products receive labels according to the regulatory thresholds and suppliers are not allowed to respond. We denote that counterfactual by (1), *demand only*. We then compute counterfactual (2), *price response*, where in addition to the labels, we allow suppliers to optimally choose prices while keeping nutritional content constant. We use counterfactual (2) to measure additional changes in consumer surplus driven by competition and product differentiation, which can decrease or increase markups. The differences in consumer surplus between (1) and (2) are thus ambiguous. Finally, in counterfactual (3), *equilibrium*, we allow firms to also change the nutritional content of their products. This corresponds to the full equilibrium model presented in Section 4. The expected change in consumer surplus from counterfactual (2) to (3) is also ambiguous. While firms improve product quality by reducing the concentration of critical nutrients, production costs increase, which leads to higher prices to consumers. Whether the policy in (3) increases or decreases consumer surplus and welfare relative to (0) is therefore an empirical question.

Table 4: Policy counterfactuals

Counterfactual	**Description**
(0) no intervention	No intervention
(1) demand only	Labels at place but no supply responses
(2) price response	(1) + firms choose prices optimally (p_{jt})
(3) equilibrium	(1) + (2) + firms choose nutritional content optimally (w_{jt})

Notes: The table summarizes the main counterfactuals simulated in Section 6.

We extend our model to account for additional market imperfections, such as externalities in the form of financial health-care costs (fiscal externalities), or internalities in the form of self-control problems, time-inconsistency, or misperceptions about the individual damage caused by critical nutrients ϕ_b. We model these additional features by multiplying the marginal damage of consuming critical nutrients by a constant λ.[43] To estimate welfare and consumer surplus we cannot use a standard revealed preferences approach, as in our setting consumer choices do not necessarily maximize utility. We follow Allcott (2013), who offer a framework to calculate consumer surplus in situations where consumers' ex-ante expected utility differs from the one they actually experience when consuming their chosen alternative.

The average consumer surplus in market t under counterfactual (x) is given by

$$CS^t(x) = \sum_b \frac{1}{\alpha_b} \sum_j \left\{ \int_{\Theta_{bjt}^{(x)}} (\delta_{ijt} - \alpha_b p_{jt}^{(x)} - w_{jt}^{(x)} \phi_b \lambda) di \right\}$$

[43] We are implicitly assuming that the additional marginal damage from externalities and internalities from consuming critical nutrients is proportional to the estimated preferences over nutritional intake. One could think that fiscal externalities do not vary by type and should be proportional to $\frac{1}{\alpha_b}$ instead. Under the current parameter estimates, this does not make any difference because $\frac{\hat{\phi}_l}{\hat{\alpha}_l} \approx \frac{\hat{\phi}_h}{\hat{\alpha}_h}$. Notice that λ could, in principle, be different for sugar and calories.

where $p_{jt}^{(x)}$ and $w_{jt}^{(x)}$ are the price and nutritional content of product j in market t in counterfactual (x). $\Theta_{bjt}^{(x)}$ is the set of consumers from income group b that 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.

Let's denote $\Delta CS^t(x) = CS^t(x) - CS^t(0)$ as the average change in consumer surplus between counterfactuals (x) and (0) in market t. We can decompose the change in consumer surplus into what we call substitution- and supply-effects:

$$\Delta CS^t(x) = \sum_b \frac{1}{\alpha_b} \sum_j \left\{ \underbrace{\int_{\Delta\Theta_{bjt}^{(x)}} \delta_{ijt} di - (\alpha_b p_{jt}^{(x)} + w_{jt}^{(x)} \phi_b \lambda) \Delta s_{jt}^{(x)}}_{\text{substitution-effects}} \quad \underbrace{-(\alpha_b \Delta p_{jt}^{(x)} + \Delta w_{jt}^{(x)} \phi_b \lambda) s_{jt}^{(0)}}_{\text{supply-effects}} \right\}$$

where $\Delta y^{(x)} = y^{(x)} - y^{(0)}$ and $\Delta\Theta_{bjt}^{(x)}$ is the set of consumers from income group b that choose product j in counterfactual (x) but not in counterfactual (0). Note that in counterfactual (1) we isolate substitution effects, as $\Delta p_{jt}^{(1)} = \Delta w_{jt}^{(1)} = 0$. In counterfactual (2) we force $\Delta w_{jt}^{(2)}$ to be zero, while in counterfactual (3) we capture the full expression. For the main part of our analysis, unless stated different, we focus on results for the case where $\lambda = 1$ (i.e. where there are no additional market imperfections). We present our main results in Figure 12.

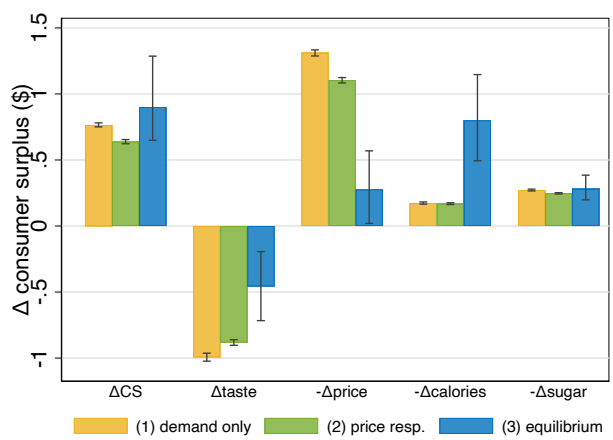


Figure 12: Changes in consumer surplus under different counterfactuals

Notes: The first three bars of the figure show the change in consumer surplus from counterfactual (0) to counterfactuals (1), (2), and (3), respectively. Bars 4-15 decompose those changes into changes in taste/experience of consuming cereal, changes in price paid, changes in caloric intake and changes in sugar intake. Each bar is normalized to show the contribution of each dimension to consumer surplus in dollars. For example, a positive value in the contribution from calorie intake means that consumers are consuming lower quantities of calories under that counterfactual. We present confidence interval from the Montecarlo simulations. Counterfactual (3) has larger confidence intervals due to variation in ζ_j^n embedded in the firms' cost function that does not show up when firms do not reformulate products.

We find that moving from a world with no intervention, (0), to one where products get labeled but suppliers do not respond, (1), increases average consumer surplus in \$0.76 a year. This corresponds to 3% of the average yearly expenditure on cereal products. In the absence of supply-side responses,

consumers shift demand from high-in-critical-nutrients to low-in-critical-nutrients products. Since in the breakfast cereal market calorie and sugar content is negatively correlated with prices, consumers end up consuming products that are cheaper but, according to the model, with lower taste (e.g. oatmeals).

We then allow firms to optimally set prices in response to the policy by simulating counterfactual (2). We find that prices of unlabeled products go up while prices of labeled ones go down. Overall, prices increase by 0.15% on average and gains in consumer surplus relative to counterfactual (0) are \$0.64 a year per capita (15% lower than under counterfactual (1)).

Under counterfactual (3), firms do not only choose prices, but also the nutritional content of their products. We find large gains in consumer surplus from reducing calorie intake, most of it driven by products becoming healthier due to reformulation.[44] Gains in consumer surplus due to lower intake of critical nutrients is 142% larger than under counterfactual (1). However, reformulation increases production costs, which leads to higher prices. The net effect is an average gain in consumer surplus under counterfactual (3) of \$0.9 a year, 18% larger than under counterfactual (1).[45]

On the firms' side, average yearly profits per capita increase \$0.15, with substantial heterogeneity across firms. While some firms increased their profits in around 20%, others lost more than 50% (see Appendix A, Figure A.8). Who wins and loses is closely related to how labels shifted consumers' beliefs. Firms with products that were believed to be healthy but ended up labeled are the ones with the highest losses. This may explain why some firms opposed so strongly to the Chilean Food Act when it was first implemented.

Finally, we consider an additional counterfactual in which consumers are perfectly informed about nutritional content of products.[46] This exercise informs us about the total welfare losses due to lack of information in the cereal market and allow us to assess how close food labels get to the best-case scenario of perfect information. We find that the food labeling policy achieves 32% of the consumer surplus gains that would be obtained under the perfect information counterfactual (see Appendix A, Figure A.9).[47]

6.2. *The design of food labeling policies*

In this subsection, we 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 surplus vary under different

[44] Changes from reducing sugar intake are smaller. One hand, products are reducing the concentration of sugar. On the other hand, more products are unlabeled in counterfactual (3), which increases the average concentration of sugar among unlabeled products in (3). The latter effect offset the potential benefits of the first effect.

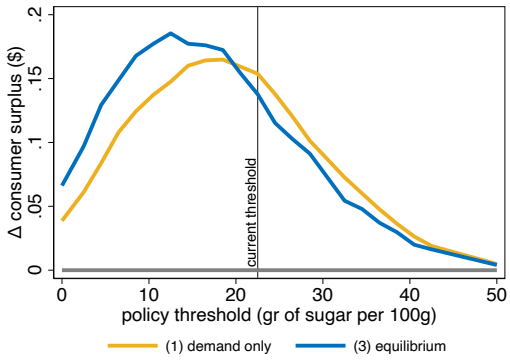
[45] We present results decomposing the gains in consumer surplus between substitution and supply effects in Appendix A, Figure A.7.

[46] This counterfactual also takes into account demand and supply forces driven by fully informed consumers. Additional model details are presented in Appendix K.2

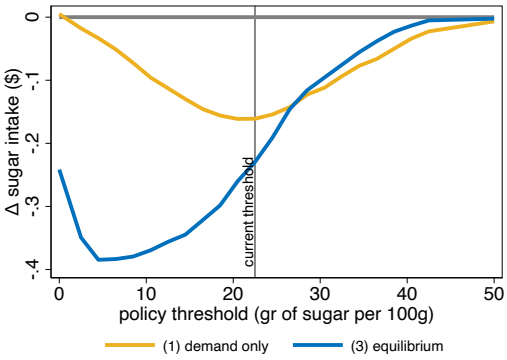
[47] This exercise informs us about the welfare losses incurred by consumers from not acquiring the information from the nutritional fact tables in the back of the package. Our estimates imply that consumers would be indifferent between remaining uninformed and paying 0.65¢ for each product in the choice set to be fully informed.

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, policy makers can choose a different regulatory threshold that induces larger reductions in critical nutrients. To clarify the analysis, we simplify our model and allow for miss-information only in sugar.[48]

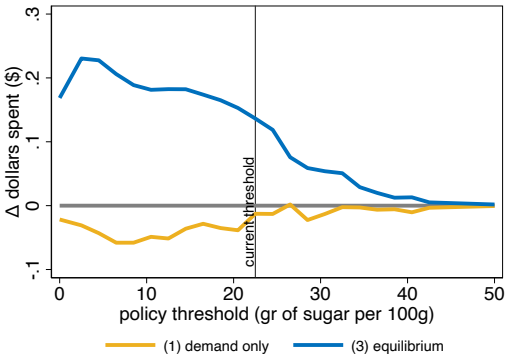
We focus our analysis on counterfactuals (1)–only demand responses–and (3)–equilibrium model. Figure 13(a) shows the gains in consumer surplus under counterfactuals (1) and (3) for different policy thresholds. A naive policymaker seeking to maximize consumer surplus but that ignores equilibrium effects would set the policy threshold at 18gr/100gr, value at which consumer surplus is maximized under counterfactual (1). Consumer surplus under (3), however, is maximized at 12.5gr/100gr, where it is 7.5% larger than under the naive threshold.[49]



(a) Consumer surplus



(b) Sugar intake



(c) Dollars spent

Figure 13: Changes in consumer surplus, sugar intake, and dollars spent over different policy thresholds

Notes: The figure plots average outcomes of interest under different regulatory thresholds under counterfactuals (1) and (3) relative to (0). Panel (a) shows the gains in consumer surplus, panel (b) shows changes in sugar intake converted to dollars using the parameters of the utility function, and panel (c) shows changes in dollars spent.

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

[49] It is not always the case that the threshold that maximizes consumer surplus under counterfactual (3) is to the left of the one under counterfactual (1). The relative position of the two thresholds depends on the underlying distribution of beliefs, demand, bliss points, and bunching costs of the different products.

As seen in Figure 13(b), tighter thresholds are quite effective in reducing sugar intake under the equilibrium model. Decreases in sugar intake increase consumer surplus up to \$0.38 when the threshold is set at 4gr/100gr. This represents a 7.5% reduction in total sugar intake. This is important when thinking about cases in which λ, the parameter that accounts for additional market imperfections, is greater than 1, as reductions in sugar intake become more effective in increasing consumer surplus.[50] On the other hand, equilibrium prices are higher due to reformulation. At the same threshold of 4gr/100gr, increases in prices decrease consumer surplus in \$0.2 (see Figure 13(c)). This represents an increase in total expenditure of 0.7%.

6.3. *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).[51] Most sugar taxes are structured as a per-ounce tax on any product with added sugar. However, Allcott et al. (2019b) suggest to use 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 that same tax structure here. 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, where sales taxes are not observed by consumers in Chile. We denote by ψ the marginal value of public funds. To calculate consumer surplus, we give the tax money to consumers through a lump sum transfer (i.e. $\psi = 1$).

Extending the model from Section 4.2 to include sugar taxes, the firm's problem is given by:

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

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:

$$\begin{aligned} \nabla c_{jt}(w^*_{jt}) &= -\tau \\ p^*_{jt} &= c_{jt}(w^*_{jt}) + \tau w^*_{jt} + \Delta^{-1}_{(j,\cdot)} \mathbf{s_t} \end{aligned}$$

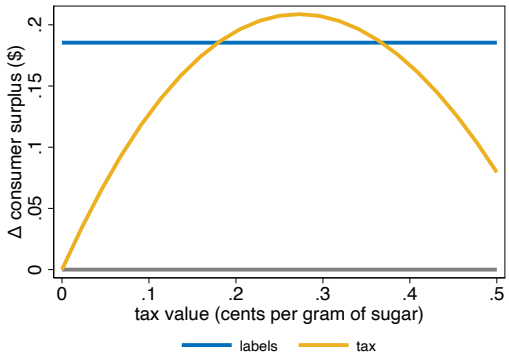
where the (j, k) element of Δ is given by equation (13). In this setting, firms have incentives to deviate from the bliss-point and reduce the nutritional content of their products to pay lower taxes. Moreover, the price equation has an additional term given by the tax, which is proportional to the sugar content, and gets passed to consumers through higher prices.

In Figure 14(a), we present gains in consumer surplus at different tax values. The optimal sugar tax (i.e. the tax that maximizes consumer surplus) is set at 0.27¢ per gram of sugar. This is not far

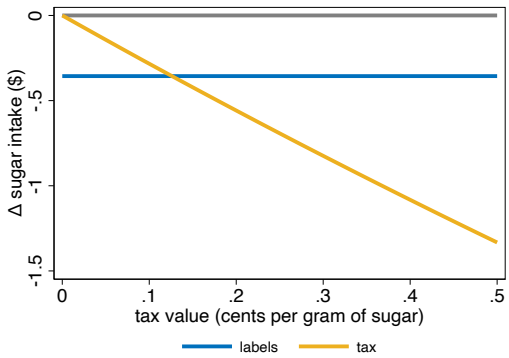
[50] We show changes in consumer surplus for $\lambda = 1.5$ in Appendix A, Figure A.10

[51] The main focus of these taxes is on sugar-sweetened beverages, with some implementations on solid food products in some countries.

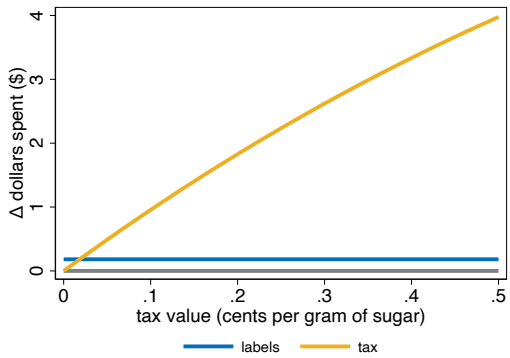
from sugar taxes implemented in some American cities.[52] Gains in consumer surplus with optimal sugar taxes are 12.5% larger than under food labels at the optimal policy threshold.



(a) Consumer surplus



(b) Sugar intake



(c) Dollars spent

Figure 14: Gains in consumer surplus over different tax levels

Notes: The figure plots average outcomes of interest under different tax values. Panel (a) shows the gains in consumer surplus, panel (b) shows changes in sugar intake converted to dollars using the parameters of the utility function, and panel (c) shows changes in dollars spent. The blue line correspond to the outcomes under food labels at the regulatory threshold that maximizes consumer surplus. In Appendix A, Figure A.11, we decompose the effects into demand- and supply-side effects.

Figures 14(b) and 14(c) show the change in sugar intake and dollars spent induced by the policy. Taxes turn out to be more effective in reducing sugar intake than food labels. However, they do it at a greater direct financial cost to consumers. Under the optimal tax level, consumers spend 2.4 additional dollars a year in taxes, equivalent to 7% of the total expenditure in cereal. Because taxes collected are relatively high, our results are sensitive to the choice of ψ, the marginal value of public funds.[53]

Note that, in contrast to food labels, sugar taxes are granular instruments that levy on products

[52] Philadelphia and Berkeley are the first two cities to pass a sugar tax in the US. 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, for example. In Philadelphia the tax is 1.5¢ per ounce, equivalent to 0.48¢ per gram of sugar.

[53] In Appendix A, Figure A.10 we set $\psi = 0.95$. Gains in consumer surplus under optimal taxes become 43% lower than under food labels at the optimal policy threshold.

with higher levels of sugar more heavily. This is important for two reasons. First, they have the potential to incentivize firms to reformulate all 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.

6.4. *Food labels vs. sugar taxes*

In this subsection, we discuss situations in which food labels should work better than sugar taxes and vice-versa. We first compare both instruments in settings where λ, the parameter that accounts for additional market imperfections, or ψ, the marginal value of public funds, are different from one. We then discuss the efficiency of both instruments in settings with heterogeneous agents where some consumers may have better calibrated beliefs than others.

6.4.1. *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 missinformation 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 $\lambda = 1.48$ and $\lambda = 2.07$ 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 range of policies targeted to adults in the United States have marginal values of public funds that go from $\psi = 0.7$ to $\psi = 1.1$.[54]

In Figure 15, 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 as they are better designed to deal with market imperfections not directly related to misinformation on w_{jt}. Taxes, however, impose a large burden on consumers who end up spending up to 7% more in cereal. If the marginal value of public funds ψ is small, the resources collected through taxes will not contribute much to the total surplus. The smaller the value of ψ, the less effective taxes will be.

6.4.2. *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 the point, we consider a simple model in which half of the consumers have prior beliefs given by our estimates in Section 5, and the other half have accurate beliefs (i.e. $\mu_{jb} = \nu_j$, $\Sigma_{jb} \to 0$). We call them

[54] Hendren and Sprung-Keyser (2020) estimate, for example, an average marginal value of public funds of 0.44 for job training programs, 0.77 for housing programs, 0.85 for disability insurance programs, and 0.89 for health care programs. Policies targeting children are estimated to have a much larger marginal value of public funds that can go up to $\psi = 43.6$ for the case of the Perry Preschool project, for example. We don't show results for these values, in which case, sugar taxes become strictly better than food labels.

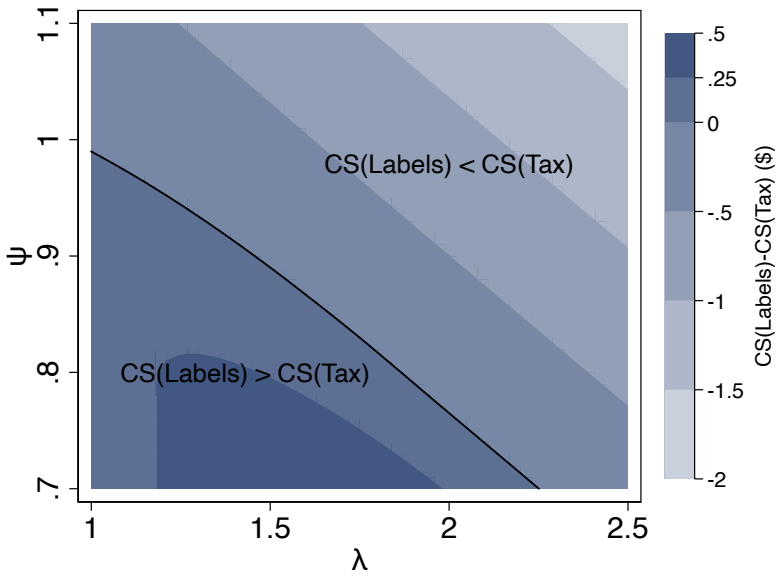


Figure 15: Differences in consumer surplus under different values of λ and ψ

Notes: This figure corresponds to a contour plot that represents the difference in gains in consumer surplus between a food labeling policy and sugar taxes as a function of λ and ψ. For each value of λ and ψ, we choose policy threshold (for labels) and tax values that maximize consumer surplus. In the bottom-left zone, food labels are more effective than taxes to increase consumer surplus. In the top-right zone are taxes are more effective than food labels.

uninformed and informed consumers, respectively. We focus on the case where 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, the effects of food labels will only affect decisions of uninformed individuals and not of those who are informed and were making optimal choices ex-ante, even when the instrument is not targeted itself. Taxes, on the other hand, are blunt instruments that generally change the actions of all consumers, benefiting some while hurting others. We illustrate this point through additional simulations in Appendix A, Figure A.12, and show that, in this simple model, sugar taxes are 50% less efficient when they can not be targeted.

6.5. *Distributional consequences of food labels and sugar taxes*

In this subsection, we study the distributional consequences of food labels and sugar taxes. 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 to determine the incidence of each policy.

The first parameter is the extent to which low-SES consumers are more or less inclined to prefer high-in-sugar products than high-SES consumers. While food labels improve consumer surplus by providing information about the healthiness of products, taxes correct consumer behavior by inflating prices of high-in-sugar products. If low-SES consumers prefer high-in-sugar products more, taxes will

disproportionally charge them more. Depending on how the tax money is spent by the government, sugar taxes can benefit high-SES consumer relatively more. In the United States, for example, consumers with household income below $10,000 purchase 25% additional grams of added sugar per calorie than households with income above $100,000 (Allcott et al., 2019).[55] 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 with respect to sugar taxes in this context is that the former can be better targeted towards the uniformed population. In the absence of equilibrium effects, food labels mainly affect behavior of uninformed consumers, while taxes will distort behavior of both uninformed and informed consumers, even if the latter are already making optimal choices. Using survey data, Allcott et al. (2019a) find that American 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. Food labels are therefore more likely to be progressive than sugar taxes.

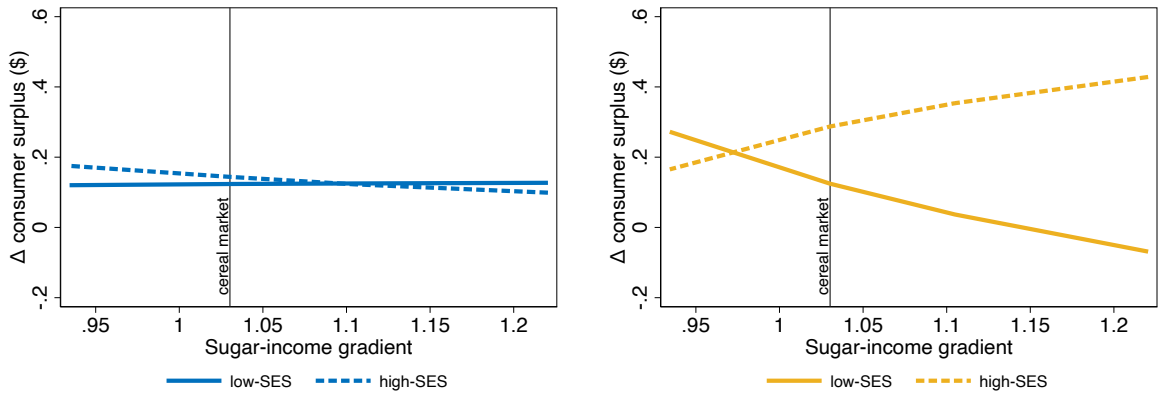
6.5.1. *Sugar-income gradient*: We define the sugar-income gradient as the ratio between the grams of sugar per dollar spent purchased in the absence of regulation by low- and high-SES consumers. A value of 1.2, for example, means that low-SES customers get 20% more sugar for every dollar spent than high-SES customers. In our model, we vary the sugar-income gradient by differentially changing the relationship between preferences over the taste of products, δ_{jb}, and products' sugar bliss-points, ν_j, for low- and high-SES consumers. The more correlated preferences and baseline sugar content are for low-SES individuals relative to high-SES individuals, the higher the sugar-income gradient will be in our simulations.[56]

Figure 16 shows the main results. Figure 16(a) shows the average gains in consumer surplus for low- and high-SES consumers of moving from the *no intervention* counterfactual, (0), to the *equilibrium* counterfactual, (3), under the policy threshold that maximizes total consumer surplus for different values of the sugar-income gradient. We find that gains in consumer surplus are similar for the two groups and stable across different values of the sugar-income gradient.

Figure 16(b) shows the gains in consumer surplus of moving from the *no intervention* counterfactual, (0), to the taxes counterfactual under the tax level that maximizes total consumer surplus for different values of the sugar-income gradient. We find that gains in consumer surplus tend to be larger for high-SES individuals. This is particularly true when the sugar-income gradient at baseline is larger, meaning that sugar taxes can exacerbate existing income-driven inequalities.

[55] Allcott et al. (2019a) also document that households in the US with annual income below $10,000 consume double as much sugar-sweetened as households with income above $100,000. This is also true in our data, where low-SES consumers are 43% more likely to buy sugar-sweetened soft drinks (see Appendix F.2, Table F.1).

[56] From the estimation results from Section 5, the correlation between preferences for taste δ_{jb} and a product's sugar bliss point ν_j is 0.7 and 0.68 for low- and high-SES individuals respectively. We increase the sugar-income gradient by decreasing the correlation between high-SES individuals' preferences and the bliss-points. We provide additional simulation details in Appendix K.



(a) Food labels

(b) Sugar taxes

Figure 16: Sugar-income gradient

Notes: This figure shows the average gains in consumer surplus for low- and high-SES individuals when implementing food labels and sugar taxes under different values of the sugar-income gradient. Panel (a) shows values for a food labeling policy where the policy threshold is set to maximize total gains in consumer surplus. Panel (b) shows values for a tax policy where the tax value is set to maximize total gains in consumer surplus. In Panel (b), tax money is returned to consumers proportional to their baseline expenditure in the absence of the policy.

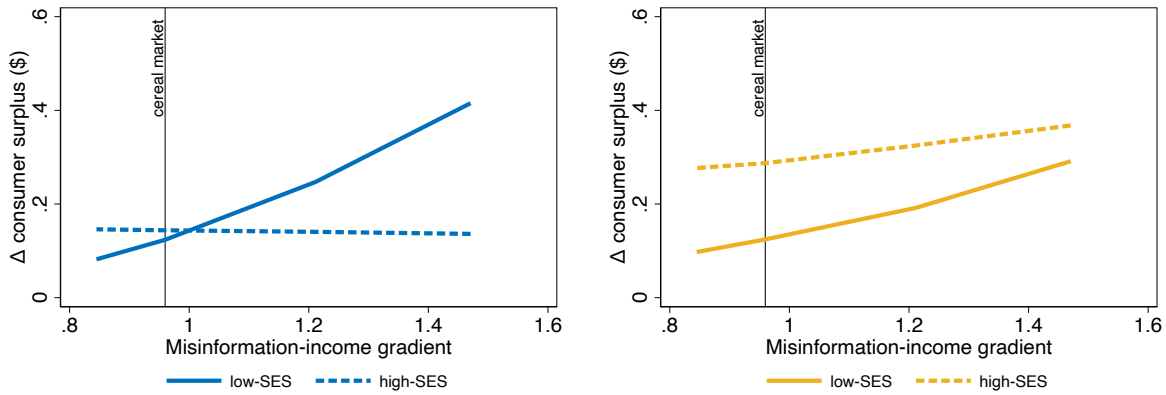
6.5.2. *Misinformation-income gradient*: We define the misinformation-income gradient as the ratio between the root-mean-square deviation of beliefs relative to the bliss points for low- and high-SES consumers.[57] In our model, we vary the misinformation-income gradient by differentially changing the relationship between beliefs over products's nutritional content, μ_{jb}, and products' sugar bliss-points, ν_j, for low- and high-SES consumers. The less correlated beliefs and baseline sugar content are for low-SES individuals relative to high-SES individuals, the higher the misinformation-income gradient will be in our simulations.[58]

Figure 17 shows the main results of this exercise. Figure 17(a) shows the average gains in consumer surplus for low- and high-SES consumers of moving from the *no intervention* counterfactual, (0), to the *equilibrium* counterfactual, (3), under the policy threshold that maximizes total consumer surplus for different values of the misinformation-income gradient. Intuitively, gains in consumer surplus are larger for low-SES individuals when they are relatively less informed about the nutritional content of products. Gains in consumer surplus for high-SES individuals, on the other hand, is constant across specifications.

Figure 17(b) shows the gains in consumer surplus of moving from the *no intervention* counterfactual, (0), to the taxes counterfactual under the tax level that maximizes total consumer surplus for different values of the misinformation-income gradient. Unlike food labels, gains in consumer surplus

[57] We calculate the root-mean-square deviation for consumer type b as $RMSD_b = \sqrt{\sum_j \omega_j (\mu_{jb} - \nu_j)^2}$, where ω_j are weights given by the total grams of product j purchased in the pre-policy period.

[58] From the estimation results from Section 5, the correlation between beliefs μ_{jb} and a product's sugar bliss point ν_j is 0.7 and 0.68 for low- and high-SES individuals respectively. We increase the misinformation-income gradient by decreasing the correlation between low-SES individuals' beliefs and the bliss-points. We provide additional simulation details in Appendix K.



(a) Food labels

(b) Sugar taxes

Figure 17: Misinformation-income gradient

Notes: This figure shows the average gains in consumer surplus for low- and high-SES individuals when implementing food labels and sugar taxes under different values of the misinformation-income gradient. Panel (a) shows values for a food labeling policy where the policy threshold is set to maximize total gains in consumer surplus. Panel (b) shows values for a tax policy where the tax value is set to maximize total gains in consumer surplus. In Panel (b), tax money is returned to consumers proportional to their baseline expenditure in the absence of the policy.

are now shared between low- and high-SES consumers. When low-SES individuals are more misinformed, the regulator chooses higher taxes to correct their behavior that disproportionally benefit high-SES individual through redistribution.

7. Policy discussion: Beyond cereal

So far, we focused our analysis on the breakfast cereal market. Our framework, however, can be used to study the effects of food labels in categories other than cereal. In this section, we discuss how our model primitives can change when studying other product categories. We first discuss demand- and supply-side parameters that determine the market equilibrium. We then discuss the policy implications of extending our analysis to other product categories.

On the demand side, food labels induce consumers to substitute away from products that are perceived to be healthy but were actually high in critical nutrients. Two important features of a product category determine how much food labels can affect consumer demand. First, categories in which labeled and unlabeled products are closer substitutes are more likely to show larger substitution effects. Second, food labels will be more effective in shaping consumer demand on categories in which they are more informative. In the category of soft drinks, for example, consumer beliefs about sugar concentration are relatively accurate (see Appendix C, Figure C.3). When we estimate the effects of food labels on demand for soft drinks following the event-study design from Equation (1), we find that the relative change of equilibrium quantities sold between labeled and unlabeled products in the soft drinks category is half of the size that for products in the breakfast cereal category (see Appendix E).

On the supply side, firms react to the policy by changing prices and reformulating their products. In markets with imperfect competition, changes in prices will be determined by the extent to which food labels affect products' residual demand in each category through changes in competition, product differentiation, and market segmentation. Differences in the extent to which products get reformulated, on the other hand, can be explained by three important features of a product category. First, firms will have larger incentives to reformulate when they expect labels to have a larger impact on consumer demand. Second, categories for which products' nutritional content in the pre-policy period are closer to the regulatory threshold will tend to present more bunching. Third, categories in which products can be reformulated at a lower cost while keeping taste constant are more likely to be reformulated. In Appendix E, we show results that are consistent with these predictions. We find that in categories such as yoghurt or juice, in which firms can reformulate their products by substituting sugar with other low-cost sweeteners that mimic the products' taste, almost all products are bunching at the regulation threshold. In contrast, in categories such as cereal or cookies, sugar also works as a bulking agent and cannot be easily replaced by low-cost sweeteners. Our findings suggest substantially less bunching in these categories where reformulation is more costly.

The results presented in Figure 3 summarize the aggregate effects across all categories. Note that in multi-category contexts, the choice of the regulatory threshold for food labeling policies is far from trivial. On one hand, the policymaker wants to set tight thresholds when products are easy to reformulate. On the other hand, the policymaker wants to set potentially higher and more informative thresholds on categories in which reformulation is more costly and products are high in critical nutrients. The choice of the policy threshold needs to account for the effects of food labels in all categories together. A potential solution is to implement category-specific thresholds, or a multiple-threshold policy, in which labels are not binary but provide more granular information through multi-level labels (e.g. traffic light labeling implemented in the United Kingdom). However, complex policy designs can be less effective if they turn out to be confusing to consumers.

Finally, there are additional features of product categories that can have implications when thinking about implementing food labels or sugar taxes. 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 in improving diet quality. Other market imperfections, such as lack of self control or time inconsistency, can be important drivers of consumer bias in these categories. As our model suggest, sugar taxes can be a better tool to fight obesity in these cases. Besides, in categories where low-SES consumers are more likely to prefer sugary products or have more misaligned beliefs about products' nutritional content, food labels present distributional benefits over sugar taxes that need to be considered. Our findings suggest that the optimal policy is to combine food labels with sugar taxes, with larger taxes on categories in which non-informational biases are larger and lower taxes in categories in which the sugar-income gradient is larger.[59]

[59] In Appendix A, Figure A.13, we simulate a policy that combining food labels with sugar taxes in the breakfast cereal market. We show that the combined policy achieves gains in consumer surplus that are 30% larger relative to using each instrument by itself.

8. Conclusion

In this paper, we study the equilibrium effects of FoPL policies on nutritional intake and consumer welfare. Although providing information to consumers usually improves their welfare, the equilibrium consequences that arise from large-scale implementations of FoPLs are ambiguous. Food labels can, for example, help firms to differentiate their products and increase 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 potentially increasing consumer prices as a result of increased production costs. In this paper, we provide extensive evidence of such equilibrium effects of the Chilean Food Act, the first mandatory national FoPL regulation to be implemented in the world. Three key findings arise from our empirical analysis. First, the FoPL 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 surplus. We find that FoPLs can be an effective way to improve diet quality and combat obesity. Food labels help consumers by providing them with information about the products' true nutritional content, allowing them to make better-informed purchasing decisions. In the absence of supply-side responses, labels increase average consumer surplus by \$0.76 a year, equivalent to 3% of average cereal expenditure. When accounting for equilibrium responses, firms change products' prices and nutritional contents in response to the policy to maximize profits. We show that prices of unlabeled products go up while those of labeled products go down, undermining the welfare benefits of food labels. Moreover, food labels create a sharp discontinuity in the demand function at the policy threshold, inducing firms to reformulate their products to avoid receiving a label. However, reducing the concentration of critical nutrients is costly, and causes firms to raise prices which get passed on to consumers. Overall, supply-side responses enhance the effects of food labels on nutritional intake by 142% and increase gains in consumer surplus by 18%.

We then use our model to compare food labels to sugar taxes, the most prominent alternative policy. When compared to sugar taxes, food labels present both advantages and disadvantages. We show that food labels are more effective in tackling misinformation but less effective to deal with other market imperfections such as fiscal externalities, lack of self control, or time inconsistency. Food labels are a non-financial instrument that do not involve monetary transfers from consumers to the state. In settings with low marginal value of public funds, food labels turn out to be more efficient. We also use our model to study the distributional consequences of food labels and sugar taxes. We show that food labels are more progressive than sugar taxes, especially in settings where the poor tend to consume more sugary products or where 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. While our findings show that equilibrium effects augment the positive effects of food labeling in Chile, the theoretical predictions are ambiguous. 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 to compare FoPL regulations to alternative policy instruments to target obesity.

Food labels are a new and promising policy tool with the capacity to improve diet quality and combat obesity. While this paper covers important features of FoPLs, there are still several unanswered questions. First, this paper focuses on a policy design where labels act as a binary signal. It is an open question whether more granular labels could be more effective in improving diet quality. On one hand, granularity improves the information provided to consumers. On the other hand, simplicity makes the information easier to acquire, which is especially relevant in a setting where detailed information is already available in the back of the package. Second, FoPLs can incentivize firms to design new healthy products targeted to more informed consumers, improving the bundle of available products in the long run. Finally, measuring long-run outcomes on health and wellbeing will be crucial to assessing the effectiveness of FoPLs.

References

Abaluck, J. and J. Gruber (2011). Choice inconsistencies among the elderly: evidence from plan choice in the medicare part d program. *American Economic Review 101*(4), 1180–1210.

Ackerberg, D. A. and G. S. Crawford (2009). Estimating price elasticities in differentiated product demand models with endogenous characteristics.

Aguilar, A., E. Gutierrez, E. Seira, et al. (2019). The effectiveness of sin food taxes: evidence from mexico. *Working Paper*.

Alé-Chilet, J. and S. Moshary (2020). Beyond Consumer Switching: Supply Responses to Food Packaging and Advertising Regulations. *Working Paper*.

Allcott, H. (2013). The welfare effects of misperceived product costs: Data and calibrations from the automobile market. *American Economic Journal: Economic Policy 5*(3), 30–66.

Allcott, H., R. Diamond, J. Dube, J. Handbury, I. M. Rahkovsky, and M. Schnell (2019). Food deserts and the causes of nutritional inequality. *Quarterly Journal of Economics*.

Allcott, H. and C. Knittel (2019). Are consumers poorly informed about fuel economy? evidence from two experiments. *American Economic Journal: Economic Policy 11*(1), 1–37.

Allcott, H., B. B. Lockwood, and D. Taubinsky (2019a). Regressive sin taxes, with an application to the optimal soda tax. *The Quarterly Journal of Economics 134*(3), 1557–1626.

Allcott, H., B. B. Lockwood, and D. Taubinsky (2019b, August). Should we tax sugar-sweetened beverages? an overview of theory and evidence. *Journal of Economic Perspectives 33*(3), 202–27.

Araya, S., A. Elberg, C. Noton, and D. Schwartz (2020). Identifying food labeling effects on consumer behavior. *Working Paper*.

Bernheim, B. D. and D. Taubinsky (2018). Behavioral public economics. *In: Handbook of Behavioral Economics - Foundations and Applications 1*(5), 381–516.

Bollinger, B., P. Leslie, and A. Sorensen (2011). Calorie Posting in Chain Restaurants. *American Economic Journal: Economic Policy 3*(February), 91–128.

Correa, T., M. Reyes, L. S. Taillie, C. Corvalán, and F. R. Dillman Carpentier (2020). Food advertising on television before and after a national unhealthy food marketing regulation in chile, 2016–2017. *American Journal of Public Health* (0), e1–e6.

DellaVigna, S. and M. Gentzkow (2019). Uniform pricing in us retail chains. *The Quarterly Journal of Economics 134*(4), 2011–2084.

Draganska, M., M. Mazzeo, and K. Seim (2009). Beyond plain vanilla: Modeling joint product assortment and pricing decisions. *QME 7*(2), 105–146.

Dranove, D. and G. Z. Jin (2010). Quality disclosure and certification: Theory and practice. *Journal of Economic Literature 48*(4), 935–63.

Dranove, D., D. Kessler, M. McClellan, and M. Satterthwaite (2003). Is more information better? the effects of report cards on health care providers. *Journal of political Economy 111*(3), 555–588.

Dubé, J.-P., G. J. Hitsch, and P. E. Rossi (2010). State dependence and alternative explanations for consumer inertia. *The RAND Journal of Economics 41*(3), 417–445.

Dubois, P., R. Griffith, and M. O'Connell (2017, 04). The Effects of Banning Advertising in Junk Food Markets. *The Review of Economic Studies 85*(1), 396–436.

Dubois, P., R. Griffith, and M. O'Connell (2020, November). How well targeted are soda taxes? *American Economic Review 110*(11), 3661–3704.

Elbel, B., R. Kersh, V. L. Brescoll, and L. B. Dixon (2009). Calorie labeling and food choices: a first look at the effects on low-income people in New York City. *Health affairs 28*(6), 1110–1121.

Fan, Y. (2013). Ownership consolidation and product characteristics: A study of the us daily newspaper market. *American Economic Review 103*(5), 1598–1628.

Farhi, E. and X. Gabaix (2020). Optimal taxation with behavioral agents. *American Economic Review 110*(1), 298–336.

Finkelstein, E. A., K. L. Strombotne, N. L. Chan, and J. Krieger (2011). Mandatory menu labeling in one fast-food chain in king county, Washington. *American Journal of Preventive Medicine 40*(2), 122–127.

Finkelstein, E. A., J. G. Trogdon, J. W. Cohen, and W. Dietz (2009). Annual medical spending attributable to obesity: payer-and service-specific estimates. *Health affairs 28*(5), w822–w831.

FNE (2014). Denuncia contra Carozzi por conductas anticompetitivas. Technical report, Fiscalía Nacional Económica, Santiago, Chile.

Frank, R. E. (1962). Brand choice as a probability process. *The Journal of Business 35*(1), 43–56.

Greenstone, M., P. Oyer, and A. Vissing-Jorgensen (2006). Mandated disclosure, stock returns, and the 1964 securities acts amendments. *The Quarterly Journal of Economics 121*(2), 399–460.

Griffith, R., M. O'Connell, and K. Smith (2017). The importance of product reformulation versus consumer choice in improving diet quality. *Economica 84*(333), 34–53.

Handel, B. R. and J. T. Kolstad (2015, August). Health insurance for "humans": Information frictions, plan choice, and consumer welfare. *American Economic Review 105*(8), 2449–2500.

Hastings, J. S. and J. M. Weinstein (2008). Information, school choice, and academic achievement: Evidence from two experiments. *The Quarterly journal of economics 123*(4), 1373–1414.

Hausman, J. A. (1996). Valuation of new goods under perfect and imperfect competition. In *The economics of new goods*, pp. 207–248. University of Chicago Press.

Hendren, N. and B. Sprung-Keyser (2020). A unified welfare analysis of government policies. *The Quarterly Journal of Economics 135*(3), 1209–1318.

Historia de la Ley 20.606 (2011). Sobre composición nutricional de los alimentos y su publicidad. http://www.bcn.cl/obtienearchivo?id=recursoslegales/10221.3/37370/1/HL20606.pdf.

Houde, S. (2018). The incidence of coarse certification: Evidence from the energy star program. *Working Paper 18*, 290.

Ippolito, P. M. and A. D. Mathios (1990). Information, advertising and health choices: A study of the cereal market. *The RAND Journal of Economics 21*(3), 459–480.

Ippolito, P. M. and A. D. Mathios (1995). Information and advertising: The case of fat consumption in the united states. *The American Economic Review 85*(2), 91–95.

Ito, K. and J. M. Sallee (2018). The economics of attribute-based regulation: Theory and evidence from fuel economy standards. *Review of Economics and Statistics 100*(2), 319–336.

Jacobs, A. (2018, February). In Sweeping War on Obesity, Chile Slays Tony the Tiger. *New York Times*.

Jin, G. Z. and P. Leslie (2003). The effect of information on product quality: Evidence from restaurant hygiene grade cards. *The Quarterly Journal of Economics 118*(2), 409–451.

Kiesel, K. and S. B. Villas-Boas (2013). Can information costs affect consumer choice? Nutritional labels in a supermarket experiment. *International Journal of Industrial Organization 31*(2), 153–163.

Lê, K.-A., F. Robin, and O. Roger (2016). Sugar replacers: from technological challenges to consequences on health. *Current Opinion in Clinical Nutrition and Metabolic Care 19*(4), 310–315.

Lim, J. H., R. Rishika, R. Janakiraman, and P. Kannan (2020). Competitive effects of front-of-package nutrition labeling adoption on nutritional quality: Evidence from facts up front–style labels. *Journal of Marketing 84*(6), 3–21.

Masters, R. K., E. N. Reither, D. A. Powers, Y. C. Yang, A. E. Burger, and B. G. Link (2013). The impact of obesity on us mortality levels: the importance of age and cohort factors in population estimates. *American journal of public health 103*(10), 1895–1901.

Miller, N. H. and M. C. Weinberg (2017). Understanding the price effects of the millercoors joint venture. *Econometrica 85*(6), 1763–1791.

MINSAL (2019, July). Evaluación Ley de Alimentos N20.606. Technical report, Ministerio de Salud, Santiago, Chile.

Nevo, A. (2001). Measuring Market Power in the Ready-to-Eat Cereal Industry. *Econometrica 69*(2), 307–342.

OECD (2019). *OECD Reviews of Public Health: Chile.*

Pachali, M. J., M. J. Kotschedoff, A. van Lin, B. J. Bronnenberg, and E. van Herpen (2020). How do nutritional warning labels affect prices? Technical report.

Reyes, M., M. L. Garmendia, S. Olivares, C. Aqueveque, I. Zacarías, and C. Corvalán (2019). Development of the chilean front-of-package food warning label. *BMC public health 19*(1), 906.

Roe, B. E., M. F. Teisl, and C. R. Deans (2014). The economics of voluntary versus mandatory labels. *Annu. Rev. Resour. Econ. 6*(1), 407–427.

Sacks, G., M. Rayner, and B. Swinburn (2009). Impact of front-of-pack 'traffic-light' nutrition labelling on consumer food purchases in the UK. *Health Promotion International 24*(4), 344–352.

Taillie, L. S., M. Reyes, M. A. Colchero, B. Popkin, and C. Corvalán (2020). An evaluation of chiles law of food labeling and advertising on sugar-sweetened beverage purchases from 2015 to 2017: A before-and-after study. *PLoS medicine 17*(2), e1003015.

TFEU (2016). Treaty on the Functioning of the European Union, Part Three - Union Policies and Internal Actions, Title XV - Consumer Protection, Article 169.

WHO (2018). Factsheet No. 311. *World Health Organization.*

Wisdom, J., J. S. Downs, and G. Loewenstein (2010). Promoting healthy choices: Information versus convenience. *American Economic Journal: Applied Economics 2*(2), 164–178.

Wollmann, T. G. (2018, June). Trucks without bailouts: Equilibrium product characteristics for commercial vehicles. *American Economic Review 108*(6), 1364–1406.

Woodward, S. E. and R. E. Hall (2012). Diagnosing consumer confusion and sub-optimal shopping effort: Theory and mortgage-market evidence. *American Economic Review 102*(7), 3249–76.

Zhu, C., R. A. Lopez, and X. Liu (2015). Information Cost and Consumer Choices of Healthy Foods. *American Journal of Agricultural Economics 98*(1), 41–53.

Appendix for:

Equilibrium Effects of Food Labeling Policies

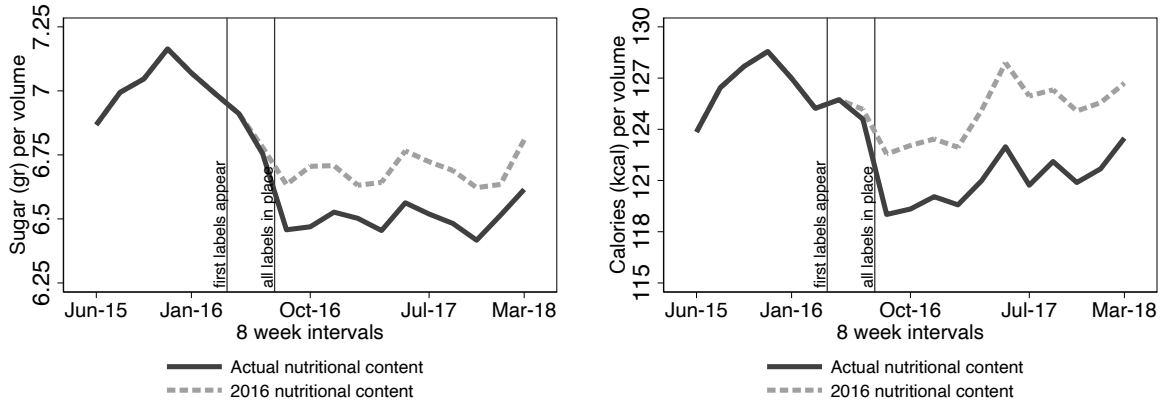
(Not for publication)

Nano Barahona Cristóbal Otero Sebastián Otero Joshua Kim

November 6, 2020

Table of Contents

Appendix A: Additional Figures



(a) Sugar intake

(b) Calorie intake

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

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

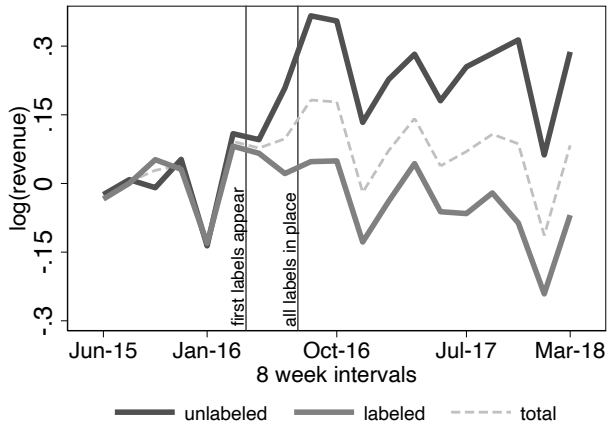
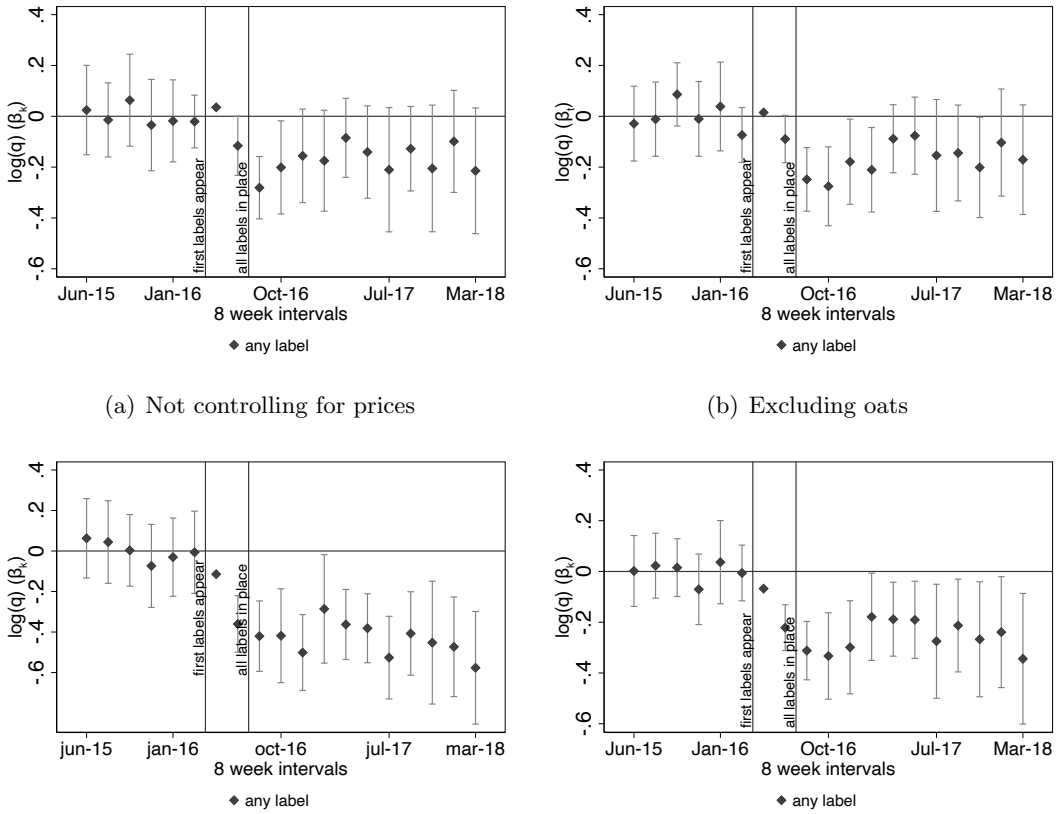


Figure A.2: Log-revenue of labeled and unlabeled ready-to-eat-cereal

Notes: This figure compares the normalized log-revenue of labeled and unlabeled products over time. One observation is the log revenue of cereal purchased across labeled and unlabeled products over eight consecutive weeks. The y-axis is normalized such that the average value for the two groups is zero in the pre-period. The dashed and the solid lines denote the labeled and unlabeled products, respectively.



(a) Not controlling for prices

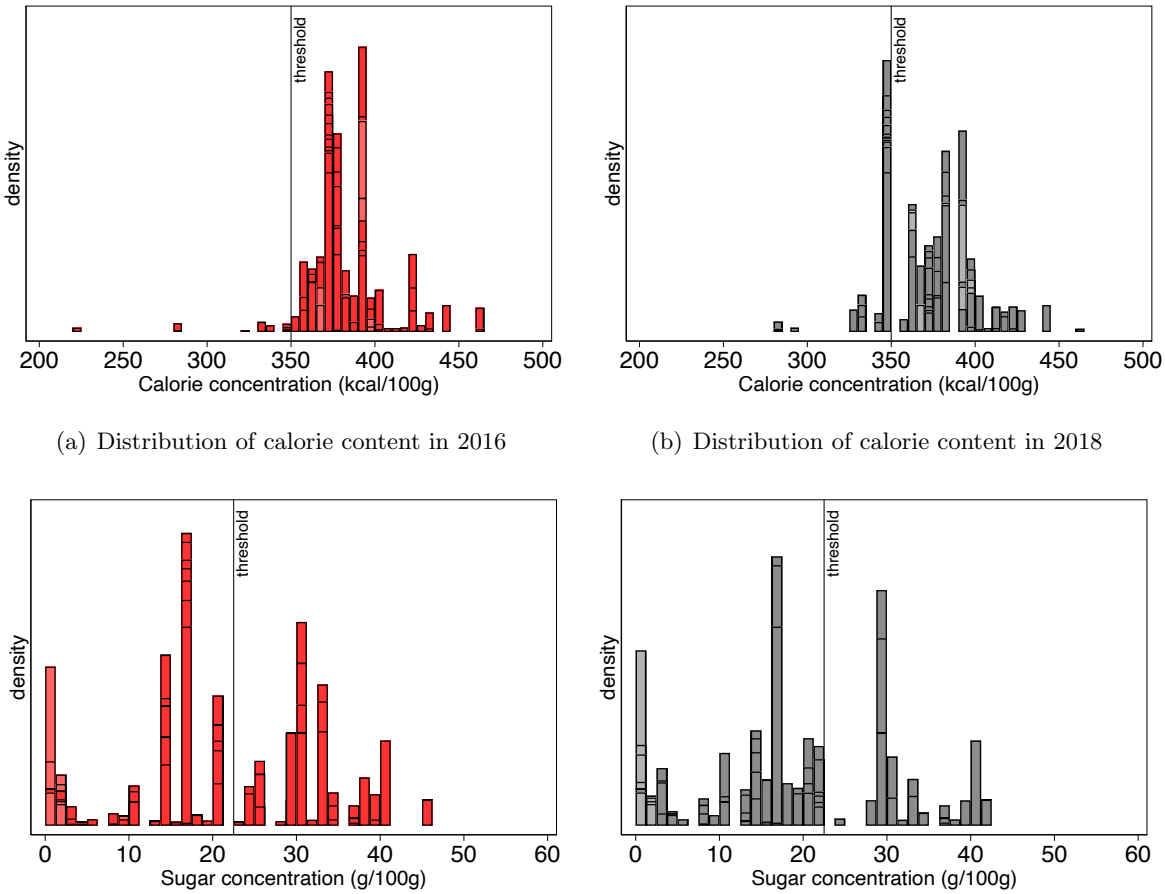
(b) Excluding oats

(c) Excluding bunching products

(d) Instrumental variables

Figure A.3: Robustness checks for event study from equation (1)

Notes: This figure presents robustness checks for equation (1). We plot the coefficients β_t of the event study regression from equation (1). Panel (a) shows results for a specification without controlling for prices on a sample of 68 products that show up in the pre and post periods, where 27 are unlabeled and 41 are labeled. Panel (b) shows results for a specification where we drop all oat products exempted from the regulation. The final sample is of 60 products that show up in the pre and post periods, where 19 are unlabeled and 41 are labeled. Panel (c) shows results for a specification where we drop all reformulated product that crossed the policy threshold in the post-policy period. The final sample is of 55 products that show up in the pre and post periods, where 14 are unlabeled and 41 are labeled. Panel (d) uses an instrumental variable approach where we instrument L_j with $\hat{P}(L_j|w_j^{pre}, r_j)$, the predicted probability of receiving a label based on products' pre-policy nutritional content w_j^{pre} and the subcategory $r_j \in \{chocolate, flakes, granola, oats, sugary\}$ where they belong to. The sample involves 27 unlabeled products and 41 labeled ones. The vertical lines delimit the 95% confidence intervals in all plots.



(a) Distribution of calorie content in 2016

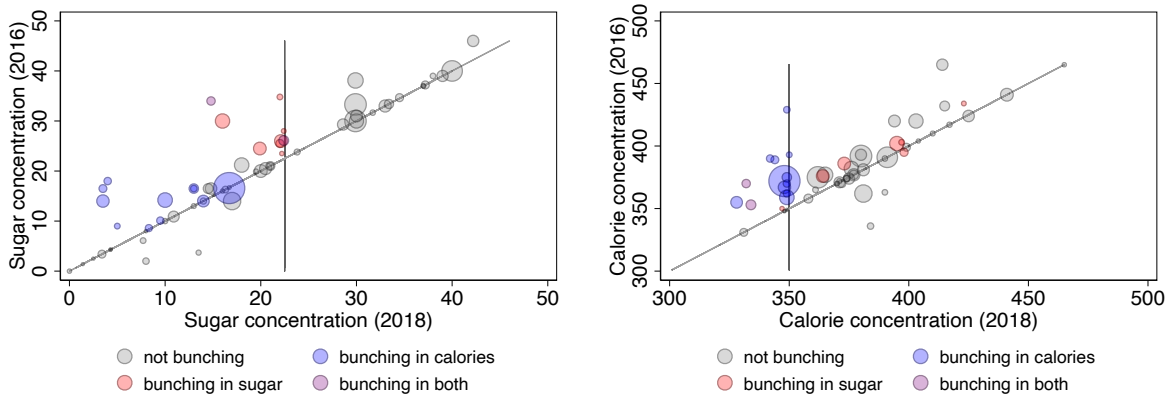
(b) Distribution of calorie content in 2018

(c) Distribution of sugar content in 2016

(d) Distribution of sugar content in 2018

Figure A.4: Distribution of calories and sugar pre- and post-legislation (includes oatmeal)

Notes: This figure plots the distribution of calories and sugar per 100g for cereal products before and after the policy implementation. Observations are weighted by pre-policy revenue. Oatmeal products are coloured with a lighter color.



(a) Sugar

(b) Calories

Figure A.5: Changes in nutritional content between before and after the policy implementation

Notes: This figures present the changes in nutritional content pf products before and after the policy. Panel (a) shows changes for sugar and Panel (b) changes for calories. 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. In each plot, the vertical lines represent the policy threshold. We also plot the 45 degree line to identify product that did not reformulate. The size of the bubbles represent pre-policy revenues. Red bubbles correspond to products that where to the right of the sugar threshold in the pre-policy period and then crossed the threshold to avoid receiving a sugar label. Blue bubbles correspond to products that where to the right of the calorie threshold in the pre-policy period and then crossed the threshold to avoid receiving a calorie label. Purple bubbles are products that got rid of both labels. For expositional purposes, Panel (b) omits three products with calorie content below 300 kcal/gr (see Figure 6 of the main article).

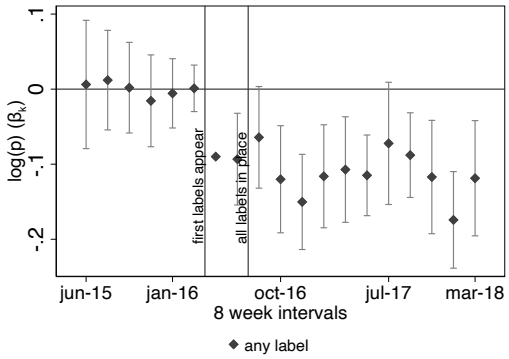
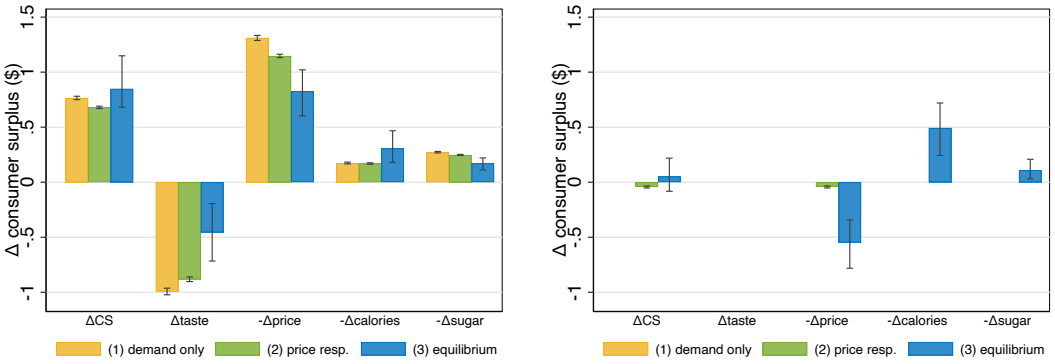


Figure A.6: Event study for prices (excluding bunching products)

Notes: This figure presents the β_t coefficients of our event study regression for prices from equation (3). The vertical lines delimit the 95% confidence intervals. We drop all reformulated product that crossed the policy threshold in the post-policy period. The regression is run on the sample of 55 products, 14 unlabeled and 41 labeled.

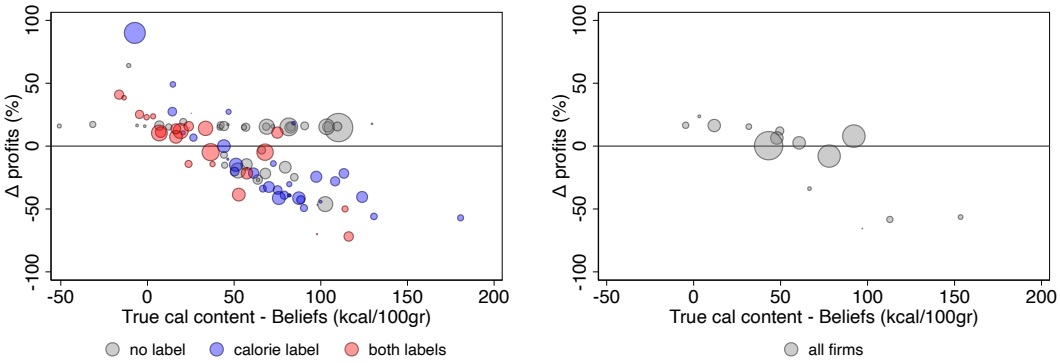


(a) Substitution effects

(b) Supply effects

Figure A.7: Changes in consumer surplus under different counterfactuals decomposed by substitution effects and supply effects

Notes: The figure decomposes the gains in consumer surplus presented in Figure 12 between substitution effects and supply effects (see Section (6.1) in the main article). The first three bars of the figure show the change in consumer surplus from counterfactual (0) to counterfactuals (1), (2), and (3) resepectively. Bars 4-15 decompose those changes into changes in taste/experience of consuming cereal, changes in price paid, changes in caloric intake and changes in sugar intake. Each bar is normalized to show the contribution of each dimension to consumer surplus in dollars. We present confidence interval from the Montecarlo simulations.



(a) Products

(b) Firms

Figure A.8: Change in profits by product

Notes: The figure presents the change in profits for each product and firm across simulations. In Panel (a), we show the change in profits by product. On the horizontal axis we plot the difference between true pre-policy calorie concentration (bliss points) and average prior beliefs about calorie content. On the vertical axis we plot the percentage change in products' profits. The size of each circle represents the average market share across simulations. The colors represent whether a product received no label, high-in-calorie label or both labels in most of the simulations. Note that some products might be labeled in some simulations but not in others. We colour circles according to their most occurring event. In Panel (b), we aggregate the results by firms.

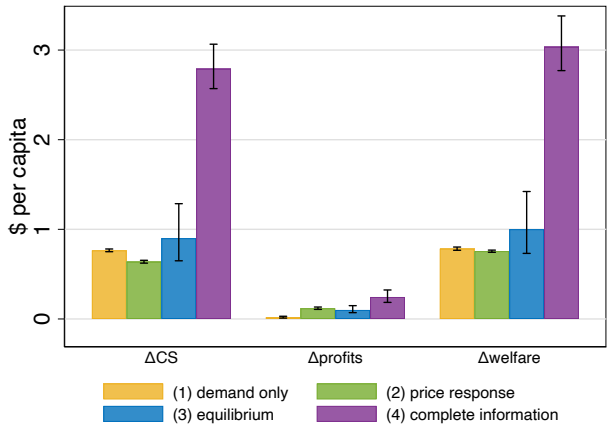
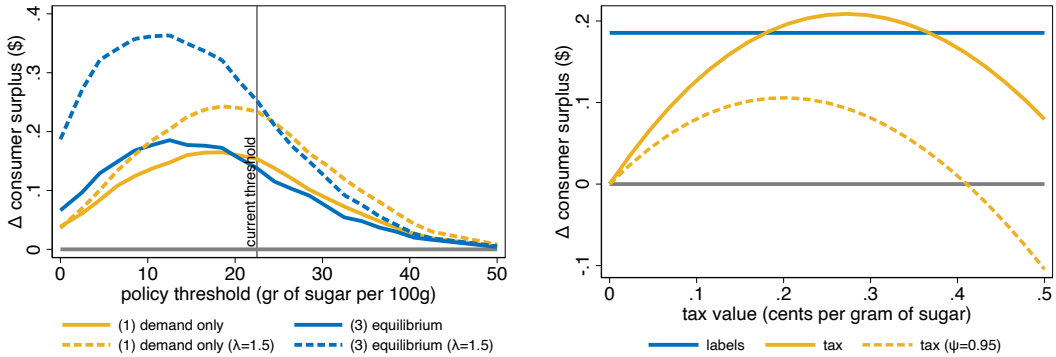


Figure A.9: Changes in consumer surplus, profits, and welfare under different counterfactuals

Notes: The figure shows changes in consumer surplus, firms' profits and total welfare from moving from counterfactual (0) to counterfactuals (1), (2), (3), and an additional counterfactual in which all consumers are perfectly informed about nutritional content (see Section 6.1 in the main article for a definition of the different counterfactuals).

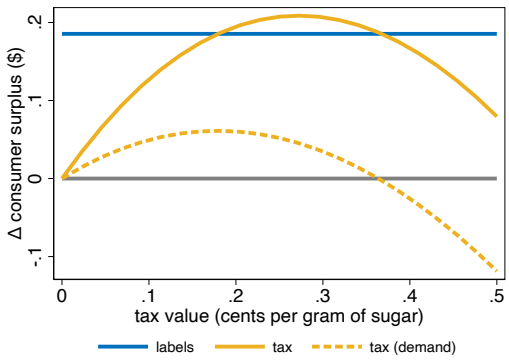


(a) Changes in consumer surplus under different thresholds

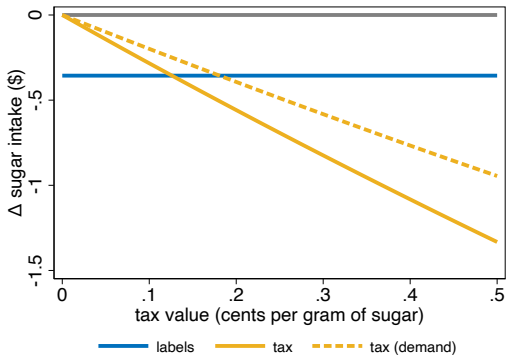
(b) Changes in consumer surplus under different thresholds

Figure A.10: Gains in consumer surplus for different values of λ and ψ

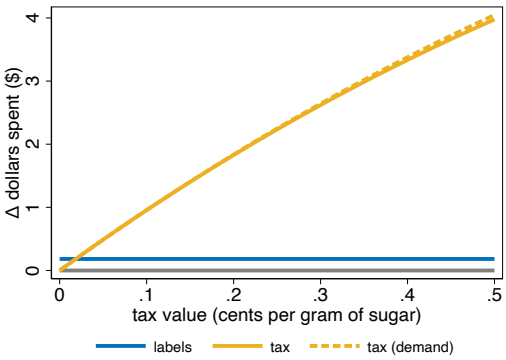
Notes: The figure plots the average change in consumer surplus under different counterfactuals. Panel (a) plots average consumer surplus under different regulatory thresholds under counterfactuals (1) and (3) relative to (0). The solid lines estimate counterfactual for the case where $\lambda = 1$, while dashed lines use $\lambda = 1.5$. Panel (b) plots average consumer surplus under different tax values. The solid line estimate counterfactuals for the case where $\psi = 1$, while the dashed line use $\psi = 0.95$.



(a) Consumer surplus



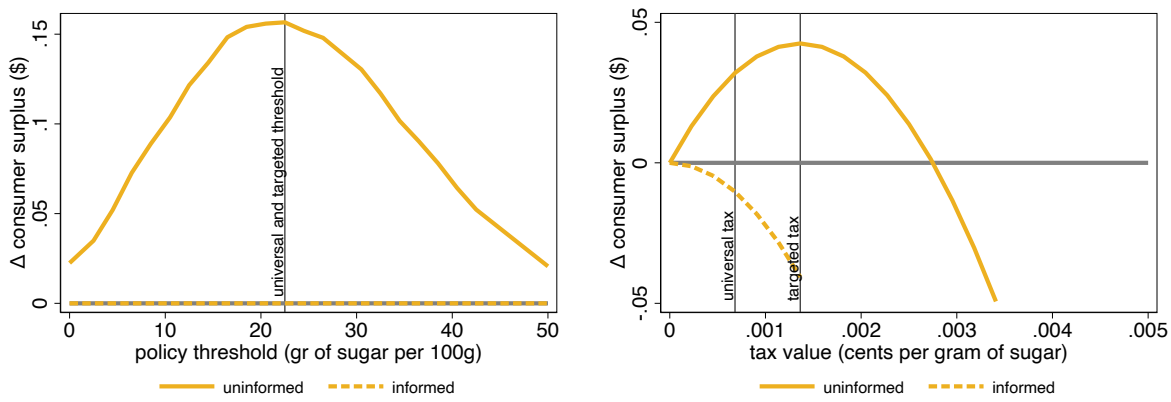
(b) Sugar intake



(c) Dollars spent

Figure A.11: Gains in consumer surplus over different tax levels

Notes: The figure plots average outcomes of interest under different tax values. Panel (a) shows the gains in consumer surplus, panel (b) shows changes in sugar intake converted to dollars using the parameters of the utility function, and panel (c) shows changes in dollars spent. The solid yellow line presents the counterfactual from the main article, that accounts for supply-side responses to taxes. The dashed yellow line isolates demand-side effects only. The blue line correspond to the outcomes under food labels at the regulatory threshold that maximizes consumer surplus.



(a) Food labels

(b) Sugar taxes

Figure A.12: Gains in consumer surplus for informed and uninformed consumers (demand only)

Notes: The figure plots average gains in consumer surplus for different regulatory thresholds and tax values for uninformed and informed consumers. Panel (a) shows the gains of consumer surplus under counterfactual (1), *demand only*, relative to (0), *no intervention*, for different regulatory thresholds. Panel (b) shows the gains of consumer surplus under sugar taxes without supply-side responses relative to counterfactual (0), *no intervention*, for different tax values. We show that in Panel (b), the regulator wants to charge a high tax only to uniformed consumers. Since this is not possible, the optimal universal tax value is lower. In Panel (a), however, the optimal threshold does not vary when we add informed consumers to the model because their effects are better targeted towards uninformed consumers.

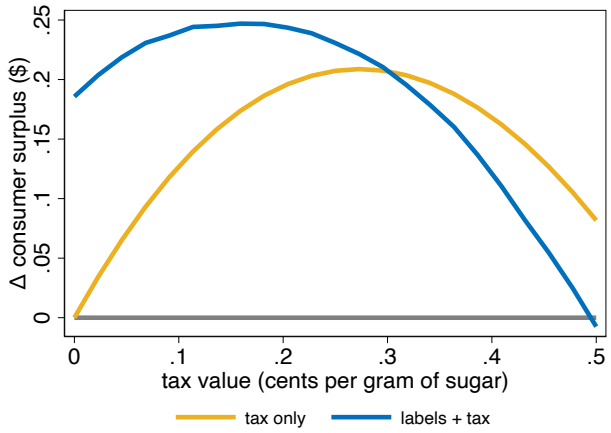


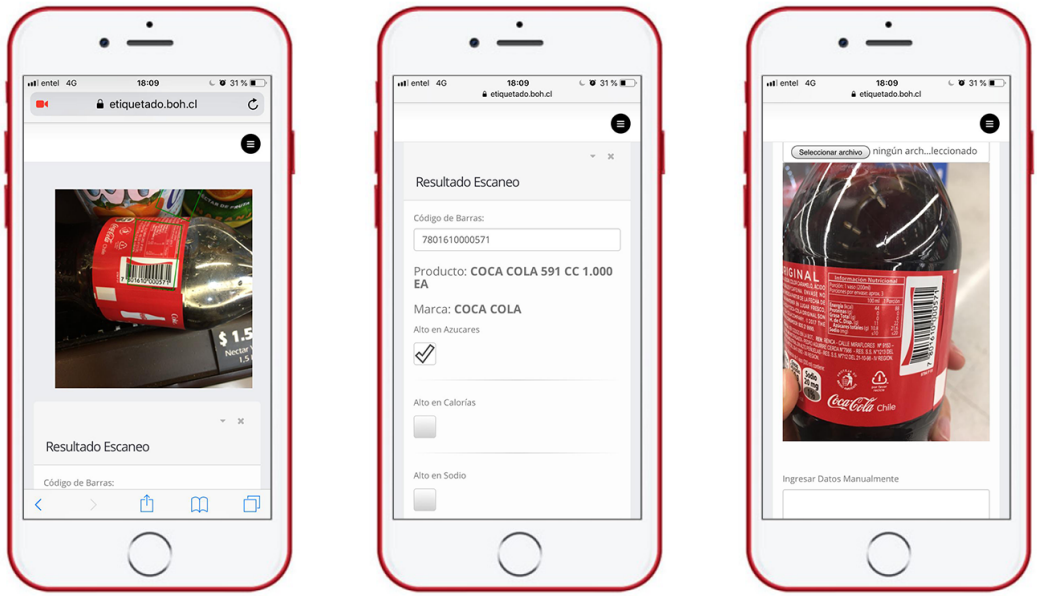
Figure A.13: Gains in consumer surplus combining food labels with sugar taxes

Notes: The figure shows changes in consumer surplus at different tax values for a counterfactual without food labels and a counterfactual with food labels that maximize consumer surplus. The yellow line correspond to the case where there are no food labels and a sugar tax. The blue line corresponds to food labels at a threshold of 12.5gr/100gr of sugar combined with sugar taxes.

Appendix B: Data Construction

B.1. *Data collection on nutritional content*

We collected nutritional data for the post-policy period from the field. To do so, we developed a camera phone app that took pictures of nutritional fact tables and linked them to the Walmart scanner-level data (see Figure B.1). Using the built-in camera of the smart phone we can scan the bar code of any given product. The software gets into our products database provided by Walmart and displays the information of the scanned product. Once the user confirms that the scanned products matches the information on the screen, the software offers the option of taking a picture to the nutrition fact table. It is then link to the original database and uploaded to a server. We then digitized the data using the services of *SunTec India*.



(a) Scan product (b) Verify product (c) Capture nutrition facts

Figure B.1: Nutritional information collection process

Notes: Panel (a) of the figure shows how the app uses the phone camera to find the barcode of the product and scan it. One the bar code is read, the app shows the enumerator the characteristics of the product that are collected from the Walmart dataset. In Panel (b), the enumerator confirms that the characteristics match to the product she is scanning and manually fills up additional information regarding the labeling status of products. In Panel (c) the app offers the enumerator to take a picture of the nutritional fact table located in the back of the package. The picture is then matched to the product and uploaded to our servers.

Using the data provided by Walmart we identified a set of 6,600 packaged products that cover more than 95% of total revenue at the country-level. From those, 6,000 were regularly sold in the four largest Walmart stores located in Santiago and created a list to give priority to those products. A team of 16 enumerators visited the stores and scanned each available product, with specific emphasis on ones from the priority list. We assigned each enumerator to

specific aisles. If a product from the priority list was not available, we visited a different store to search for them. We were able to collect data for 6,250 different products, that covered more than 90% of the revenue of food packaged products. We collected this information in March 2018, two years after the implementation of the first stage of the law in June 2016.

B.2. *Matching USDA Data to Walmart Data*

Products in categories such as cheese, fish and shellfish, alcoholic drinks, meat, fruits and vegetables, unpackaged bread, and pickles do not report their nutritional composition. For such categories, we rely on FoodData Central data from USDA. This dataset is the most comprehensive food composition data publicly available, and can be accessed online in https://fdc.nal.usda.gov/. We manually matched 1,469 products in these categories to their closest product reported in FoodData Central. In cases with no close match, we reported the nutritional information as missing.

B.3. *Survey design and implementation*

We conducted a survey to elicit consumers' beliefs about the nutritional characteristics of a set of cereal and soft-drinks products. We ran the survey in Argentina with the help of Qualtrics in August of 2019 and surveyed a total of 1,500 individuals. Ideally, we would have liked to elicit consumer beliefs in Chile before the policy implementation. Since this was not feasible, we mimicked this exercise by conducting the survey in Argentina, a country with a similar population and food market to Chile but that has not been exposed to any labelling policy. Other potential candidates where Perú or Uruguay, but both countries implemented a similar policy after Chile. We asked consumers in Argentina to give their best guess about the sugar and calorie concentration of a set products and to state how confident they are about their answers. Using this information, we elicit the first and second moments of beliefs over each product and nutrient. We also collected information about the gender, age, and household income of survey respondents.

The flow of the survey is as follows. We start with an introductory message explaining what the survey is about and asking whether they want to participate on it. We then ask respondents with multiple choice questions about their gender, age, and household income bracket. We follow-up with detailed instructions about how to answer the upcoming questions. We guide them through an example to make sure they understand how to answer the questions about beliefs. We give them feedback about their answers and ask them whether they are ready to go to the next section. In the next section, we randomize respondents into three different sets of questions: i) beliefs about calorie content in cereal products, ii) beliefs about sugar content in cereal products, and iii) beliefs about sugar content in soft drinks. We elicit their beliefs for 10 products chosen at random. After answering the questions for the 10 products,

we randomize respondents into one of the three sets again, and ask them about 10 more products. We finally ask them questions about their groceries behavior. Specifically, we ask them how often do they buy cereal in a super market, and how much they care (in a scale from 1 to 10) about different attributes when deciding what cereal to buy. The attributes are: price, brand, healthiness, and taste.

To elicit beliefs over nutritional content, we first show respondents the name, brand, and picture of the product. Figure B.2 provides an example for Frosted Flakes. We ask respondents whether they know the product presented in the picture and how much of the critical nutrient at stake do they think there is in 100gr/ml of the product. To provide them with references of the nutritional content of other known products that belong to different categories. In Figure B.3 we present the references used in each of the three sets of questions. We use the answers of this question to capture the first moment of consumers' beliefs over the nutritional content of product j.

Once respondents answer both questions from Figure B.2, we ask them how certain they are about their last answer. In particular, we ask them how likely it is that the true value of nutritional content is within an interval around their previous answer. The interval has a length of one standard deviation of the pre-policy nutritional content. We provide respondents with a help button for guidance on how to interpret probabilities.

Before implementing the survey, we conducted two pilot surveys with a sample size of 100 customers. In the pilot-surveys, we tested different products to use as references. One of the main takeaway from that exercise is that consumers' responses were sensitive to the references we gave them. Nevertheless, the relative distances between their answers was robust across the different designs. For that reason, throughout our analysis, we work with relative distances between products rather than with the absolute numbers provided by respondents. In Section 5 of the paper we use an estimation procedure to recover the absolute values using the moment conditions driven by consumers purchasing behavior.

Zucaritas - Kellogs:

¿Conoce este producto?

Sí	No
○	○

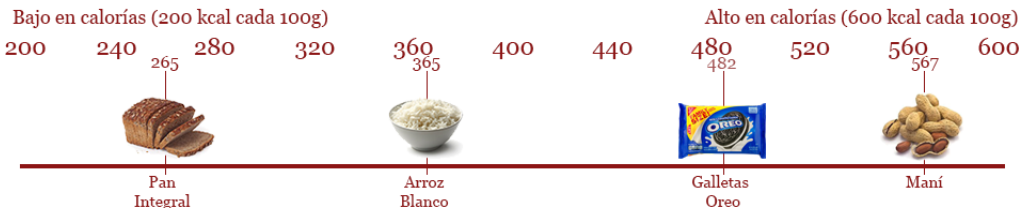
¿Cuántos gramos de **azúcar** cree que hay en 100 gramos de este producto?

En la siguiente imagen le mostramos el contenido de azúcar por cada 100 gramos de otros productos para que pueda usar de referencia:

Bajo en azúcar (0gr/100gr) Alto en azúcar (60gr/100gr)
0 6 12 18 24 30 36 42 48 54 60

34

Figure B.2: Survey questions about nutritional content: first moment of beliefs



(a) References for calories in breakfast cereal

(b) References for sugar in breakfast cereal

(c) References for sugar in soft drinks

Figure B.3: Survey references for cereal and soft drinks

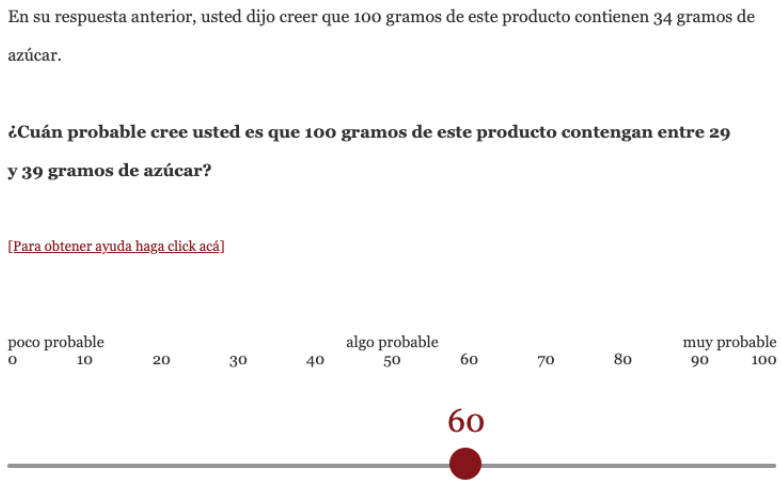
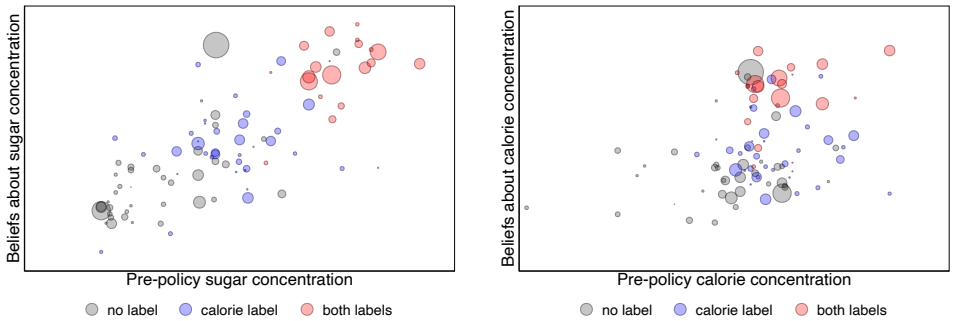


Figure B.4: Survey questions about nutritional content: second moment of beliefs

Appendix C: Beliefs Survey Results

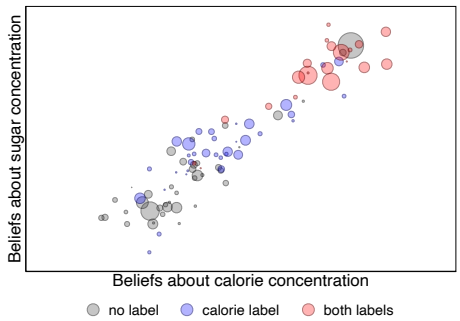
C.1. *Survey results: cereal*

In this subsection we present the results from the survey about beliefs over concentration of calories and sugar of cereal products. We find that respondents have relatively accurate beliefs about the sugar content of cereals, but fail to predict the calorie content on them. Moreover, while observed nutritional content of calories and sugar is not highly correlated, beliefs about them among respondents is. Our interpretation of these results is that consumers tend to associate low-in-sugar cereals as low in both sugar and calories. As a result, products that were low in sugar but received a high-in-calorie label, were the most affected by the policy (see Section 3.2.2 for details).



(a) Relationship between beliefs about sugar content and observed pre-policy sugar content

(b) Relationship between beliefs about calorie content and observed pre-policy calorie content



(c) Relationship between beliefs about sugar and calorie content

Figure C.1: First moment of beliefs about calorie and sugar content for breakfast cereal products

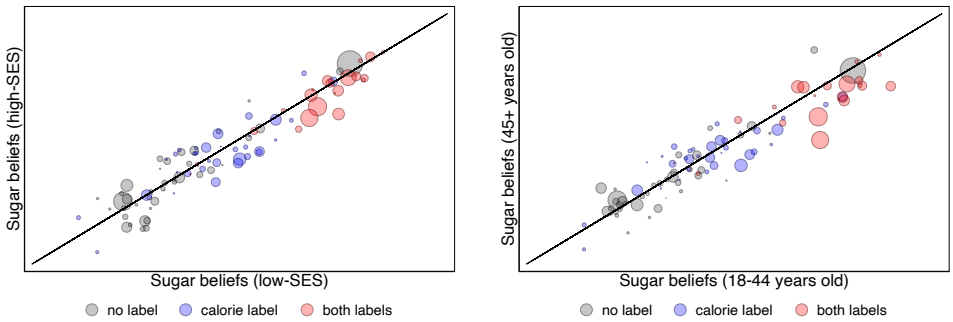
Notes: Circles in gray, blue, and red correspond to products that got zero labels, a high-in-calories label, or both high-in-calories and high-in-sugar labels respectively. The size of the circles are given by the total pre-policy revenue of each product.

Figure C.1(a) describes the relationship between the average value of respondents' beliefs about sugar concentration of each product and products' observed pre-policy sugar concen-

tration. Circles in gray, blue, and red correspond to products that got zero labels, a high-in-calories label, or both high-in-calories and high-in-sugar labels respectively. The size of each circle is given by the total pre-policy revenue of that product. The correlation between the first moment of consumers' beliefs and the observed pre-policy sugar concentration is 0.71. Figure C.1(b) describes the relationship between the average value of respondents' beliefs about calorie concentration of each product and products' observed pre-policy calorie concentration. The correlation in this case is 0.23. Respondents' beliefs about sugar and calorie content are highly correlated. Results are presented in Figure C.1(c). The correlation between the two sets of beliefs is 0.97, much higher than the correlation between the observed pre-policy concentration of sugar and calories, that is only 0.27.

C.2. *Survey results: consumer heterogeneity*

We use respondents' self-reported characteristics to explore heterogeneities in beliefs across different income groups and age. We do not find substantial differences between the groups.[1]



(a) Beliefs for different income groups (b) Beliefs for different age groups

Figure C.2: First moment of beliefs about sugar content for breakfast cereal products for different groups

Notes: Circles in gray, blue, and red correspond to products that got zero labels, a high-in-calories label, or both high-in-calories and high-in-sugar labels respectively. The size of the circles are given by the total pre-policy revenue of each product. The black diagonal line represents the 45 degrees line.

Figure C.2 shows the relationship between beliefs about sugar concentration of respondents from group A and B, where A and B correspond to different subgroups in each subfigure. The black diagonal line corresponds the 45 degrees line. In Figure C.2(a) we compare beliefs of low- and high-SES respondents (as defined in Section 5). In Figure C.2(b) we compare respondents 18-44 years old agains 45+ years old. Results look very similar when looking at beliefs about the concentration of calories. As seen in Figure C.2, beliefs between different groups do not differ to a great extent. The largest heterogeneity shows up when comparing the beliefs

[1] We also explore differences in gender and between groups that report different preferences over taste and healthiness of products and find similar results.

about sugar concentration between respondents of different age. Older respondents tend to underestimate the sugar content of sugary products relative to their younger counterparts.

C.3. *Survey results: soft drinks*

In this subsection we present the results about beliefs over soft drinks' concentration of sugar, the only critical nutrient that was labeled in this category. The observed pre-policy concentration of sugar follows a bimodal distribution driven by diet and non-diet drinks. We find that respondents do a good job understanding that diet drinks are lower in sugar. Results are presented in Figure C.3. The accuracy of beliefs over sugar content implies that labels came at no surprise in this category, explaining the smaller change in demand we document for soft drinks in Figure **??**.

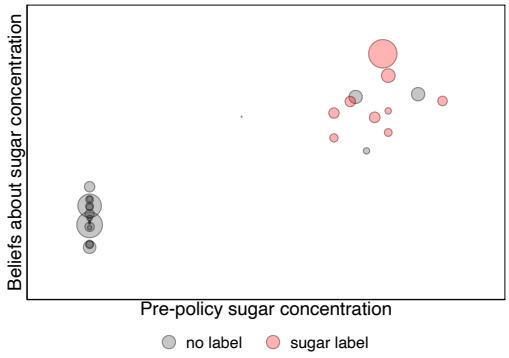


Figure C.3: First moment of beliefs about sugar content for soft drinks products

Notes: Circles in gray and red correspond to products that got zero labels and a high-in-sugar label respectively. The size of the circles are given by the total pre-policy revenue of each product.

Appendix D: Between Category Substitution

In Section 3.2, we looked at whether consumers decreased their consumption of labelled products relative to unlabelled products, within a particular food category. In this section, we examine whether consumers may also be shifting their consumption of food products across categories.

To do so, we define broader groups of products containing multiple categories in which one could expect some substitution to happen. For instance, we check whether there was substitution between categories for product categories that are likely to be eaten at breakfast: eggs, yoghurt, bread, fruits, jams, and breakfast cereal. Then, within each broad group, we compare revenues before and after the policy of categories with high and low share of products labeled. Figure D.1 plots the share of revenue coming from different categories over time for different groups of categories. In panel (a), we show results for breakfast products, panel (b) shows results for all drinks, panel (c) groups food rich in carbohydrates, panel (d) groups different sources of meat, panel (e) has different desserts, and panel (f) has candies and snacks.

Categories are ordered from top to bottom according to the share of labeled products it contains (weighted by total revenue). The darker the color of the area, the larger the share of labeled products there are. In Panel (a), for instance, 0% of egg products are labeled, while cereals category, the category with most labeled products in this group, has 62% of their products labeled. Categories such as chocolates, cookies and snacks (in panel (f)), are coloured in dark blue and have more than 99% of their products labeled.

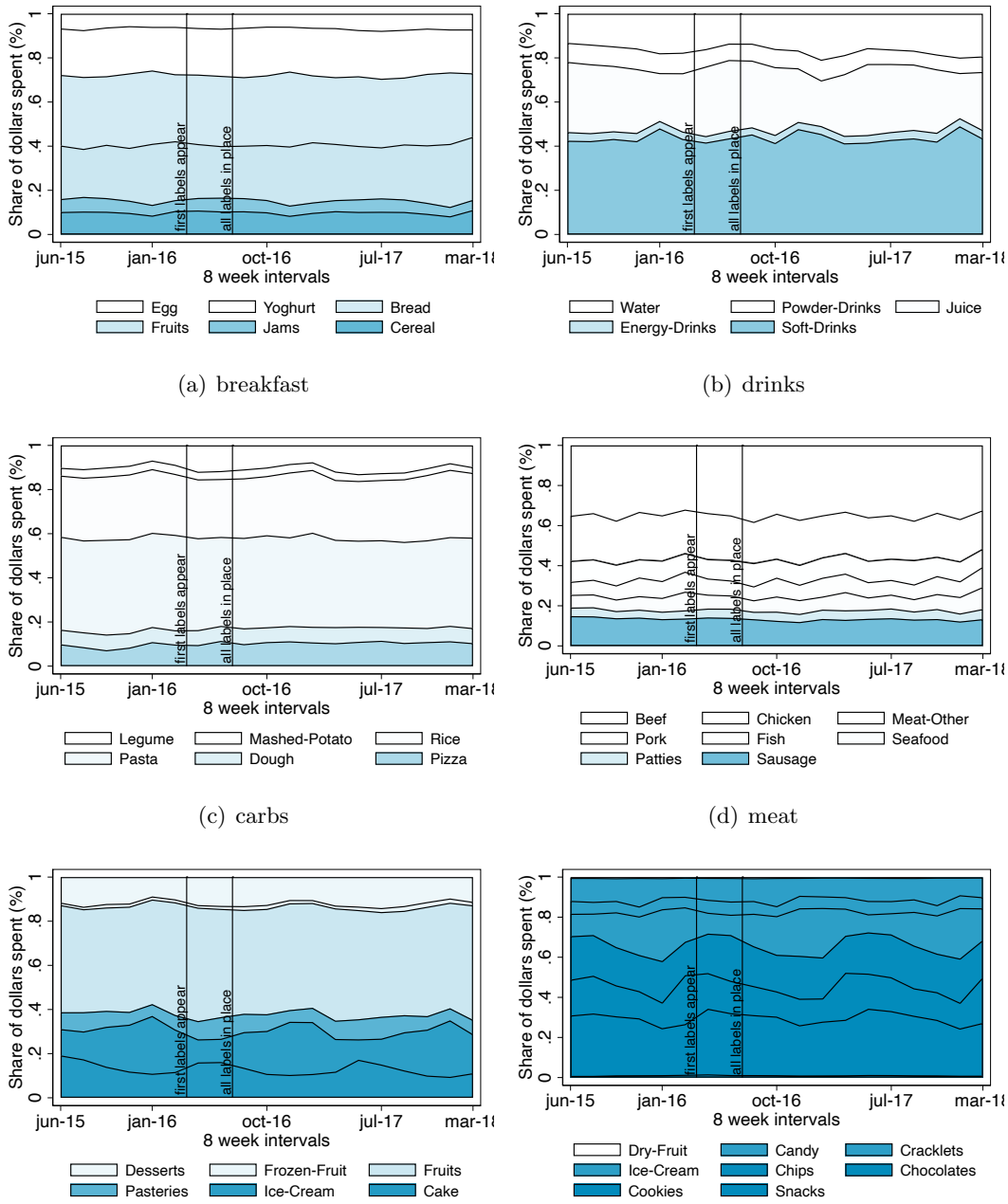
Figure D.1 suggests there is little to no evidence that consumers are shifting consumption from highly labeled categories, such as breakfast cereals, soft drinks, or sausages, to low labeled categories such as eggs, juices, or chicken. In panel (a), for instance, the share of breakfast spending going to cereals averages 9.9% both in the pre- and post-period.

We also look at the total amount spent per capita on breakfast items and drinks in Figure D.2. Results for other groups look similar. We don't show them to save space. We find that, if something, total amount spent on breakfast items and drinks has steadily increased over time. This is true for both low and highly labeled categories.

To formalize these results, we pool all categories together and run the following regression:

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

where r_{cst} denotes the total revenue from products of 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, δ_t denotes period fixed-effects and d_{cs} refers to catgory-store fixed effects. We normalize the β_t coefficient corresponding to the first period post-adoption to be equal to zero. Observations are



(a) breakfast

(b) drinks

(c) carbs

(d) meat

(e) dessert

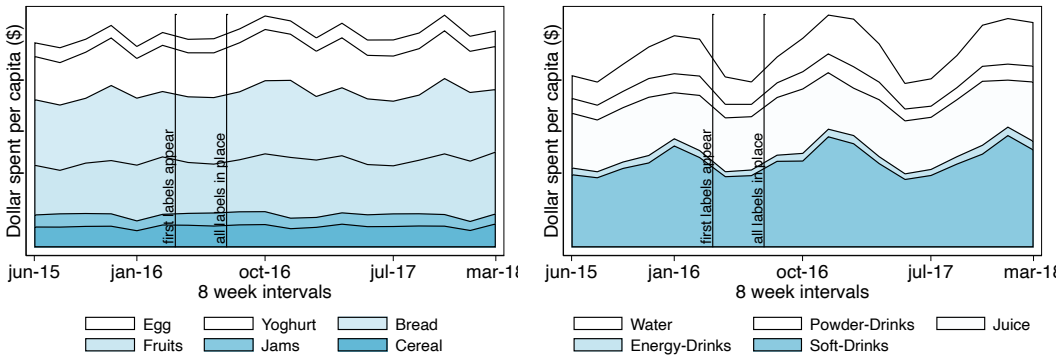
(f) snacks

Figure D.1: Share of dollars spent across different 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 where no product received a label, dark-blue areas (e.g. snacks) are categories where all products received at least one label. We show there are no differential changes of dollars spent between low-in-labels and high-in-labels categories.

weighted by category-store pre-policy revenues and standard errors clustered at the category level.

Figure D.3 displays the results from estimating Equation (D.1). Both in the pre- and post-



(a) breakfast

(b) drinks

Figure D.2: Total spending per capita of different categories

Notes: The figure shows the evolution of total dollars spent in each category within broader groups of products. We focus on breakfast products and drinks. We show that total dollars spent have increase in all categories, regardless of whether they have a high share of labeled products or not.

period, the difference in coefficients are small and none of them are significantly different from zero. Note that the variance of the estimates increase in the months of January and February. As 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 do that, coefficients are much more precise and still not statistically different from zero.

The regression results are consistent with the results in figure D.1. We thus conclude that the extent to which consumers substituted towards other categories is small and therefore we ignore it from our analysis alongside the main article.

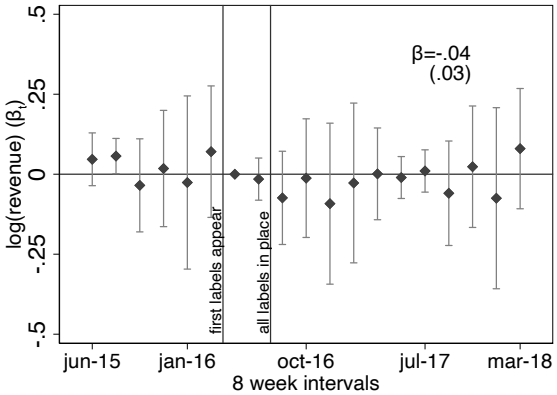


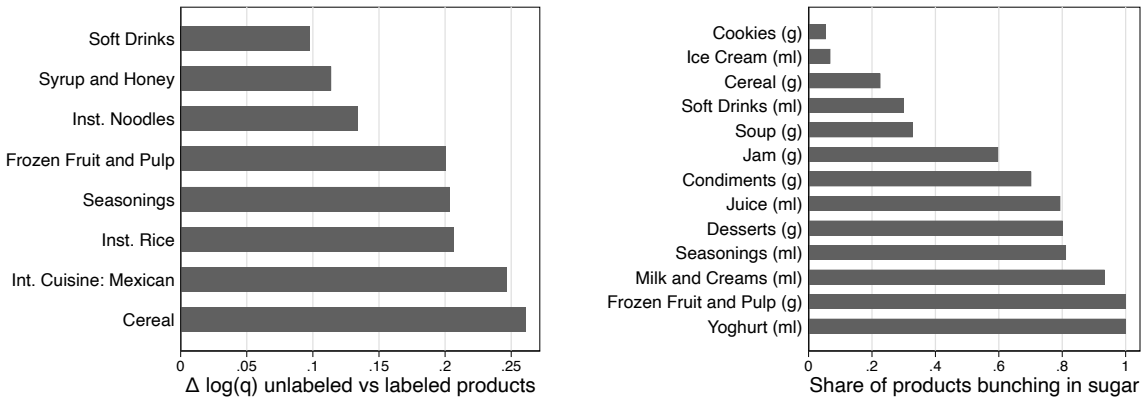
Figure D.3: Total spending per capita of different categories

Notes: The figure presents the β_t coefficients from Equation (D.1). The vertical lines delimit the 95% confidence intervals. These regressions are run on the 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.

Appendix E: Other product categories

In this section, we explore the effects of the Chilean Food Act on other categories. We show that the main reduced-form results are not particular for the cereal market but also expand to other categories. We perform two separate analyzes in the same vein as in Section 3. First, we present descriptive event study plots similar to Figure 4 to the show the impact of the policy on demand for labeled and unlabeled products. Second, we explore bunching at the regulation threshold as evidence of firm's strategic behavior.

We first study the effects of the policy on equilibrium quantities sold following the event-study design of Equation (1). We limit our attention to eight different categories and subcategories that meet the criteria described below. The eight selected categories represent 5.7% of pre-policy revenue of all food products and 11.9% of pre-policy revenue of all labeled products. In Figure 1(a), we present the relative change in quantities sold between unlabeled vs. labeled products due to the policy for each category. Our findings confirm that consumers substituting from labeled to unlabeled products did not only happen in the cereal market, and reveal some degree of heterogeneity in consumer responses across categories. We discuss such heterogeneity in Section 7 of the main article.



(a) Changes in equilibrium quantities sold

(b) Share of products bunching in sugar

Figure E.1: Changes in demand and supply for additional categories

Notes: This figure summarizes the findings on changes in equilibrium quantities and bunching from Appendix E. Panel (a) shows the changes in equilibrium quantities between labeled and unlabeled products from estimating Equation (1) on different product categories. The products used in Panel (a) represent 12% of the pre-policy revenue of labeled products in the sample. The other 88% belong to categories where the results from Equation (1) can not be interpreted as causal. Panel (b) shows the pre-policy revenue weighted share of products at the right of the threshold in sugar in the pre-policy period that reduced the concentration of sugar to be at the left of the regulatory threshold in the post-policy period. The products used in Panel (b) represent 54% of the pre-policy revenue of all products that were at the right of the policy threshold in the pre-policy period.

We then look at the extent to which firms reformulated their products in different categories. We focus on reformulation in sugar and restrict our attention to categories that meet

the criteria described below. This gives us a total of 13 categories that represent 15.5% of pre-policy revenue of all food products and 53.6% of pre-policy revenue of products at the right of the threshold for which we collected nutritional content data. In Figure 1(b), we plot the share, weighted by pre-policy revenue, of products surpassing the sugar regulatory threshold in the pre-policy period that reformulated to be at the left of the threshold in the post-policy period. We find that, while in some categories 100% of the products were reformulated to cross the regulatory threshold, in other categories less than 10% did. We discuss these results in Section 7 of the main article.

We discuss sample selection and show results for each of the selected categories in detail below.

E.1. *Selection of Categories*

For the purpose of the 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: i) products are sufficiently similar such consumers would consider to substitute from one to another as a result of the regulation, ii) there is sufficient variation in terms of the share of products that receive a label, and iii) for the purpose of estimating a differences-in-difference model, we would need that unlabeled and labeled products within the category to follow similar pre-trends in the absence of the policy. All of these conditions are met for the cereal products and that is one of the main reasons of why we make it the focus of our analysis.

Exploring categories that meet these conditions in our data is not straightforward. First, 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 the 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 deal with these issues, we selected and combined certain categories, and within those we restricted our analysis to products that have the potential to behave as close substitutes. In addition, we visually inspected and kept those in which labeled and unlabeled products followed similar pre-trends.

In a second analysis, we present histograms of the nutritional content of products to assess firm's strategic responses to the policy. This exercise is similar to the one presented in Figure 6 of the main article. Organizing categories for this exercise requires different conditions than the one before. We focus our attention in categories in which the distribution of sugars and calories are not entirely to the left of the regulation 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 levels.

E.2. *Sample Coverage*

In Table E.1, we show the share of the revenue covered by the categories included in 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 lay either below or above the policy threshold in the post-policy period and label them as "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 unlabaled products were not following 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 the total revenue.

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

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

Notes: Column (1) presents 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%. Column (2) presents the share of labeled products within each of the categories. Column (3) presents the share of total revenue among labeled products.

Column (2) indicates the share of products, weighted by revenue, that received a warning

label within a given category. Column (3) indicates the share of the total revenue revenue among 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.

In Table E.2, we show the share of the revenue covered by the categories included in supply-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 lay either below or above the policy threshold in the pre-policy period and label them as "Mostly below" and "Mostly above". Together, these two groups represent close to 67% of the revenue, and include categories such as fruit, meat, salads, candy, and chocolate. Another 17.5% of total revenue corresponds to 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 the total revenue.

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

Table E.2: Selected categories to study the impact of food labels on product reformulation

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

Notes: Column (1) presents 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%. Column (2) presents the share of labeled products within each of the categories. Column (3) presents the share of total revenue among labeled products.

E.3. *Event studies: Changes in equilibrium quantities*

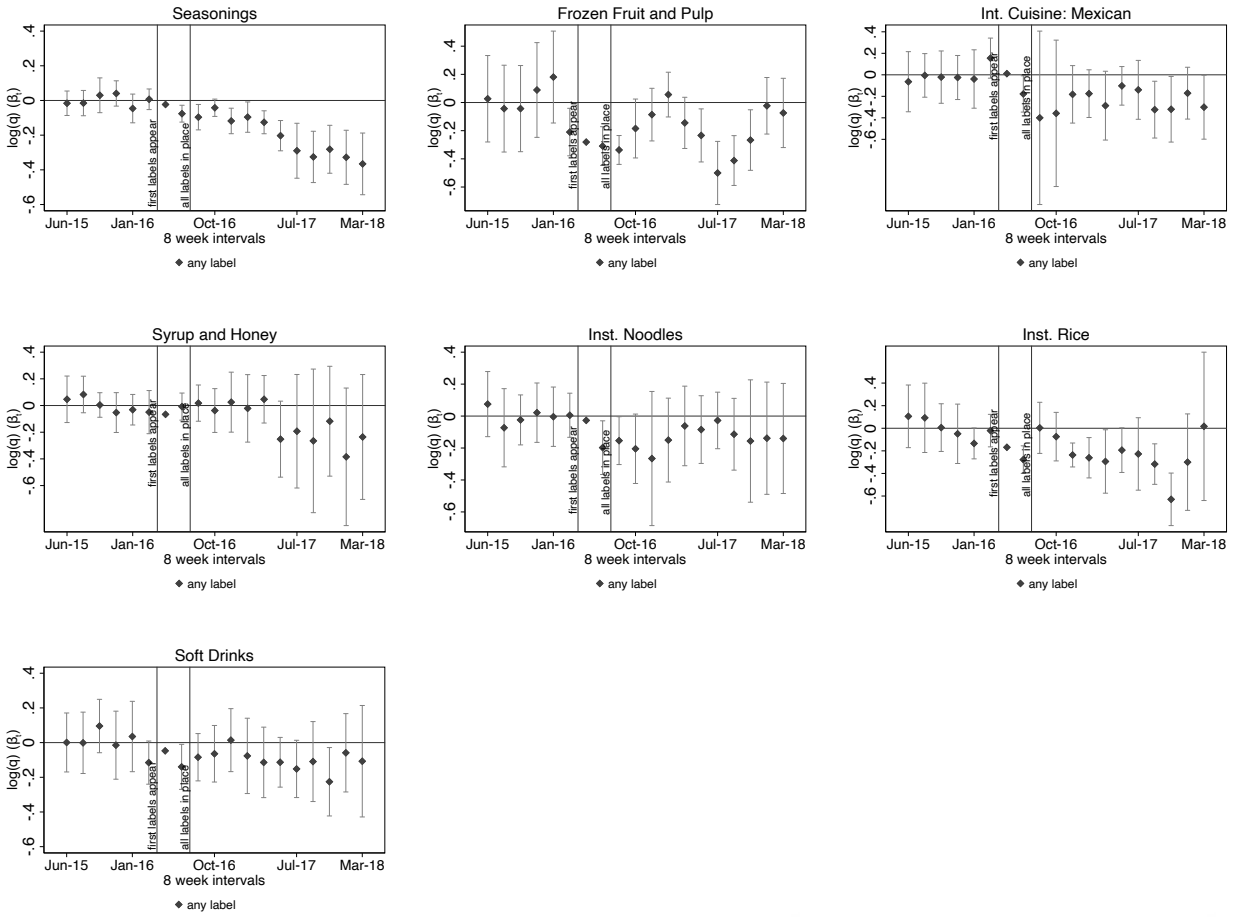


Figure E.2: Event study by category

Notes: This figure presents the coefficients of our event study regressions. Each panel presents the β_t coefficients from Equation (1) for selected categories.

E.4. *Histograms: Supply-side responses*

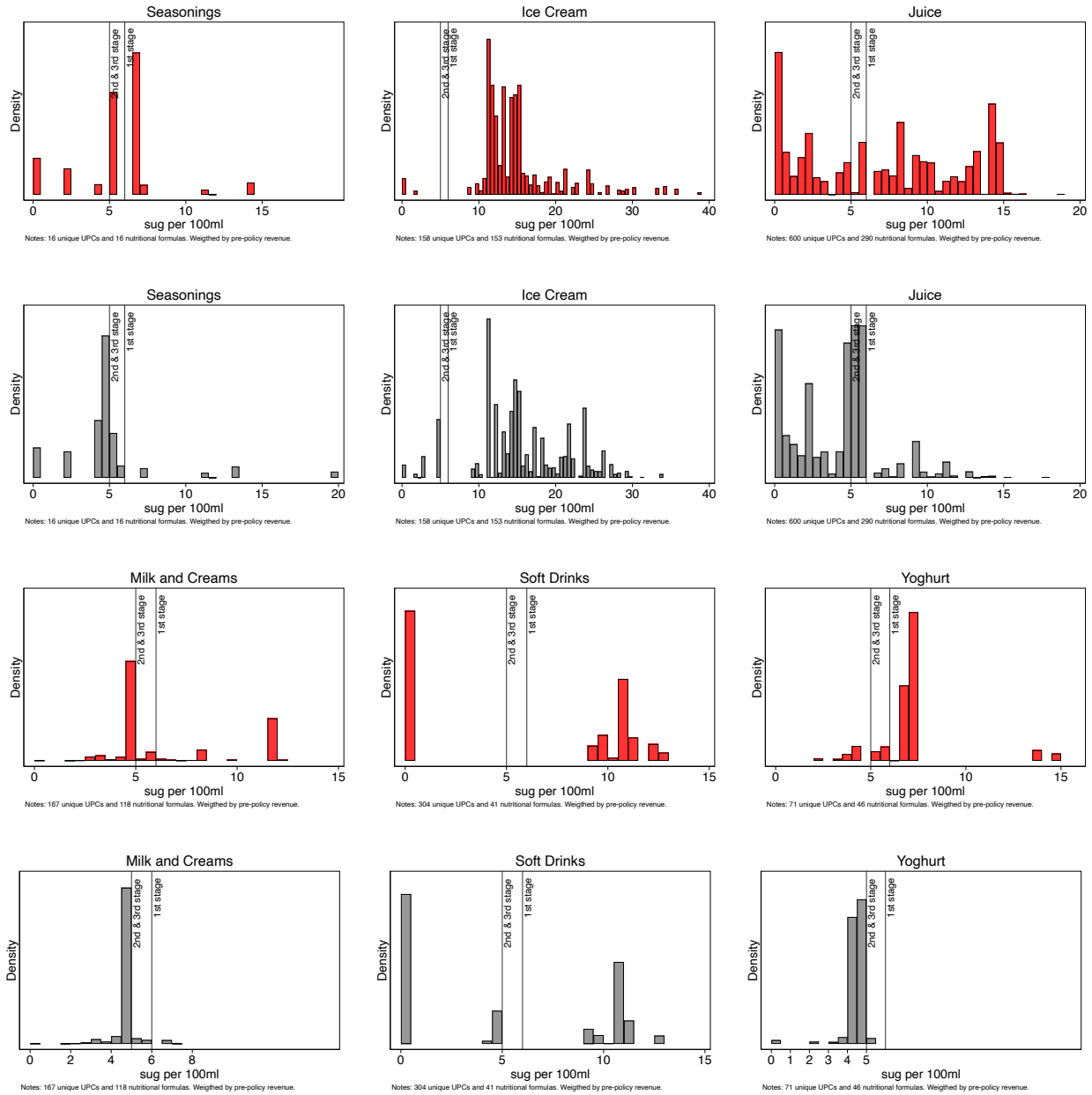


Figure E.3: Distribution of sugar content pre- and post-policy for liquids in selected categories

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.

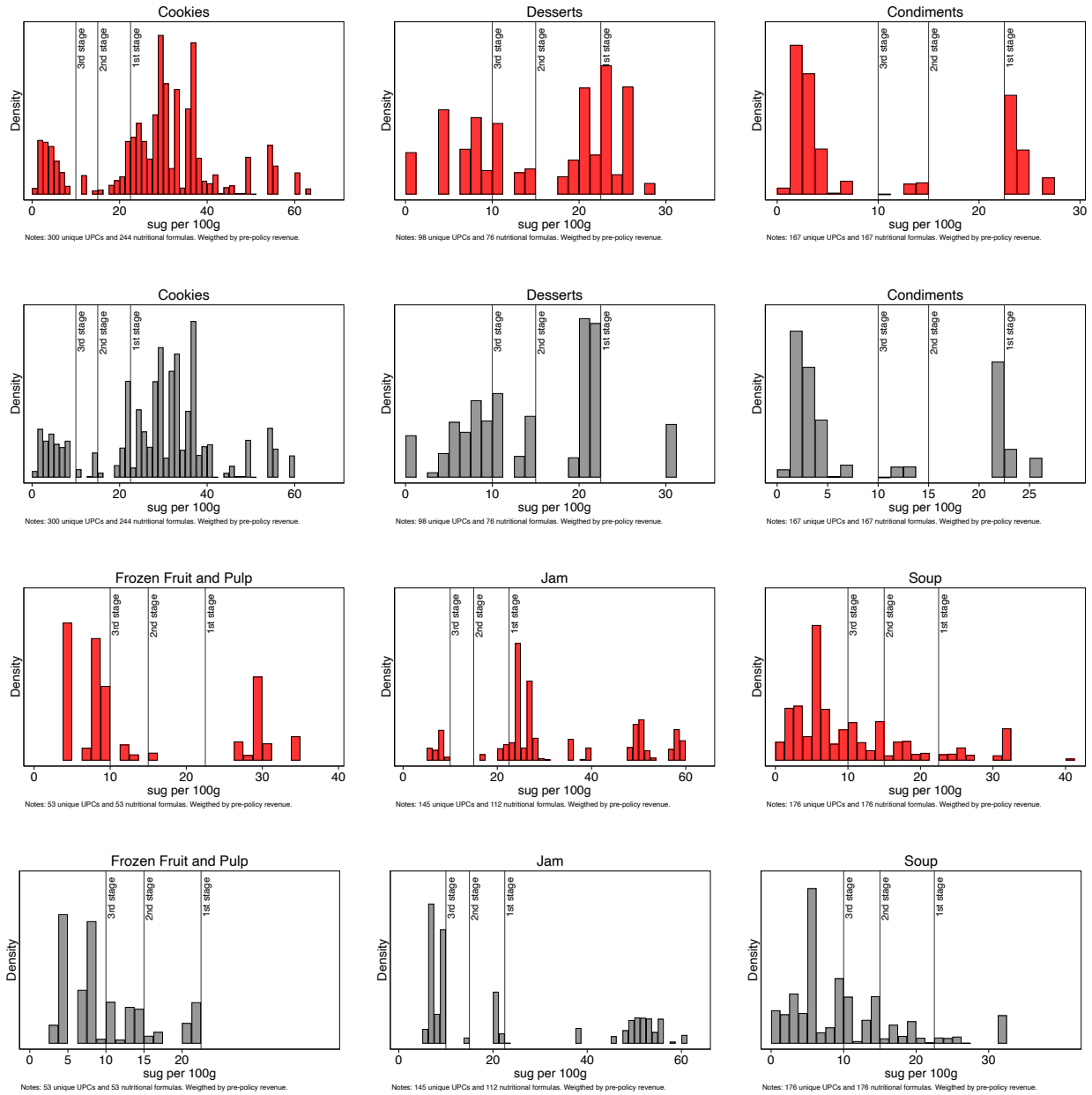


Figure E.4: Distribution of sugar content pre- and post-policy for solids in selected categories

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.

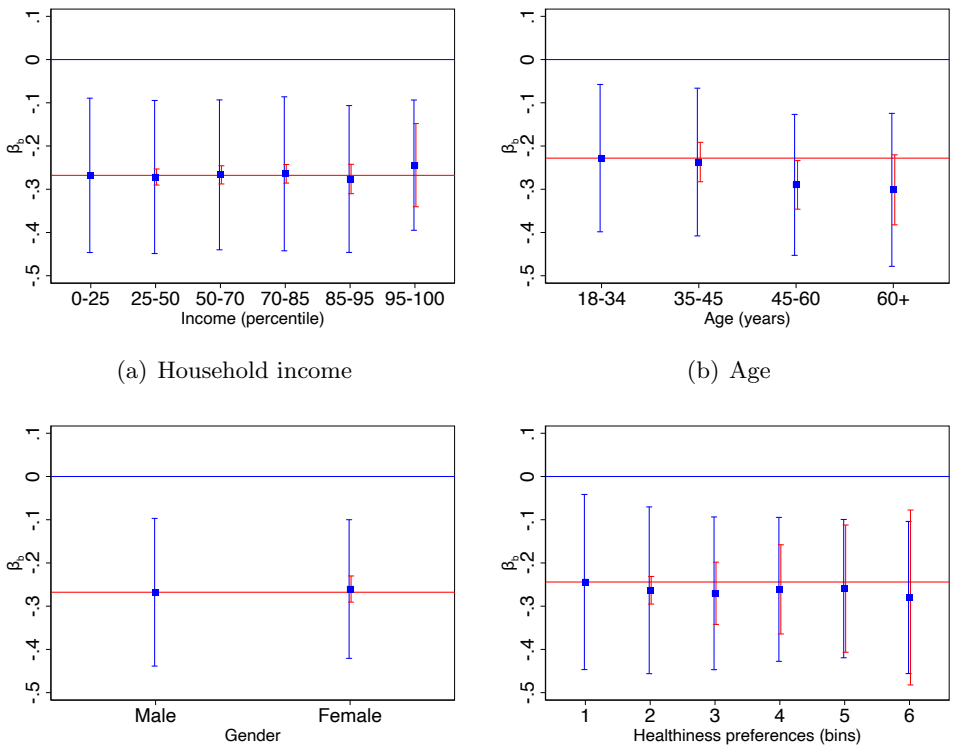
Appendix F: Consumer heterogeneity

F.1. *Policy effects by individual characteristics*

In this subsection we estimate the effects of the policy for different types of individuals. We find the policy had similar effects for consumers with different characteristics. To explore potential heterogeneous impacts of the policy, we estimate the following equation:

$$\log(q_{jstb}) \quad = \quad \beta_b \cdot \text{Post}_t \cdot L_j + \gamma_b \cdot p_{jst} + \delta_{bjs} + \delta_{bt} + \varepsilon_{bjst} \tag{F.1}$$

where q_{bjst} denotes the amount of grams of product j purchased by individuals of type-bin b in store s and period t, Post_t is a dummy variable that takes the value of one after the policy implementation date, and β_b and γ_b are coefficients specific to each individual group. Weights and standard errors are implemented as in Equation (1).



(a) Household income

(b) Age

(c) Gender

(d) Healthiness index

Figure F.1: Policy effects for different consumer types

Notes: This figure shows the coefficients β_b from Equation (F.1) for different consumer characteristics. Blue vertical lines represent 95% confidence intervals for a test against the null $\beta_b = 0$. Red vertical lines represent 95% confidence intervals for a test against the null $\beta_b = \beta_1$.

We divide individuals based on four categories: household income, age, gender, and a

healthiness index based on pre-policy purchases in categories different from cereal.[2] Results are presented in Figure F.1. We find no statistically significant differences of the effects of the policy on equilibrium quantities for household income, gender, and healthiness index. We do find that consumers 45 years old and older decreased their consumption of labeled products relative more than younger groups. Nevertheless, even though these differences are statistically significant, they are sufficiently large to explain the differences between low-in- and high-in-calorie products from Figure 5(b) in Section 3.

F.2. *Low- and high-income individuals' baseline characteristics*

In this subsection we compare pre-policy characteristics of low- and high-SES consumers. We report the main summary statistics in Table F.1.

Table F.1: Consumer characteristics in pre-policy period (48 weeks)

	Low SES	High SES
Average age	47.0	49.0
Share of female (percent)	68.5	70.3
Share that bought cereal (percent)	90.2	90.3
Number of weeks with cereal purchases	7.0	7.9
Number of cereal products purchased	4.7	5.0
Total grams of cereal purchased (kg)	4.84	5.49
Total dollars spent on cereal (USD)	22.36	26.36
Average price paid (USD/kg)	4.998	5.143
Average package size (kg)	0.455	0.443
Average sugar intake (gr/100gr)	16.76	17.07
Average calorie intake (kcal/100gr)	384.27	383.96
Share of grams of cereal from each subcategory (percent):		
Oat-meals	31.1	28.4
Sugary cereal	19.7	21.3
Chocolate cereal	29.0	27.1
Granola	9.7	10.3
Corn flakes	10.6	12.9
Other categories:		
Share of liters of soft drinks that are diet (percent)	35.2	50.5
Share of meters of toilet paper from premium brands (percent)	20.9	29.0

Notes: The table presents summary statistics for low- and high-SES consumers, where low-SES consumers are those below the 70th percentile of the income distribution based the National Census and high-SES are those above.

We find that high-SES consumers in our sample tend to be older and more likely to be female. Since we identify households through Walmart's loyalty program, the interpretation of a high rate of female customers is that households are more likely to register a female as

[2]To build the healthiness index we calculate the amount of sugar, calories, saturated fat and sodium consumed per gram of food and liter of drinks. We then implement a principal component analysis to reduce the space to a single-dimensional index.

the head of the household in the loyalty program. We also find that high-SES customers buy cereal more often, buy more and spend more money on them. We also find that high-SES customers are more likely to buy higher-in-sugar cereal, mostly driven by the differences in demand for Oat-meals between low- and high-SES individuals (oat-meals are low in sugar and cheaper). When looking at other categories, high-SES customers are more likely to buy diet soft drink products and premium brands of toilet paper.

Appendix G: About the reformulation of products

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

We conducted interviews with the 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 their 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" that 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 can not distinguish between old and new versions of the product. Only if a product successfully passes the different tests, 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 arise as an alternative to replace sugars (e.g. sucralose acesulfame-K, saccharin steviol glycosides). Firms usually also use taste enhancers to amplifying 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 that artificial sweeteners do not. Without it, cereals crumble. Polyols, widely used in the diabetic food industry, act as bulking agents and provide thicknnes and structure to the 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 sweet enhancers allow a higher level of sweetness intensity while maintaining the important physicochemical properties of sugars (Lê et al., 2016). Replacing sugar by these ingredients results in a more expensive product to produce, raising ingredients' costs of cereal by more than 20% according to the product managers.

Appendix H: Toy Model

We develop a simplified version of the model from Section 4 with only one inside good and one outside good. The simplified model embodies important features of our setting and illustrates the main forces behind FoPL policies.

H.1. *Setup*

Our model consists of a continuum of risk neutral consumers, indexed by $i \in \mathcal{I}$. There is a single inside good and an outside good in the market. The inside good, denoted by 1, is characterized by its price p and its concentration of a single critical nutrient w (e.g. sugar). The outside good is denoted by 0.

The utility that a consumer gets from consuming product 1 is given by

$$u(p, w, \epsilon) = -\alpha p - \phi w + \epsilon \tag{H.1}$$

where ϵ is an idiosyncratic preference shock independently distributed across consumers with pdf $f(\epsilon)$. The utility obtained from consuming good 0 is normalized to zero ($u_0 = 0$), as well as its price and nutritional content ($p_0 = 0$,$w_0 = 0$).

Consumers observe p and their realization of ϵ but are uninformed regarding the nutritional content of product 1, w. Their expected utility of consuming good 1 instead of good 0 is given by

$$\mathbb{E}_\pi[u] = -\alpha p - \phi\, \mathbb{E}_\pi[w|L] + \epsilon \tag{H.2}$$

where $L \in \{\text{pre-policy}, \text{no}, \text{yes}\}$ denotes the labeling status of product 1 and $\mathbb{E}_\pi$ denotes the expectation operator over beliefs π. We refer to the operator $\mathbb{E}_\pi$ as $\mathbb{E}$ to ease notation.

The share of consumers purchasing product 1 after observing label L is given by

$$s(p, \mathbb{E}[w|L]) = \int_{\alpha p + \phi\, \mathbb{E}[w|L]}^{\infty} f(\epsilon) d\epsilon \tag{H.3}$$

and sugar intake and consumer surplus are determined by

$$SI(p, w, L) = s(p, \mathbb{E}[w|L]) w \tag{H.4}$$

$$CS(p, w, L) = \frac{1}{\alpha} \int_{\alpha p + \phi\, \mathbb{E}[w|L]}^{\infty} u(p, w, \epsilon) f(\epsilon) d\epsilon \tag{H.5}$$

respectively.

Product 1 is produced by a firm with marginal cost $c(w) = \bar{c} + \Lambda(w - \nu)^2$, where

$$\nu = \begin{cases} \nu^H & \text{with probability } q \\ \nu^L & \text{with probability } 1 - q \end{cases} \tag{H.6}$$

where $\nu^L < \nu^H$.

The firm maximizes profits as in section 4. The firm's profits are giving by

$$PS(p, w, L) = (p - c(w))s(p, \mathbb{E}[w|L]) \tag{H.7}$$

We assume that consumers have common prior beliefs (π) over the nutritional content w that are ex-ante right when there is no policy intervention. That is, their beliefs are given by equation (H.6).

The timing of the game is as follows: i) The value of ν is realized. ii) The social planner mandates or not a food labeling policy. iii) Firms choose the value of p and w. iv) consumers observe the labeling status of the product. v) consumer decide what product to purchase.

We focus on different counterfactuals of interest motivated in Section 6. First, we characterize the equilibrium when the social planner decides not to implement any labeling policy (0). We then analyze a counterfactual where the labeling policy is at place but firms' decisions in step iii) are fixed at the no-intervention optimum (1). We then allow firms to optimally decide prices in step iii) but fix the nutritional content of its product at the no-intervention levels (2). Finally, we analyze the case in which firms choose both prices and nutritional content in step iii) (3).

H.2. *No-intervention counterfactual (0)*

We first analyze the case without any intervention. We denote this counterfactual as (0). under (0), expected nutritional content is given by $\mathbb{E}[w|L = pre] = \mathbb{E}[\nu]$. After ν is realized, the firm chooses the value of w that minimizes marginal cost ($w = \nu$) and sets the optimal price under no intervention $\hat{p}$ according to the first order conditions:

$$\hat{p} = \bar{c} - \frac{s(\hat{p}, \mathbb{E}[w|L = pre])}{s_p(\hat{p}, \mathbb{E}[w|L = pre])} = \bar{c} + \frac{s(\hat{p}, \mathbb{E}[\nu])}{\alpha f(\alpha\hat{p} + \phi\,\mathbb{E}[\nu])} \tag{H.8}$$

where $s_p(p, w)$ is the derivative of $s(p, w)$ with respect to p.

Expected consumer surplus is given by

$$\begin{aligned}\mathbb{E}[CS(0)] &= \mathbb{E}\left[\frac{1}{\alpha}\int_{\alpha\hat{p}+\phi E[w|L=pre]}^{\infty} u(\hat{p},w,\epsilon)f(\epsilon)d\epsilon\right] \\ &= \frac{1}{\alpha}\int_{\alpha\hat{p}+\phi\,\mathbb{E}[\nu]}^{\infty} u(\hat{p},\mathbb{E}[\nu],\epsilon)f(\epsilon)d\epsilon \end{aligned} \tag{H.9}$$

where $CS(x)$ is the consumer surplus under counterfactual (x).

Expected sugar intake is given by

$$\begin{aligned}\mathbb{E}[SI(0)] &= \mathbb{E}[s(\hat{p},\mathbb{E}[w|L=pre])w] \\ &= s(\hat{p},\mathbb{E}[\nu])\,\mathbb{E}[\nu] \end{aligned} \tag{H.10}$$

where $SI(x)$ is the average intake of nutrient w under counterfactual (x).

H.3. *Demand-only counterfactual (1)*

We then analyze the case where both p and w are fixed at the no intervention equilibrium levels but labels are at place. We denote this counterfactual as (1). We focus on a policy given by the threshold y such that the product gets labeled if $w > y$ and not if $w \leq y$. We focus on the interesting case where $\nu^L < y < \nu^H$, such that product 1 gets labeled with probability q and unlabeled with probability $1-q$. In this case, we have that $\mathbb{E}[w|L] = \nu$, and expected consumer surplus is given by

$$\mathbb{E}[CS(1)] = \mathbb{E}\left[\frac{1}{\alpha}\int_{\alpha\hat{p}+\phi\nu}^{\infty} u(\hat{p},\nu,\epsilon)f(\epsilon)d\epsilon\right] \tag{H.11}$$

Proposition 1. *Consumer surplus under a labeling policy with threshold y is greater or equal than under no labeling policy for any policy threshold.*

Proof. Let's define

$$g(w) = \frac{1}{\alpha}\int_{\alpha p+\phi w}^{\infty} u(p,w,\epsilon)f(\epsilon)d\epsilon$$

such that $\mathbb{E}[CS(0)] = g(\mathbb{E}[w])$, and $\mathbb{E}[CS(1)] = \mathbb{E}[g(w)]$. Note that $\frac{\partial g(w)}{\partial w} = -\frac{\phi}{\alpha}s(p,w)$, which implies that $g(w)$ is a convex function in w (because $s(p,w)$ is decreasing in w). Then, by Jensen's inequality, we will have that $\mathbb{E}[CS(1)] \geq \mathbb{E}[CS(0)]$. □

Expected sugar intake is given by

$$\mathbb{E}[SI(1)] = \mathbb{E}[s(\hat{p},\nu)\nu] \tag{H.12}$$

Proposition 2. *Let $s_w(p,w)$ and $s_{ww}(p,w)$ be the first and second derivative of the demand function with respect to w, such that $s_w(p,w) < 0$. Expected sugar intake will always decrease with a labeling policy regulatory if $\frac{s_{ww}(p,w)w}{2|s_w(p,w)|} < 1$ for every value of $w \in [\nu^L, \nu^H]$, and will always increase if $\frac{s_{ww}(p,w)w}{2|s_w(p,w)|} > 1$ in the same range.*

Proof. Let's define

$$g(w) = s(\hat{p}, w)w$$

and note that

$$\begin{aligned} \mathbb{E}[SI(0)] &= \mathbb{E}[s(\hat{p}, \mathbb{E}[w|L])w] = g(\mathbb{E}[w]) \\ \mathbb{E}[SI(1)] &= \mathbb{E}[s(\hat{p}, \mathbb{E}[w|L])w] = \mathbb{E}[g(w)] \end{aligned}$$

Since $g''(w) = s_{ww}(\hat{p}, w)w + 2s_w(\hat{p}, w)$ and $s_w(\hat{p}, w) < 0$, we have that $\frac{s_{ww}(p,w)w}{2|s_w(p,w)|} < 1$ implies that $g(w)$ is concave and, by Jensen's inequality, $\mathbb{E}[SI(1)] \leq \mathbb{E}[SI(0)]$. When $\frac{s_{ww}(p,w)w}{2|s_w(p,w)|} > 1$, $g(w)$ is convex and $\mathbb{E}[SI(1)] \geq \mathbb{E}[SI(0)]$. □

Proposition 2 highlights important features of the model. When the labeling policy is at place, product 1 will get labeled with probability q, in which case its demand, $s(\hat{p}, \mathbb{E}[w|L])$, will decrease relative to the no policy scenario. With probability $1-q$ it will get unlabeled, and its demand, $s(\hat{p}, \mathbb{E}[w|L])$, will increase. Whether ex-ante expected demand, $\mathbb{E}[s(\hat{p}, \mathbb{E}[w|L])]$, increases or decreases depends on the sign of $s_{ww}(\hat{p}, \mathbb{E}[w|L])$. If the demand function is convex, expected demand of product 1 will increase. If it is concave, it will decrease.

To assess what happens to expected sugar intake, we need to account for two different substitutions. One the one hand, there is an "overall between product substitution," where, in expectation, consumers substitute from the outside good to product 1 when the demand function is convex (and vice-versa). If product 1 has more sugar than the outside option, this mechanism will push expected sugar intake to be larger under the labeling policy. On the other hand, there is a "between states-of-the-world substitution," where consumers consume more of product 1 when the state of the world is one in which product 1 has lower amounts of sugar and less when it has more. This second force will always decrease expected sugar intake. Whenever $s_{ww}(p,w)w$ is positive and large enough, the first force will dominate and the labeling policy will increase expected sugar intake under counterfactual (1).

H.4. *Price-response counterfactual (2)*

In this subsection, we incorporate supply-side price responses. Because the pricing decision is done after ν is realized, we have that the optimal price schedule $\tilde{p}(\nu)$ is given by

$$\tilde{p}(\nu) \quad = \quad \bar{c} + \frac{s(\tilde{p}(\nu), \nu)}{\alpha f(\alpha \tilde{p}(\nu) + \phi \nu)} \tag{H.13}$$

Expected consumer surplus is given by

$$\mathbb{E}[CS(2)] \quad = \quad E\left[\frac{1}{\alpha}\int_{\alpha\tilde{p}(\nu)+\phi\nu}^{\infty} u(\tilde{p}(\nu), \nu, \epsilon) f(\epsilon) d\epsilon\right] \tag{H.14}$$

Proposition 3. *Consumer surplus under counterfactual (2) can be either higher or lower than under counterfactual (0).*

Proof. Let's define

$$g(w) = \frac{1}{\alpha}\int_{\alpha\tilde{p}(w)+\phi w}^{\infty} u(\tilde{p}(w), w, \epsilon) f(\epsilon) d\epsilon$$

such that $\mathbb{E}[CS(0)] = g(\mathbb{E}[w])$, and $\mathbb{E}[CS(2)] = \mathbb{E}[g(w)]$.

Note that

$$\frac{dg(w)}{dw} = -\frac{1}{\alpha} s(\tilde{p}(w), w) \frac{d(\alpha\tilde{p}(w) + \phi w)}{dw}$$

and

$$\frac{d^2 g(w)}{dw^2} = -\frac{1}{\alpha}\left[\left(s_p(\tilde{p}(w), w)\frac{d\tilde{p}(w)}{dw} + s_w(\tilde{p}(w), w)\right)\left(\alpha\frac{d\tilde{p}(w)}{dw} + \phi\right) + \alpha\frac{d^2\tilde{p}(w)}{dw^2} s(\tilde{p}(w), w)\right] \tag{H.15}$$

where

$$\frac{d\tilde{p}(w)}{dw} = -\frac{s_w(\tilde{p}(w), w) s_p(\tilde{p}(w), w) - s(\tilde{p}(w), w) s_{pw}(\tilde{p}(w), w)}{2 s_p(\tilde{p}(w), w)^2 - s_{pp}(\tilde{p}(w), w) s(\tilde{p}(w), w)}$$

If $\frac{d^2 g(w)}{dw^2} < 0$ for $w \in [\nu^L, \nu^H]$, then $\mathbb{E}[CS(2)] > \mathbb{E}[CS(0)]$. If $\frac{d^2 g(w)}{dw^2} > 0$ in the same interval, we have $\mathbb{E}[CS(2)] < \mathbb{E}[CS(0)]$

We show that the sign of $\frac{d^2 g(w)}{dw^2}$ is ambiguous with an example. Assume ϵ follows a logistic distribution (i.e. $f(\epsilon) = \frac{e^{-\epsilon}}{(1+e^{-\epsilon})^2}$). Then, $s_p(\tilde{p}(w), w) = -\alpha s(1-s)$, $s_w(\tilde{p}(w), w) = -\phi s(1-s)$, $s_{pp}(\tilde{p}(w), w) = -\alpha^2 s(1-s)(2s-1)$, $s_{pw}(\tilde{p}(w), w) = -\alpha\phi s(1-s)(2s-1)$, $\frac{d\tilde{p}(w)}{dw} = -\frac{\phi s}{\alpha}$, and

$\frac{d^2\tilde{p}(w)}{dw^2} = \frac{\phi^2}{\alpha}s(1-s)^2$. Replacing the values in Equation (H.15) we get

$$\frac{d^2 g(w)}{dw^2} = -\frac{\phi^2}{\alpha}s(1-s)^2(2s-1)$$

which can be greater or lower than zero. □

An interesting result from proposition 3 is that labeling policies can even decrease consumer surplus when supply-side responses are introduced. Under a labeling policy, firms can increase product differentiation and extract higher rents from consumers, making the overall effect of the policy ambiguous.

H.5. *Equilibrium counterfactual (3)*

In this subsection we allow the firm to reformulate its product to avoid receiving a label. For tractability, we focus on the case where the policy threshold is at $y = \nu^L$.

Under counterfactual (3), if the firm is bunching, the concentration of sugar of product 1 is given by

$$\dot{w} \quad = \quad \nu^L \tag{H.16}$$

Since product 1 is always to the left of the threshold, it does not get labeled. The expected nutritional content will be given by $\mathbb{E}[w|L] = \nu^L$ in both states.

Under bunching, prices are given by

$$\dot{p}(\Lambda) \quad = \quad \begin{cases} \bar{c} + \Lambda\left(\nu^H - \nu^L\right)^2 + \frac{s(\dot{p}(\Lambda),\nu^L)}{\alpha f(\alpha\dot{p}(\Lambda)+\phi\nu^L)} & \text{with probability } q \\ \bar{c} + \frac{s(\dot{p}(\Lambda),\nu^L)}{\alpha f(\alpha\dot{p}(\Lambda)+\phi\nu^L)} & \text{with probability } 1-q \end{cases} \tag{H.17}$$

Expected consumer surplus is given by

$$\mathbb{E}[CS(3)] \quad = \quad \mathbb{E}\left[\frac{1}{\alpha}\int_{\alpha\dot{p}(\Lambda)+\phi\nu^L}^{\infty} u(\dot{p}(\nu,\Lambda),\nu^L,\epsilon)f(\epsilon)d\epsilon\right] \tag{H.18}$$

If firms do not decide to bunch, prices and consumer surplus are as described in Section H.4. Notice that, when $\nu = \nu^H$, then firm's profits when it decides to bunch or not to bunch are given by

$$PS(\text{bunch}|\nu = \nu^H) = \frac{s^2(\dot{p}(\Lambda),\nu^L)}{\alpha f(\alpha\dot{p}(\Lambda)+\phi\nu^L)}$$
$$PS(\text{not bunch}|\nu = \nu^H) = \frac{s^2(\tilde{p}(\nu^H),\nu^H)}{\alpha f(\alpha\tilde{p}(\nu^H)+\phi\nu^H)}$$

respectively.

Proposition 4. *When ϵ follows a logistic distribution (i.e. $f(\epsilon) = \frac{e^{-\epsilon}}{(1+e^{-\epsilon})^2}$) and firms are allowed to reformulate, consumer surplus under a labeling policy with threshold $y = \nu^L$ is greater or equal than when firms are not allowed to reformulate.*

Proof. Notice that with probability $1 - q$, we have that $\nu = \nu^L$ and the firm does not need to decide whether to bunch or not as true content is already below the policy threshold. In such case, $\dot{p}(\Lambda) = \tilde{p}(\nu^L)$, and ex-post consumer surplus conditional on $\nu = \nu^L$ is the same under counterfactual (2) and (3). With probability q, we have that $\nu = \nu^H$, in which case the firm needs to decide whether to bunch or not. If the firm decides not to bunch, $\mathbb{E}[CS(3)] = \mathbb{E}[CS(2)]$. We now need to show that if the firm decides to bunch, $\mathbb{E}[CS(3)] \geq \mathbb{E}[CS(2)]$, provided it is profitable for it to bunch in the first place. Let

$$g(\delta) = \int_{\delta}^{\infty} (-\delta + \epsilon) f(\epsilon) d\epsilon$$

such that $E[CS(3)|\nu = \nu^H] = g(\alpha\dot{p}(\Lambda) + \phi\nu^L)$, $E[CS(2)|\nu = \nu^H] = g(\alpha\tilde{p}(\nu^H) + \phi\nu^H)$, and $\frac{dg(\delta)}{d\delta} < 0$. Moreover, the firm will only bunch if its profits when bunching are larger than when not. That is, the firm will bunch if

$$\frac{s^2(\dot{p}(\Lambda), \nu^L)}{\alpha f(\alpha\dot{p}(\Lambda) + \phi\nu^L)} \geq \frac{s^2(\tilde{p}(\nu^H), \nu^H)}{\alpha f(\alpha\tilde{p}(\nu^H) + \phi\nu^H)}$$

which implies that, under the assumption that ϵ follows a logistic distribution, the firm will bunch if and only if

$$\alpha\dot{p}(\Lambda) + \phi\nu^L \leq \alpha\tilde{p}(\nu^H) + \phi\nu^H$$

which implies that whenever it is optimal for the firm to bunch, we will have that $\mathbb{E}[CS(3)] \geq \mathbb{E}[CS(2)]$. □

Appendix I: Model limitations

I.1. *Inertia*

In this subsection we investigate the nature of inertia in purchasing decisions in our data. Researchers in both marketing and economics have documented consumer inertia in product choice (Frank, 1962; Dubé et al., 2010). There are two conceptually different explanations for the source of inertia: *structural state dependence* and *spurious state dependence*. The first one correspond to the case where past purchases directly influence the consumer's choice probabilities for different products. The second one corresponds to the case where consumers differ along some serially correlated unobserved propensity to make purchase decisions and it only arises when there are unobserved consumer-product specific preferences that are not properly accounted for.

The distinction between the two sources of inertia is important from the point of view of evaluating the equilibrium effects of FoPL policies. In our model, spurious state dependence can be captured by individual-level unobserved persistent shocks inside the experience part of the utility function δ_{ijt}. The model does not allow, however, for structural state dependence. The existence of structural state dependence can not only have consequences in the way that firms set prices, but also in the way that labels affect demand. By shocking demand with new information to consumers, labels can change the dependence path and move consumers to a new healthier equilibrium. This can amplify the positive effects of labels in the long-run. In this subsection we test for the existence of inertia in our data and explore the extent to which such inertia is driven by structural or spurious dependence.

A simple way of capturing inertia in our model is by letting the previous product choice to affect consumers' decision utility

$$\mathbb{E}_i[u_{ijt}] = \underbrace{\delta_{ijt}}_{\text{experience/taste}} - \underbrace{\alpha_i p_{jt}}_{\text{price paid}} - \underbrace{\mathbb{E}_i[w_{jt}|L_{jt}]\phi_i}_{\text{health consequences}} + \underbrace{\gamma \mathbb{1}\{s_{it} = j\}}_{\text{inertia}} \tag{I.1}$$

where all variables are as in Equation (4) from the main article. The state variable $s_{it} \in \{1, ..., J\}$ corresponds to the last product purchased by consumer i. It is difficult to distinguish empirically between structural state dependence and spurious state dependence, since the main drivers of spurious state dependence are not observed by the researcher. One possible strategy is to use a very flexible semi-parametric specification on δ_{ijt} consisting of a mixture of multivariate normal distributions to account for individual specific preferences (e.g. Dubé et al., 2010). This can be computationally demanding, especially for large datasets as the one used in this paper. Alternatively, Dubé et al. (2010) suggest to exploit variation in the products' characteristics of past purchases to identify the two types of state dependence. For

example, after conditioning on past choices and current prices, previous prices should not affect consumer choice under a model with no structural state dependence. We follow the latter approach in what follows.

Due to the large size of our dataset, we start by dropping observations in which an individual chooses not to buy cereal at all. We further restrict the attention to consumers that never buy more than one cereal at a time.[3] We end up with a sample of 128,000 unique customers that, on average, bought cereal 16 times in our sample period. Since we dropped all observations in which an individual chooses not to buy cereal, there is no outside option in this model. We estimate the following parametric model:

$$\mathbb{E}_b[u_{ijt}] \quad = \quad -\alpha_b p_{jt} - \hat{\mathbb{E}}_b[w_{jt}|L_{jt}]\phi_b + \gamma \mathbb{1}\{s_{it} = j\} + \hat{\delta}_{jb} + \hat{\xi}_{jtb} + \psi\epsilon_{ijt} \tag{I.2}$$

where $\hat{\mathbb{E}}_b[w_{jt}|L_{jt}]$, $\hat{\delta}_{jb}$ and $\hat{\xi}_{jtb}$ are taken from the estimated parameters of Section 5 of the main article. For easier comparison with our original model, we force the coefficients of $\hat{\delta}_{jb}$ and $\hat{\xi}_{jtb}$ to be 1, and allow for a flexible parameter ψ that scales the logit error ϵ_{ijt} accordingly.[4] We are interested in the sign and magnitude of γ. All results are presented in Table I.1.

We first compare our model to the one in the main article by estimating Equation (I.2) fixing $\gamma = 0$. In column (1) of Table I.1 we present the values of the estimated coefficients. They are very similar in magnitude to the coefficients from the main article presented in Table 2. In column (2), we allow for persistent and estimate Equation (2) by maximum likelihood. We get a positive and significant coefficient for γ, that suggests that consumers are willing to pay \$0.51 to \$0.55 additional dollars per 100 grams to buy the same product as in the previous purchase. As discussed above, however, $\hat{\gamma}$ in column (2) is capturing both structural state dependence as well as idiosyncratic preferences that consumer i might have over product j that are correlated across time. To illustrate this idea, we estimate the following model

$$\mathbb{E}_b[u_{ijt}] \quad = \quad -\alpha_b p_{jt} - \hat{\mathbb{E}}_b[w_{jt}|L_{jt}]\phi_b + \gamma \mathbb{1}\{s_{it} = j\} + \kappa \mathbb{1}\{m_i = j\} + \hat{\delta}_{jb} + \hat{\xi}_{jtb} + \psi\epsilon_{ijt} \tag{I.3}$$

where $m_i \in \{1, ..., J\}$ denotes consumer i's favorite product, calculated as the product that consumer i buys more often in our data. In column (3) of Table I.1 we show that the estimate of γ becomes smaller once we control for whether product j is consumer i's favorite product, suggesting that part of the perstence effect is driven by spurious state dependence. This approach, however, has several limitations. First, it does not allow for richer structures of unobserved consumer heterogeneity and only controls for preferences over the most preferred product. It might be the case, however, that the remainder persistence is driven by high

[3] Consumers buy only one product 81% of the times and only two products another 16%. 31% of customers never buy more than 1 product at a time.

[4] Since in this model there is no outside good, we do not impose a nested-logit error. The role of ψ is to scale the variance of logit error to set utility levels relative to $\hat{\delta}_{jb}$ and $\hat{\xi}_{jbt}$. Results are robust to flexibly estimate δ_{jb} and impose a fixed coefficient on $\hat{\xi}_{jtb}$ only.

Table I.1: Structural vs spurious state dependence

	(1)	(2)	(3)	(4)	(5)
α_l	0.0548***	0.0545***	0.0561***	0.0502***	0.0549***
	(0.00018)	(0.00018)	(0.00022)	(0.00067)	(0.00016)
α_h	0.0509***	0.0503***	0.0515***	0.0463***	0.0509***
	(0.00018)	(0.00018)	(0.00021)	(0.00066)	(0.00016)
ϕ_l^s	0.0220***	0.0234***	0.0205***	0.0208***	0.0223***
	(0.00052)	(0.00055)	(0.00062)	(0.00092)	(0.00046)
ϕ_h^s	0.0227***	0.0249***	0.0242***	0.0221***	0.0233***
	(0.00055)	(0.00056)	(0.00064)	(0.00097)	(0.00048)
ϕ_l^c	0.0162***	0.0156***	0.0169***	0.0162***	0.0161***
	(0.00016)	(0.00017)	(0.00020)	(0.00030)	(0.00015)
ϕ_h^c	0.0150***	0.0142***	0.0154***	0.0149***	0.0148***
	(0.00017)	(0.00018)	(0.00020)	(0.00031)	(0.00015)
γ		0.0282***	0.0200***		0.00650***
		(0.00010)	(0.00011)		(0.00014)
κ			0.0368***		
			(0.00012)		
β_p				-0.00371***	
				(0.00064)	
β_ξ				0.0499***	
				(0.00541)	
ρ					0.659***
					(0.00472)
Observations	77893459	77893459	77893459	23268433	77893459

Notes: This table shows the main results from estimating consumer inertia under different models. Column (1) compares the estimated coefficients of a model with no inertia using the new sample to the one in the main article. Column (2) estimates Equation (I.2). Column (3) estimates equation (I.3). Column (4) estimates Equation (I.4). Note that the number of observations is smaller because we need to drop market-consumer pairs for which not all products where available in the past purchasing period. Column (5) estimates Equation (I.6). Standard errors clustered at the consumer level are presented in parenthesis. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

preferences over other products that are not captured by m_i. Second, both variables s_{it} and m_i are functions of consumer choices, and therefore, are likely to be correlated with ϵ_{ijt}, creating an endogeneity problem.

To overcome the endogeneity problem we exploit the panel structure of the data. In a model with structural state dependence, products' past prices and other characteristics can influence the consumer's state variable s_{it} and thus affect subsequent choices. In contrast, in a model with spurious state dependence, past prices and other characteristics should not influence the persistence in choices over time. To test for the presence of structural state dependence, we estimate the following model

$$\mathbb{E}_b[u_{ijt}] \quad = \quad -\alpha_b p_{jt} - \hat{\mathbb{E}}_b[w_{jt}|L_{jt}]\phi_b + \beta_p p_{jt'} + \beta_\xi \hat{\xi}_{jt'_i} + \hat{\delta}_{jb} + \hat{\xi}_{jtb} + \psi\epsilon_{ijt} \tag{I.4}$$

where $p_{jt'_i}$ corresponds to the price of product j in the period when consumer i made her last purchase, and $\hat{\xi}_{jt'_i}$ corresponds to the unobserved demand shock of product j in that same period. The term $\hat{\xi}_{jt'_i}$ captures products' characteristics in market t'_i, such as the position on the shelf or other promotional strategies (e.g. including a game in the back of the box for cereal products aimed at kids). Notice that Equation (I.4) does not include the inertia term from previous regressions. The idea is that, in the absence of structural state dependence, β_p and β_ξ should be close to zero. A model with structural state dependence, on the other hand, would predict that $\beta_p < 0$ and $\beta_\xi > 0$. Column (4) of Table I.1 rejects the null that there is no structural state dependence. The coefficients for β_p and β_ξ are of the expected sign and statistically different from zero. These findings motivate our next exercise.

We estimate a two-step model where we exploit variation in product characteristics and market conditions from consumer i's last purchase taking a control function approach. In the first step, we recover a proxy for the idiosyncratic preferences of consumer i over each available product by estimating

$$\mathbb{E}_b[u_{ijt'_i}] \quad = \quad -\alpha_b p_{jt'_i} - \hat{\mathbb{E}}_b[w_{jt'_i}|L_{jt'_i}]\phi_b + \hat{\delta}_{jb} + \hat{\xi}_{jt'_i b} + \psi\epsilon_{ijt'_i} \tag{I.5}$$

Since we do not observe expected utility in the data, $\epsilon_{ijt'_i}$ can not be directly estimated. Instead, we can compute $\eta_{ijt'_i} = \mathbb{E}[\epsilon_{ijt'_i}|s_{it}]$, which contains information about consumer i's idiosyncratic preferences $\epsilon_{ijt'_i}$ over product j in market t'_i. Notice that $\eta_{ijt'_i}$ will be higher when $s_{it} = j$. Moreover, higher values of $p_{jt'_i}$ and lower values of $\hat{\xi}_{jt'_i b}$ will imply larger values of $\eta_{ijt'_i}$ when $s_{ij} = j$ and lower values of $\eta_{ijt'_i}$ when $s_{ij} \neq j$. Finally, markets with more products available will generate larger larger values of $\eta_{ijt'_i}$ when $s_{ij} = j$ and lower values of $\eta_{ijt'_i}$ when $s_{ij} \neq j$.

In the second step, we use the observed variation in $\eta_{ijt'_i}$ to estimate a model that allows for inertia, as well as persistence in the idiosyncratic taste over product j

$$\mathbb{E}_b[u_{ijt}] \quad = \quad -\alpha_b p_{jt} - \hat{\mathbb{E}}_b[w_{jt}|L_{jt}]\phi_b + \gamma\mathbb{1}\{s_{it} = j\} + \hat{\delta}_{jb} + \hat{\xi}_{jtb} + \rho\psi\eta_{ijt'_i} + \psi\epsilon_{ijt} \tag{I.6}$$

We present results in column (5) of Table I.1. We find that once we control for idiosyncratic preferences inferred from the previous purchase, the coefficient on persistence effects still remains positive and significant, but of a smaller magnitude. The control function approach suggests that consumers are willing to pay between \$0.12 and \$0.13 additional dollars per 100 grams to buy the same product as in the previous purchase, 77% less as suggested by the MLE estimates from column (2).

I.2. *Salience effects*

In this subsection we investigate the potential salience effects of food labels in the market of cereal. Salience refers to the situation in which an attribute of an item or environment attracts more attention, and subsequently receives more weight when making decisions. In section 3.2.2, 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 give 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 5(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 3.2.2. We split our sample of labeled products into two groups: products below the median in the calorie concentration distribution (20 products), and products above the median in the calorie 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:

$$\log(q_{jst}) \quad = \quad \beta_t^l \cdot L_j \cdot Low_j^c + \beta_t^h \cdot L_j \cdot High_j^c + \gamma \cdot \log(p_{jst}) + \delta_{js} + \delta_t + \varepsilon_{jst} \qquad \text{(I.7)}$$

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

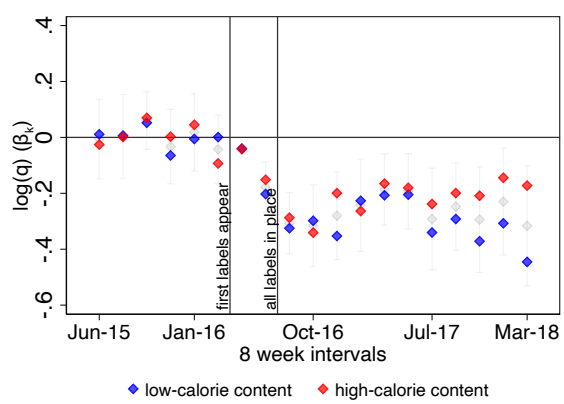


Figure I.1: Changes in equilibrium quantities by calorie concentration

Notes: This figure displays the coefficients from Equation (I.7). Coefficients in blue and red denote β_t^l, β_t^h respectively. The vertical lines delimit the 95% confidence intervals. These regressions are run on the sample of 68 ready-to-eat cereal that show up in the pre and post periods. The sample involves 27 unlabeled products and 41 labeled ones.

Results from Equation (I.7) are shown in Figure I.1. Coefficients in blue and red denote β_t^l and β_t^h estimates respectively. Coefficients in light grey denote β_t coefficients from Equation (1). Products with low calorie concentration (blue dots) and high calorie concentration (red

dots) saw a similar reduction in equilibrium quantities.[5] If anything, high in calorie products seem to experience lower reductions in demand, as opposed to what we would expect under strong salience effects.

I.2.1. *Combination of salience effects and change in beliefs*: The previous model of salience rules out the hypothesis that salience is the main mechanism through which labels affects demand as opposed to information. It does not rule out, however, a model where labels change beliefs about w_{jt} but also consumers' perception over the parameter ϕ_i, the marginal health damage from consuming critical nutrients. In such model, salience effects increase the weight that consumers give to their *expected value* of calorie and sugar content when making decisions. We do not have statistical power to distinguish between this model and the model in the main article where ϕ_i is fixed. However, we can interpret our estimates as capturing both changes in beliefs and changes in perceived ϕ_i. In the counterfactuals, we estimate welfare from the perspective of the social planner, in which the marginal damage from consuming critical nutrients is fixed.

I.3. *Advertising*

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

The data we use consists on 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). From all ads during the pre-policy period, only 0.5% of them displayed a product belonging to the breakfast cereal category. Moreover, 9 products appeared in ad in the pre-policy period and only 6 in the post-policy period. The average number of ads per product in 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

[5] Splitting products according to sugar concentration is less interesting. Because sugar concentration is highly correlated with beliefs about calorie concentration (see Figure C.1), results look similar to Figure 5(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.

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

$$\mathbb{E}_b[u_{ijt}] \quad = \quad -\alpha_b p_{jt} - \mathbb{E}_b[w_{jt}|L_{jt}]\phi_b + \gamma_b A_{jt} + \delta_{jb} + \delta_{T(t)b} + \delta_{S(t)b} + \xi_{jtb} + \epsilon_{ijt} \tag{I.8}$$

where A_{jt} is a measure of advertising intensity for product j in market t, and all other variables follow the model parametrization described in Section 5.1 of the main article.[6] We use three different measures of advertising intensity: i) average daily number of ads per channel, ii) average daily ad minutes per channel, and iii) average daily minutes times rating points per channel. Since we only have two snapshots of advertising intensity, we follow the same strategy used for reformulation and changes in beliefs, and assume all the changes happened at the time of the policy implementation. We present results in Table I.2. In column (1) we fix $\gamma_b = 0$ and recover the parameters from the model estimated in the main article. Columns (2)-(4) present results using each measure of advertising intensity described above.

Table I.2: Robustness to Including Advertising Effects

	(1)	(2)	(3)	(4)
α_l	0.0548***	0.0550***	0.0550***	0.0552***
	(0.0142)	(0.0144)	(0.0144)	(0.0145)
α_h	0.0503***	0.0505***	0.0505***	0.0507***
	(0.0156)	(0.0158)	(0.0158)	(0.0159)
ϕ_l^s	0.0280**	0.0283**	0.0280**	0.0280**
	(0.0109)	(0.0113)	(0.0112)	(0.0109)
ϕ_h^s	0.0257**	0.0265***	0.0261**	0.0257**
	(0.0103)	(0.0102)	(0.0102)	(0.0103)
ϕ_l^c	0.0135***	0.0136***	0.0135***	0.0136***
	(0.0043)	(0.0043)	(0.0043)	(0.0043)
ϕ_h^c	0.0121***	0.0122***	0.0122***	0.0121***
	(0.0038)	(0.0039)	(0.0039)	(0.0038)
γ_l		0.00077	0.00045	0.0014
		(0.0029)	(0.0068)	(0.0025)
γ_h		0.0022	0.0042	0.0033
		(0.0032)	(0.0069)	(0.0024)
Observations	333384	333384	333384	333384

Notes: This table shows the main results from estimating Equation (I.8). Each column uses a different measure of advertising intensity. Column (1) ignores advertising effects. Column (2) uses average daily number of ads per channel for each product. Column (3) uses the average daily ad minutes per channel per product. Column (4) uses average daily minutes times rating points per channel per product. Standard errors clustered at the market level are presented in parenthesis. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

[6] We estimate the model following the same methodology as in Section 5.1, including $A_j \times d_b$ as additional instruments.

In all four columns, coefficient magnitudes are almost identical across specifications. Moreover, the coefficients on γ_b are small in magnitude and not statistically different from zero. Our estimates in column (i) imply that consumers are willing to pay between \$0.014 and \$0.044 extra per 100 grams of cereal for each additional ad shown in every channel, every day. Similarly, column (ii) implies that consumers are willing to pay between \$0.008 and \$0.08 extra for each additional minute of ads shown in every channel, every day. Finally, column (iii) suggests that consumers are willing to pay between \$0.025 and \$0.065 extra per 100 grams of cereal for each additional percentage point of viewers watching an additional minute of ads every day.

Appendix J: Robustness to alternative model specifications

In this appendix we estimate a variation of version of the demand model estimated in Section 5. To simplify estimation, we take $\hat{\mu}$ as given from the main specification in the paper and estimate the rest of the parameters except stated differently. The advantage of doing so is that once we know μ, the rest of the parameters enter linearly into the moment conditions in most of the specifications and estimation becomes significantly faster.

J.1. *Including nutritional content in taste component of the utility function*

An important assumption from our model is that taste is invariant to product reformulation. This assumption is important as it simplifies the estimation of the supply-side of the model. In Appendix G we provide a detailed description of the reformulation process and why we think the assumption is reasonable. In this Section, we use our demand model to corroborate our claims using the data. To do so, we allow taste to vary with product reformulation. In particular, we estimate

$$\mathbb{E}_b[u_{ijt}] \quad = \quad -\alpha_b p_{jt} - \mathbb{E}_b[w_{jt}|L_{jt}]\phi_b + w_{jt}\gamma_b + \delta_{jb} + \delta_{T(t)b} + \delta_{S(t)b} + \xi_{jtb} + \epsilon_{ijt}$$

where $w_{jt}\gamma_b$ captures potential changes in taste due to changes in w_{jt}. Note that because changes due to reformulation and changes in beliefs due to the the labels are not highly correlated, γ_b and ϕ_b are separately identified. We present our results in Table J.1, where the coefficients for γ_b are small in magnitude and not statistically different from zero.

Table J.1: Estimated parameters allowing for changes in taste due to reformulation

α_l	0.05613***	ϕ_l^s	0.02583**	ϕ_l^c	0.01316***	γ_l^s	0.00160	γ_l^c	0.00257
	(0.0149)		(0.0118)		(0.00417)		(0.00865)		(0.00285)
α_h	0.0515***	ϕ_h^s	0.02467**	ϕ_h^c	0.01122***	γ_h^s	-0.00405	γ_h^c	0.00489
	(0.0162)		(0.01152)		(0.00375)		(0.01332)		(0.00374)
ρ	0.9915***								
	(0.0049)								

Notes: Nutritional content is measured in grams of sugar and kilocalories per each gram of cereal respectively. Prices are measured in dollars per 100gr of cereal. Standard errors are clustered at the market level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

J.2. *Including additional unobserved heterogeneity in consumer preferences*

In this section we add random coefficients to the preferences over health by using the following specification:

$$\mathbb{E}_b[u_{ijt}] \quad = \quad -\alpha_b p_{jt} - \mathbb{E}_b[w_{jt}|L_{jt}]\phi_i + \delta_{jb} + \delta_{T(t)b} + \delta_{S(t)b} + \xi_{jtb} + \epsilon_{ijt}$$

where $\phi_i = \phi_b + \sigma_\phi v_i$ and v_i follows a bi-normal distribution with mean zero and variance $\Sigma_v = \begin{bmatrix} \sigma^s & 0 \\ 0 & \sigma^c \end{bmatrix}$. We present results in Table J.2.

Table J.2: Estimated parameters with additional unobserved heterogeneity in consumer preferences

α_l	0.0557***	ϕ_l^s	0.05814***	ϕ_l^c	0.01259***
	(0.0059)		(0.01068)		(0.00278)
α_h	0.0512***	ϕ_h^s	0.05765***	ϕ_h^c	0.01162***
	(0.0067)		(0.00912)		(0.00262)
ρ	0.9917***	σ^s	0.0347	σ^c	0.0254
	(0.0043)		(0.0572)		(0.0174)

Notes: Nutritional content is measured in grams of sugar and kilocalories per each gram of cereal respectively. Prices are measured in dollars per 100gr of cereal. Standard errors are clustered at the market level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

J.3. *Testing for alternative intra-nest correlation structure*

In section we test for alternative nest specifications. The nest structure of the logit-error plays an important role in our model to guide the substitution patterns between different products. We estimate a generalized nested logit model with two layers of nest. The first layer has two nests. One that contains all inside goods, and one that contains the outside good. On a second layer, we impose that all products that belong to a given sub-category to belong to the same nest. Subcategories are given by $r_j \in \{chocolate, flakes, granola, oats, sugary\}$. We denote by ρ the intra-nest correlation of the first layer of nests, and ρ_r the intra-nest correlation of the second layer of nests. To identify ρ_r, we use the number of products for a given nest available in the market as an additional instrument.

Results are presented in Table J.3. We find that when including the two layers of nests together, the first one shows up to be important and the second one not. Omitting the first layer and only including the second one leads to a positive intra-nest correlation in the second layer of nests. We argue it such positive correlation is mostly driven by differential substitution patterns to the outside good.

Table J.3: Estimated parameters allowing for an alternative intra-nest correlation structure

α_l	0.0521***	ϕ_l^s	0.02847**	ϕ_l^c	0.01218***
	(0.0137)		(0.01121)		(0.00344)
α_h	0.0477***	ϕ_h^s	0.02625**	ϕ_h^c	0.01080***
	(0.0150)		(0.01066)		(0.00303)
ρ	0.9955***	ρ_r	-0.0025		
	(0.0042)		(0.0062)		

Notes: Nutritional content is measured in grams of sugar and kilocalories per each gram of cereal respectively. Prices are measured in dollars per 100gr of cereal. Standard errors are clustered at the market level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

J.4. *Robustness to alternative fixed effects specification*

In section we test for a more flexible parametrization on δ_{ijt}. In particular, we estimate a model in which

$$\delta_{ijt} = \delta_{jS(t)b} + \delta_{T(t)b} + \xi_{jtb} + \epsilon_{ijt} \tag{J.1}$$

where $\delta_{jS(t)b}$ are product-store fixed effects specific to each consumer type, and $\delta_{T(t)b}$, ξ_{jtb} and ϵ_{ijt} are defined as in the main article. Results are presented in Table J.4.

Table J.4: Estimated parameters allowing for flexible fixed effects

α_l	0.0627***	ϕ_l^s	0.02273*	ϕ_l^c	0.01658***
	(0.0149)		(0.01174)		(0.00451)
α_h	0.0542***	ϕ_h^s	0.01935*	ϕ_h^c	0.01682***
	(0.0166)		(0.01105)		(0.00462)
ρ	0.9906***				
	(0.0037)				

Notes: Nutritional content is measured in grams of sugar and kilocalories per each gram of cereal respectively. Prices are measured in dollars per 100gr of cereal. Standard errors are clustered at the market level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

J.5. *Robustness to naive Bayesian assumption*

In Section 5, we assume that consumers form their beliefs using the observed labels (or lack thereof) and applying Bayes rule, not taking into account strategic reformulation by firms. We make this assumption for several reasons. First, interviews with consumers in Chile

suggest that they did not realize that products might be bunching at the regulatory threshold. Second, this assumption simplifies the calculation of consumers' posteriors and the solution of the market equilibrium. Here, we make the opposite extreme assumption where consumers overestimate the amount of bunching when updating beliefs. In particular, we assume that posteriors are given by a weighted average between the expected value of w_{jt} conditional on w_{jt} being lower than the threshold and the policy threshold, where the weights are given by the prior probability that consumers assign to the product to be on each side of the threshold. That is, if a product does not receive a label, posterior expected value over w_{jt} is given by

$$\mathbb{E}[w_{jt}|L_{jt} = no] \quad = \quad Pr(w_{jt} \leq \bar{w})\, \mathbb{E}[w_{jt}|w_{jt} \leq \bar{w}] + (1 - Pr(w_{jt} \leq \bar{w}))\bar{w}$$

where $\bar{w}$ represents the policy threshold. Note that in this case, consumers are over-estimating the amount of bunching in the economy. We present results in Table J.5. We find coefficients that are comparable to the ones estimated in our baseline specification.

Table J.5: Estimated parameters allowing for consumers that internalize bunching

α_l	0.0549^{***}	ϕ_l^s	0.03357^{***}	ϕ_l^c	0.01393^{***}
	(0.0141)		(0.01174)		(0.00431)
α_h	0.0504^{***}	ϕ_h^s	0.03255^{***}	ϕ_h^c	0.01245^{***}
	(0.0155)		(0.01130)		(0.00384)
ρ	0.9918^{***}				
	(0.0046)				

Notes: Nutritional content is measured in grams of sugar and kilocalories per each gram of cereal respectively. Prices are measured in dollars per 100gr of cereal. Standard errors are clustered at the market level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

J.6. *Robustness to different second order moments in beliefs*

In this Section we show that our estimates are robust to different values for the second moment of beliefs Σ_{jb}. Let $\hat{\Sigma}_{jb}$ be the values obtained from the beliefs survey as explained in Appendix C. We present our results in Table J.6. In Panel A, we estimate a model in which the second moment of beliefs are homogenous across products using the average value of the variance of beliefs recovered from the survey over all products. Results are consistent with the ones presented in the main article. In Panels B and C, we estimate the model after arbitrarily decreasing and increasing the variance of beliefs over nutritional content of each product in 50% respectively. We find that smaller values of Σ_{jb} tend to deliver higher preference parameters over nutritional content.

Table J.6: Estimated parameters scaling the value of the second moment of beliefs

Panel A: $\Sigma_{jb} = \frac{1}{J}\sum_{j=1}^{J}\hat{\Sigma}_{jb}$							
α_l	0.0547^{***}	ϕ_l^s	0.02729^{**}	ϕ_l^c	0.01355^{***}	ρ	0.9919^{***}
	(0.0141)		(0.01099)		(0.00432)		(0.0046)
α_h	0.0502^{***}	ϕ_h^s	0.02459^{**}	ϕ_h^c	0.01215^{***}		
	(0.0155)		(0.01028)		(0.00382)		
Panel B: $\Sigma_{jb} = 0.5\hat{\Sigma}_{jb}$							
α_l	0.0542^{***}	ϕ_l^s	0.03719^{***}	ϕ_l^c	0.01454^{***}	ρ	0.9921^{***}
	(0.0140)		(0.01201)		(0.00452)		(0.0046)
α_h	0.0497^{***}	ϕ_h^s	0.03673^{***}	ϕ_h^c	0.01271^{***}		
	(0.0154)		(0.01322)		(0.00408)		
Panel C: $\Sigma_{jb} = 1.5\hat{\Sigma}_{jb}$							
α_l	0.0551^{***}	ϕ_l^s	0.02031^{**}	ϕ_l^c	0.01202^{***}	ρ	0.9918^{***}
	(0.0143)		(0.00911)		(0.00390)		(0.0047)
α_h	0.0506^{***}	ϕ_h^s	0.01751^{**}	ϕ_h^c	0.01094^{***}		
	(0.0157)		(0.00851)		(0.00341)		

Notes: Nutritional content is measured in grams of sugar and kilocalories per each gram of cereal respectively. Prices are measured in dollars per 100gr of cereal. Standard errors are clustered at the market level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

J.7. *Robustness to using instruments for prices*

A key identification assumption in our model is that prices p_{jt} are not correlated with the structural demand shocks ξ_{jtb} once we control for all fixed effects. This assumption would be violated if Walmart could predict the idiosyncratic demand shock for a given product, at a given store, and during a given period and set prices according to it. Even though it is likely that Walmart set higher prices for overall more popular products, or that it can predict that demand for cereal products is overall lower during summer break, it is hard for them to respond to very specific and high frequency demand shocks at the product-market level. We show that residual prices are not correlated with unobserved demand shocks by running a regression of log-prices against the number of customers (in logs) visiting Walmart in a given market controlling by product, period, and store fixed effects. If Walmart was able to predict demand, we should expect that stores in which more customers are expected to visit in a given period have higher average prices. We get a negative coefficient (-0.005) that is not statistically different from zero (p-value of 0.143).

Additionally, we follow three alternative approaches to estimate our model that rely on instrumental variables. First, we estimate the model using the interaction between sugar prices and pre-policy sugar concentration of products as instrument for prices. Second, we

estimate the model using prices from neighboring stores as instruments for prices. Third, we estimate the model using high frequency products' discounts as instruments for prices. Our baseline results are bounded by these different strategies.

In our first approach, we borrow the identification strategy from Alé-Chilet and Moshary (2020) and use exogenous variation on sugar prices interacted with pre-policy sugar concentration of cereal products to instrument for cereal prices. The idea is that when the price of sugar is high, the cost of sugary products should rise, which should be reflected in higher relative prices for them. We present results from this estimation procedure in Panel A of Table J.7. We find an average price elasticity of -2.1, smaller than in the main article. We think this is explained by the fact that this instrumental variable approach uses lower frequency variation in prices by ignoring short-term store-specific price variation. Since our baseline specification in the main article uses high-frequency variation, it captures a shorter-term elasticity that tends to be larger.

Our second strategy exploits managerial costs and other frictions in Walmart's pricing mechanisms. The identification strategy is similar to the instrumental variable approach used by Hausman (1996), Nevo (2001), and DellaVigna and Gentzkow (2019). The pricing department of Walmart divides its stores into different clusters of supermarkets that face similar competitors. Baseline prices of goods are established at the cluster level, allowing for store-specific deviation from them through promotions and discount. We can build instruments for p_{jt} using the average baseline price of product j in period $T(t)$ in all other stores from the cluster where $S(t)$ belongs to. This approach has the advantage of having instruments that do not depend on the store-specific idiosyncratic pricing strategy through promotions and discounts that can be correlated with ξ_{jt}. Nevertheless, it will not be valid if the demand shocks ξ_{jt} are highly correlated within cluster and baseline prices take them into consideration. We present results in Panel B of Table J.7. We find an average price elasticity of -2.3, smaller than in the main article. Similarly to our first approach, this identification strategy uses lower frequency variation in prices that ignores short-term store-specific price discounts. Since our baseline specification in the main article uses high-frequency variation, it captures a shorter-term elasticity that tends to be larger.

Our third strategy takes an opposite view and exploits product-store specific promotions and discounts as a source of exogenous variation. If baseline prices are set based on predictions of ξ_{jt} at the cluster level but promotions and discounts are not, we can use them as valid instruments. Promotions decisions are the result of a bargain process with the upstream provider and follows some heuristic rules. For instance, if Pepsi and Coca-Cola want to have their products on promotion in a given market, both will send a proposal to the store manager. Because the products are close competitors, Walmart will decide to accept the offer of one of them only. If competition is close enough, we can treat that binary decision as independent

Table J.7: Estimated parameters using instrumental variable approach

Panel A: Sugar price-shifter as instrument							
α_l	0.0421^{***}	ϕ_l^s	0.02412^{**}	ϕ_l^c	0.01394^{***}	ρ	0.9913^{***}
	(0.0102)		(0.01179)		(0.00445)		(0.0048)
α_h	0.0228^{**}	ϕ_h^s	0.01896	ϕ_h^c	0.01253^{***}		
	(0.0092)		(0.01182)		(0.00392)		
Panel B: Walmart price clusters as instruments							
α_l	0.0421^{***}	ϕ_l^s	0.02422^{**}	ϕ_l^c	0.01388^{***}	ρ	0.9914^{***}
	(0.0124)		(0.01100)		(0.00438)		(0.0048)
α_h	0.0296^{***}	ϕ_h^s	0.02054^{**}	ϕ_h^c	0.01247^{***}		
	(0.0111)		(0.01113)		(0.00389)		
Panel C: Discounts as instruments							
α_l	0.0673^{***}	ϕ_l^s	0.03259^{***}	ϕ_l^c	0.01274^{***}	ρ	0.9929^{***}
	(0.0142)		(0.01164)		(0.00421)		(0.0046)
α_h	0.0454^{***}	ϕ_h^s	0.02605^{**}	ϕ_h^c	0.01148^{***}		
	(0.0156)		(0.01048)		(0.00375)		

Notes: Nutritional content is measured in grams of sugar and kilocalories per each gram of cereal respectively. Prices are measured in dollars per 100gr of cereal. Standard errors are clustered at the market level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

from product-specific demand shocks. Store-specific stock policies are other examples where this strategy would be valid. However, if products are non-perishable, this strategy can capture short-run elasticities leading to over-estimated price elasticities. We present results in Panel C of Table J.7. We find an average price elasticity of -4.4, larger than in the main article. This strategy captures a short-run elasticity, driven by consumers increasing their stock of cereal due to the short-run discounts.

Appendix K: Additional details about counterfactual analysis

K.1. *Simulation details*

In Section 6.1, we present several policy counterfactuals. To estimate outcomes under the different counterfactuals we implement 100 Monte Carlo simulations under each of them. The simulation procedure consists on many steps presented below:

1. We assign each product j to the markets they were available in the original dataset.
2. We assign to each product-market their respective value of δ_j, $\delta_{S(t)}$, $\delta_{T(t)}$, ν_j, μ_{jb}, Σ_{jb}, and $\bar{c}_{jt}$ as estimated in Section 5.
3. Within each market, we randomly draw demand shocks ξ_{it} without replacement from the pool of residuals $\hat{\xi}_{jt}$ estimated in Section 5 and assign them to each product.
4. We draw cost parameters λ_j^k from the lognormal distribution with parameters estimated in Section 5 and assign them to each product j.
5. We solve for the market equilibrium under different policy counterfactuals in each of the markets.
6. We calculate the relevant outcomes for each market under each counterfactual.

For the counterfactuals presented in Sections 6.2 to 6.4, we modify step 2. and split it into:

2.1 We split baseline costs $\bar{c}_{jt}$ into a product-specific component and a product-market-specific component $\bar{c}_{jt} = \bar{c}_j + \bar{c}'_{jt}$.

2.2 We assign to each product-market their respective value of $\delta_{S(t)}$, $\delta_{T(t)}$, Σ_{jb}, and $\bar{c}'_{jt}$ as estimated in Section 5.

2.3 We estimate the mean vector and covariance matrix of the joint vector $[\nu_j, \mu_{jl}, \mu_{jh}, \delta_{jl}, \delta_{jh}, \bar{c}_j]$ given by $M = mean([\nu_j, \mu_{jl}, \mu_{jh}, \delta_{jl}, \delta_{jh}, \bar{c}_j])$ and $V = cov([\nu_j, \mu_{jl}, \mu_{jh}, \delta_{jl}, \delta_{jh}, \bar{c}_j])$.

2.4 We draw parameters ν_j, μ_{jb}, δ_{jb} and $\bar{c}_j$ from the normal joint distribution $N(M, V)$ and assign them to each product.

The goal of such modification is to recover smooth outcomes across different thresholds. Having fixed bliss-points ν_j across simulations, for instance, creates discontinuous jumps on the outcomes when the threshold crosses a given bliss point, turning a product from labeled to unlabeled.

For the counterfactuals presented in Section 6.5, we modify step 2.4. For illustration, let's assume we want to modify the correlation between δ_{jh} and ν_j.

2.4.1 We modify the covariance matrix V in the following way:

2.4.1.1 We create a new variable $\delta'_{jh} = \delta_{jh} + k\nu_j$.

2.4.1.2 We normalize δ'_{jh} such that $mean(\delta'_{jh}) = mean(\delta_{jh})$ and $var(\delta'_{jh}) = var(\delta_{jh})$.

2.4.1.3 We calculate $V = cov([\nu_j, \mu_{jl}, \mu_{jh}, \delta_{jl}, \delta'_{jh}, \bar{c}_j])$.

2.4.2 We draw parameters ν_j, μ_{jb}, δ_{jb} and $\bar{c}_j$ from the normal joint distribution $N(M, V)$ and assign them to each product.

K.2. *Perfect information counterfactual*

In the perfect information counterfactual, consumers are informed about the true nutritional content of the products. Therefore, their decision utility is given by

$$\mathbb{E}[u_{ijt}] = u_{ijt} = \delta_{ijt} - \alpha_i p_{jt} - w_{jt}\phi_i$$

The firm's problem is given by

$$\max_{\{p_{jt}, w_{jt}\}_{j \in \mathcal{J}_{ft}}} \sum_{j \in \mathcal{J}_{ft}} (p_{jt} - c_{jt}(w_{jt})) \cdot s_{jt}(\mathbf{p_t}, \mathbf{w_t})$$

and the firm's first order conditions are given by

$$\begin{aligned} c_w(w^*_{jt}) &= -\frac{(\square\Delta^{-1})_{(j,\cdot)}\mathbf{s_t}}{s_{jt}} \\ p^*_{jt} &= c_{jt}(w^*_{jt}) + \Delta^{-1}_{(j,\cdot)}\mathbf{s_t} \end{aligned}$$

where $c_w(\cdot)$ is the derivative of $c(\cdot)$ with respect to w, and the (j,k) elements of $\square$ and Δ are given by

$$\begin{aligned} \square_{(j,k)} &= \begin{cases} \frac{-\partial s_{kt}}{\partial w_{jt}} & \text{if } k \in \mathcal{J}_{ft} \\ 0 & \text{otherwise} \end{cases} \\ \Delta_{(j,k)} &= \begin{cases} \frac{-\partial s_{kt}}{\partial p_{jt}} & \text{if } k \in \mathcal{J}_{ft} \\ 0 & \text{otherwise} \end{cases} \end{aligned}$$

Note that the equilibrium outcome of the perfect information counterfactuals is not equivalent to the social optimum, as there is still imperfect competition.