Equilibrium Effects of Food Labeling Policies[a]

Nano Barahona[†] Cristóbal Otero[⋆] Sebastián Otero[§] Joshua Kim[‡]

March 31, 2021

[Link to Supplementary Material]

Abstract: We study a regulation in Chile that mandates warning labels on products whose sugar or calorie concentration exceeds certain thresholds. We document an overall decrease in sugar and calorie intake of 7-9%. To reveal mechanisms, we focus on breakfast cereal. On the demand side, consumers substitute from labeled to unlabeled products, a pattern that is mostly driven by products which consumers mistakenly believed to be healthy. On the supply side, we find substantial reformulation of products and bunching at the thresholds. We develop and estimate an equilibrium model of demand for food and firms' pricing and nutritional choices. We find that food labels increase consumer welfare by 3.8% of total expenditure, and that these effects are enhanced by firms' responses. We then use the model to study alternative policy designs. Under optimal policy thresholds, food labels and sugar taxes generate similar gains in consumer welfare but food labels benefit the poor relatively more.

Keywords: Food labels, equilibrium effects, misinformation, sugar taxes.
JEL Codes: D12, D22, I12, I18, L11, L81

---

[a]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 nutrition facts 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

[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).

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]

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 nutrition 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 food labels may be particularly informative 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 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,

[4] The Chilean Food Act has gained considerable 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).

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

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.

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 welfare. 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

[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.

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 6.4% 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 welfare 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 is in place, the regulation reduces sugar and calorie intake in the cereal market by 5.8% and 0.3%, respectively, resulting in average gains in consumer welfare equivalent to 3% of total cereal expenditure.[7] The gains in consumer welfare 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- 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 decrease by 0.22% on average and gains in consumer welfare relative to the no intervention counterfactual are 8% larger 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 140% but reduces the benefits from spending fewer dollars by 71%. On one hand, high-in-taste products become healthier due to reformulation. On the other hand, producing them is now more costly, increasing the average price of cereal by 2%. Overall, gains in consumer welfare under this counterfactual are 30% larger than in the absence of supply-side responses.

[7] We calculate average gains in consumer welfare 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.

We then use our model to study optimal policy design. We show that ignoring supply-side effects can lead to substantially different outcomes. Considering only demand-side effects, a social planner who wants to maximize consumer welfare should set a threshold that maximizes the information provided by labels. However, when accounting for supply-side responses, the social planner wants to set a lower threshold to provide stronger incentives for firms to improve the nutritional content of their products. By taking supply-side responses into account, the social planner can reduce sugar intake by an additional 24% and increase consumer welfare gains by 12% 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 welfare 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 welfare, 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 Gruber, 2011; Abaluck, 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 (Wisdom et al., 2010; Bollinger et al., 2011; Finkelstein et al., 2011), and FoPL regulations (Kiesel and Villas-Boas, 2013; Zhu et al., 2015; Allais 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

[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.

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 focuses on a different policy instrument and shows that it can be an effective tool to improve diet quality and combat obesity.

The remainder of 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. We include the Online Appendix at the end of the document and report on additional analyses in a separate Supplementary Material available at https://hbaraho.github.io/papers/foodlabels_supMat.pdf.

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

[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 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.

liquid.[11]

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: 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.

[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 nutrition 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.

[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.

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 nutrition 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 additional description of the fieldwork in Supplementary Material II.1.

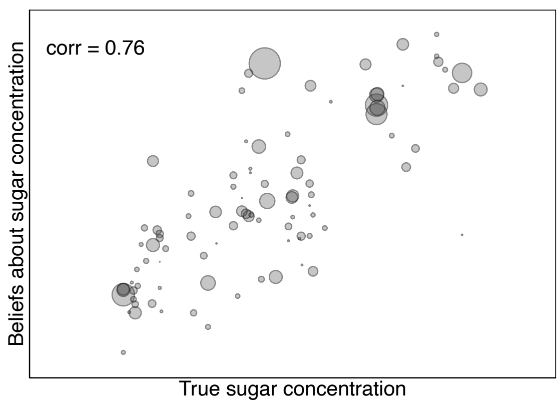
USDA: For products sold without nutrition facts tables, such as fresh produce or meat, we rely on FoodData Central data that is publicly available from the USDA. We use this data to complete missing data for categories of food other than cereal in our aggregate analysis in Section 3.1. We provide details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

[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.

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]



(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.

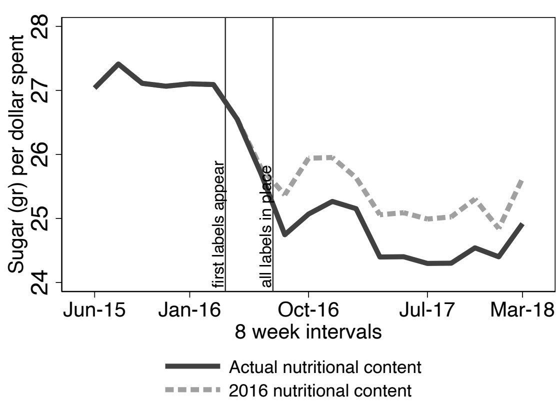
3. Descriptive evidence

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.

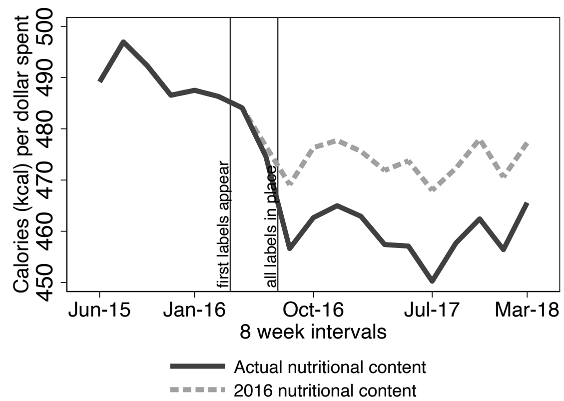
[16]In Supplementary Material III, we provide figures illustrating these correlations. We also show that beliefs are highly correlated between respondents of different socioeconomic status groups and age, and summarize the results for soft-drinks products.

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.



(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 Supplementary Material I, Figure I.1, we present similar figures dividing by volume of food purchased instead of by dollars spent.

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. This reduction can be decomposed into two parts. First, con-

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

sumers 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 Supplementary Material IV, 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 Supplementary Material V and show that our findings are not unique to the breakfast cereal market.

[18] We show this to be the case with our beliefs survey in Supplementary Material III.

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 A.1 from the online Appendix A 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 consecutive calendar weeks) and estimate the following regression:

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

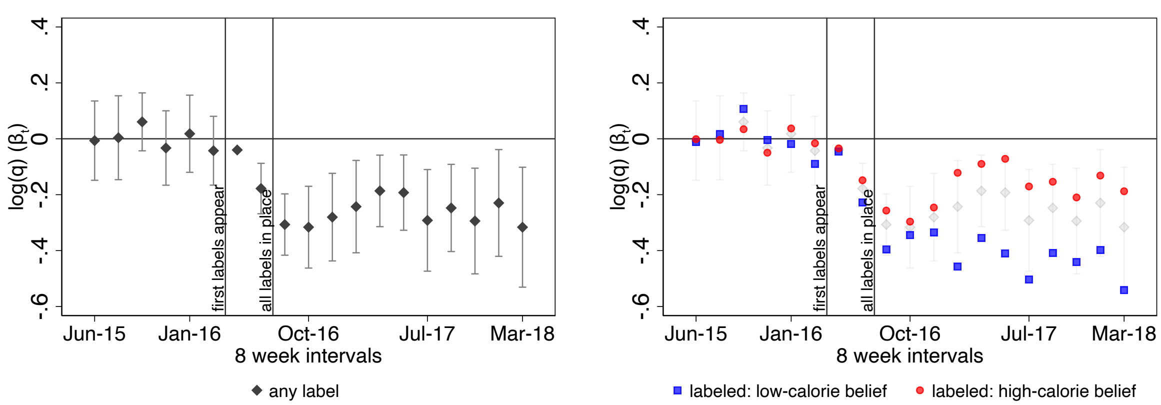
where q_{jst} denotes the grams of product j sold in store s in period t, p_{jst} refers to the product's price per 100 grams of cereal, and L_j is an indicator variable that takes the value of one if the product has one or more labels.[19] Finally, δ_{js} refers to product-store fixed-effects and δ_t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

[19] In Supplementary Material I, Figure I.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.

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 4(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 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 4: 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:

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

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

Results from Equation (2) are shown in Figure 4(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 5(a) plots the distribution of calorie concentration in 2016 for products in our

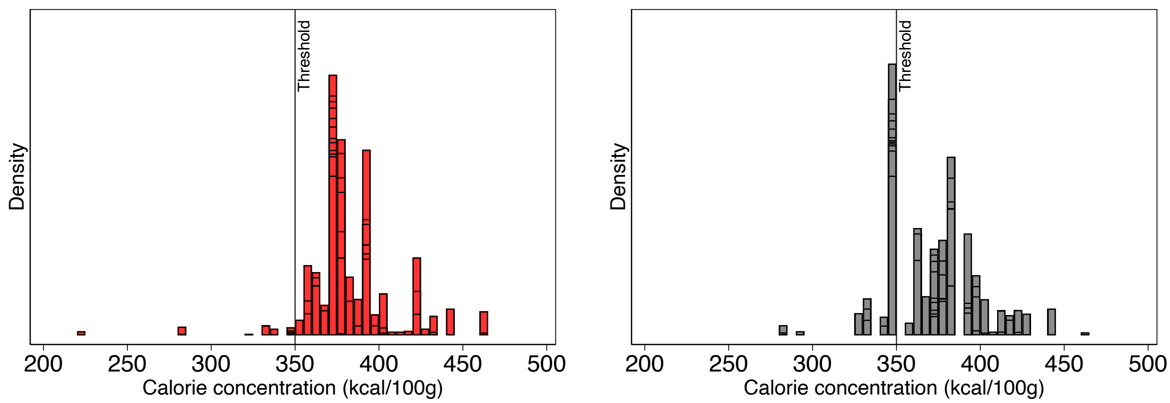
[20] The initial drop in high-calorie belief products can be explained by *novelty effects*, due to which consumers avoided all labeled products in response to an increased interest in the new regulation.

[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.

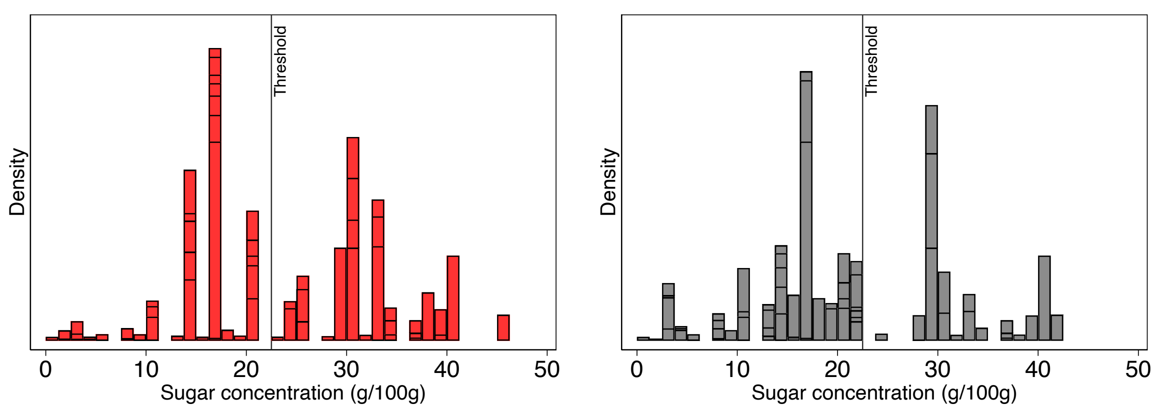
[23] There are two other potential mechanisms that can explain these findings: (i) The composition of consumers that purchase low- and high-calorie belief products might be different, and different consumers may have different policy responses. We reject this possibility in Supplementary Material VI.1. (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.

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 5(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.



(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 5: 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 Supplementary Material I, Figure I.4. In Supplementary Material I, Figure I.5, we present complementary information regarding the movement of products in the nutritional space.

We observe a similar pattern when we look at sugar concentration in Figures 5(c) and 5(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.

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 6. 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]

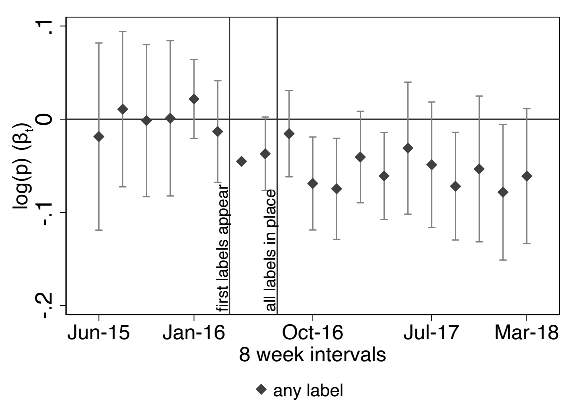


Figure 6: Event study for cereal prices

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.

[24]In Supplementary Material I, Figure I.6, we show that results hold when we drop reformulated 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 welfare 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 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).

[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.

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:

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

where $\mathbb{E}_{\pi_{ji}}$ denotes the expectation operator over prior beliefs π_{ji}, and $L_{jt} \in \{\text{pre-policy, no, yes}\}$ 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:

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

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, 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

[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.

[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.

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. For example, after the FoPL policy was introduced, firms in the breakfast cereal market substituted sugar for artificial alternatives such as sucralose and polyols.[29] This reformulation results in a more expensive product, captured in our model by the functional form of $c_{jt}(w_{jt})$.[30]

The firm's profit maximization problem is given by:

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

where s_{jt} is the market share of product j in market t, that depends on the vector of all

[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 Supplementary Material VII). 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] See Supplementary Material VII for further discussion on product reformulation.

[30] 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.

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.[31] 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 5.

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 the online Appendix B, we discuss additional theoretical results implied by the model as well as its potential limitations.

[31]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.

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 $b \in \{l, h\}$.[32] 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 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.[33]

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

[32]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 Supplementary Material VI.2.

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

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.[34]

(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.[35] 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 second moments of beliefs, Σ_{jb}.[36] We provide further details on the consumer beliefs survey and the estimation of Σ_{jb} in Supplementary Material III.

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

$$\log(s_{jtb}) - \log(s_{0tb}) = -\alpha_b p_{jt} - \mathbb{E}_b[w_{jt}|L_{jt}]'\phi_b + \rho \log(s_{j|g,tb}) + \delta_{jb} + \delta_{T(t)b} + \delta_{S(t)b} + \xi_{jtb} \quad (15)$$

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,

[34] 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 Supplementary Material X.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.

[35] 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.

[36] 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 Supplementary Material X.6, we show that our relevant elasticities are robust to different choices of Σ_{jb}.

and all the fixed effects.[37]

5.1.2. *Identification and estimation*: Identification in our model relies on the rich panel structure of our data. By including 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:

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

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. We estimate the model using the generalized method of moments (GMM). We provide further details about the identification and estimation of the demand part of the model in the online Appendix C.

5.1.3. *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 36% in the pre-policy period. These results are similar to those of Nevo (2001), who estimate demand for cereal in the U.S. 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).

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).

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

Table 2: Estimated demand parameters

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

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. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

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 Supplementary Material IV, where we show there is little evidence of between-category substitution.

We describe the demand model fit in the online Appendix D.1.

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:

$$c_{jt}(w) = \bar{c}_{jt} + (w - \nu_j)'\Lambda_j(w - \nu_j) \tag{16}$$

where $\Lambda_j = \begin{bmatrix} \lambda_j^c & 0 \\ 0 & \lambda_j^s \end{bmatrix}$ with $\lambda_j^n > 0$ for $n \in \{s, c\}$ and all products j. We assume that λ_j^n is drawn from a lognormal distribution with parameters $(\mu_\lambda^n, \sigma_\lambda^n)$. 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.[38]

[38] 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

5.2.2. *Identification and estimation*: We can recover $c_{jt}(w^*_{jt})$ and ν_j from the firm's first order conditions (Equations (11) and (12)).[39] We then estimate μ^n_λ and σ^n_λ 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.[40] We then ask, for each product, what would be the value of λ^n_j that would make firm $f(j)$ indifferent between choosing the bliss point level ν^n_j or having product j bunching at the threshold, keeping all other products' nutritional content decisions fixed.[41] We denote the indifference value by $\tilde{\lambda}^n_j$. If, in the data, we observe that product j is not bunching in nutrient n, we can infer that $\lambda^n_j > \tilde{\lambda}^n_j$, otherwise, $\lambda^n_j \leq \tilde{\lambda}^n_j$.

We estimate $(\mu^n_\lambda, \sigma^n_\lambda)$ for $n \in \{s, c\}$ using a maximum likelihood estimator that solves:

$$\max_{(\mu^n_\lambda, \sigma^n_\lambda)} \sum_n \sum_j \left[B^n_j \log\left(Pr(\lambda^n_j \leq \tilde{\lambda}^n_j) \right) + (1 - B^n_j) \log\left(Pr(\lambda^n_j > \tilde{\lambda}^n_j) \right) \right]$$

where B^n_j is a dummy variable indicating whether product j is bunching in nutrient n. Once we estimate $(\mu^n_\lambda, \sigma^n_\lambda)$, we calculate $\bar{c}_{jt}$ by solving:

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

5.2.3. *Results*: Our estimated supply parameters are presented in Table 3. To interpret these parameters, we calculate $\mathbb{E}[\lambda^n_j | B^n_j = 1]$, the expected value of λ^n_j conditional on product j bunching in nutrient n. We find an average value of $0.1864 \frac{¢}{(gr/100gr)^2}$ in the case of sugar and of $0.0289 \frac{¢}{(kcal/100gr)^2}$ 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 24.9 kcal/100gr. Putting everything together, our model finds that the average expected increase in marginal cost for products bunching in any nutrient is 4¢ per 100gr, equivalent to 6.4% of the average price of cereal.

We describe the supply model fit in the online Appendix D.2.

among products that reformulated to cross the policy threshold is 0.08.

[39] 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.

[40] 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.

[41] 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^n_j that makes firm $f(j)$ indifferent between the two equilibria.

Table 3: Estimated supply parameters

μ_λ^s	-1.335***	σ_λ^s	1.377***	μ_λ^c	1.370***	σ_λ^c	1.495***
	(0.369)		(0.344)		(0.166)		(0.274)

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

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 Supplementary Material XI.

6.1. *Equilibrium effects of food labels*

We estimate the effects of the Chilean Food Act on consumer choices, firms' production and pricing decisions, nutritional intake, and consumer welfare. To disentangle the roles of demand and supply in changes in nutritional intake and consumer welfare, we run four counterfactuals, summarized in Table 4. The benchmark counterfactual, denoted by (0), *no intervention*, corresponds to the case where no policy is in 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 this counterfactual by (1), *demand only*. We then compute counterfactual (2), *price response*, where in addition to receiving labels, we allow suppliers to optimally choose prices while keeping nutritional content constant. We use counterfactual (2) to measure additional changes in consumer welfare driven by competition and product differentiation, which can either decrease or increase prices. The differences in consumer welfare between (1) and (2) are thus ambiguous. Finally, we compute counterfactual (3), *equilibrium*, in which we also allow firms to change the nutritional content of their products. This corresponds to the equilibrium model presented in Section 4. The expected change in consumer welfare 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 under counterfactual (3) increases or decreases consumer 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.[42] To estimate welfare and consumer welfare 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 welfare in situations where consumers' ex-ante expected utility differs from that which they actually experience when consuming their chosen alternative.

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

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

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.

We denote $\Delta CW^t(x) = CW^t(x) - CW^t(0)$ as the average change in consumer welfare between counterfactuals (x) and (0) in market t. We can then decompose the change in

[42] 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.

consumer welfare into what we call substitution- and supply-effects:

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

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 otherwise stated, 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 7.

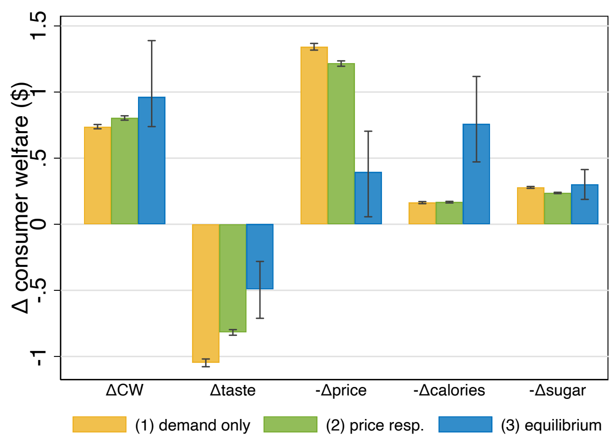


Figure 7: Changes in consumer welfare under different counterfactuals

Notes: The first three bars of the figure show the change in consumer welfare from counterfactual (0) to counterfactuals (1), (2), and (3), respectively. Bars 4-15 decompose these changes into changes in taste/experience of consuming cereal, changes in price paid, changes in calorie intake, and changes in sugar intake. Each bar is normalized to show the contribution of each dimension to consumer welfare in dollars. For example, a positive value for the contribution of calorie intake means that consumers are consuming lower quantities of calories under that counterfactual. We present confidence intervals 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 welfare by \$0.74 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 products high in critical nutrients to those low in critical nutrients. Since in the breakfast cereal market, calorie and sugar content are positively 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). Under this counterfactual, we find that prices of unlabeled products go up while prices of labeled products go down. Overall, prices decrease by 0.22% on average and gains in consumer welfare relative to counterfactual (0) are $0.80 a year per capita (8% larger than under counterfactual (1)).

Under counterfactual (3), firms not only choose prices, but also the nutritional content of their products. We find large gains in consumer welfare from reducing calorie intake, mostly driven by products becoming healthier due to reformulation.[43] Gains in consumer welfare due to lower intake of critical nutrients are 140% larger than under counterfactual (1). However, reformulation increases production costs, which leads to higher prices. The net effect is an average gain in consumer welfare of $0.96 a year under counterfactual (3), 30% larger than under counterfactual (1).[44]

On the firm side, average yearly profits per capita decrease by $0.08, with substantial heterogeneity across firms. While some firms increased their profits by around 20%, others lost more than 50% (see Supplementary Material I, Figure I.8). Who wins and who loses is closely related to how labels shift consumer beliefs. Firms with products that were believed to be healthy but ended up labeled experience the highest losses. This may explain why some firms opposed the Chilean Food Act so strongly when it was first implemented.

Finally, we consider an additional counterfactual in which consumers are perfectly informed about the nutritional content of products.[45] This exercise informs us about the total welfare losses due to lack of information in the cereal market, and allows us to assess how well food labels approximate the best-case scenario of perfect information. We find that the food labeling policy achieves 32% of the consumer welfare gains that would be obtained under the perfect information counterfactual (see Supplementary Material I, Figure I.9).[46]

[43]Changes in consumer welfare from reducing sugar intake are smaller. On one hand, firms reformulate products to have a lower concentration of sugar. On the other hand, more products are unlabeled in counterfactual (3), meaning that the average sugar concentration among unlabeled products is higher. The latter effect offsets the potential benefits of the former effect.

[44]We present results decomposing the gains in consumer welfare between substitution and supply effects in Supplementary Material I, Figure I.7.

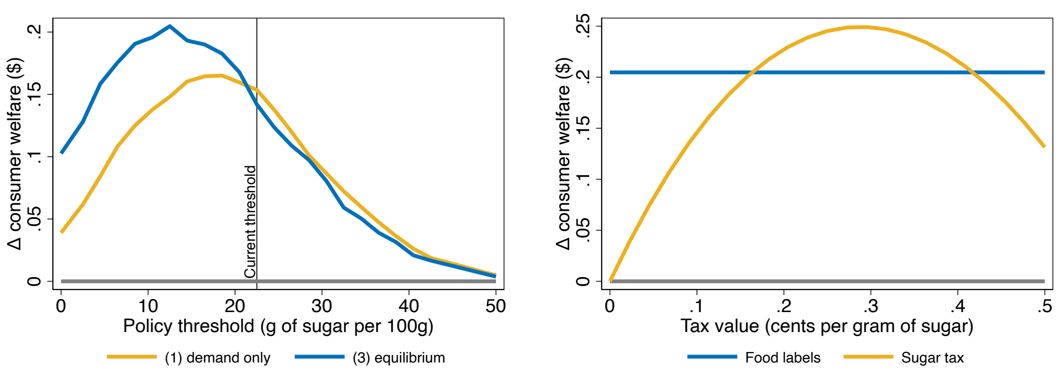
[45]This counterfactual also takes into account demand and supply forces driven by fully informed consumers. Additional model details are presented in Supplementary Material XI.2

[46]This exercise informs us about the welfare losses incurred by consumers from not acquiring the information from the nutrition facts tables on 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.

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 welfare vary under different regulatory thresholds. Intuitively, in the absence of supply-side effects, thresholds should be set such that labels' informativeness is maximized. When supply-side responses are considered, policy makers can choose a different regulatory threshold that induces larger reductions in critical nutrients. To clarify the analysis, we simplify our model to only allow misinformation regarding sugar content.[47]

We focus our analysis on counterfactuals (1), demand only responses; and (3), the equilibrium model. Figure 8(a) shows the gains in consumer welfare under counterfactuals (1) and (3) for different policy thresholds. A naive policymaker who seeks to maximize consumer welfare but ignores equilibrium effects would set the policy threshold at 18.5g/100g, the value at which consumer welfare is maximized under counterfactual (1). Consumer welfare under counterfactual (3), however, is maximized at 12.5g/100g, at which point it is 12% larger than under the naive threshold.[48]



(a) Food labels

(b) Sugar taxes

Figure 8: Changes in consumer welfare under food labels and sugar taxes

Notes: The figure plots average change in consumer welfare under counterfactuals (1) and (3) relative to counterfactual (0). Panel (a) shows the gains in consumer welfare under a food labeling policy at different regulatory thresholds, and panel (b) shows the gains in consumer welfare under under different tax values.

As seen in Figure A.2 of the online Appendix, tighter thresholds are quite effective at reducing sugar intake under the equilibrium model. Decreases in sugar intake increase

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

[48]It is not always the case that the threshold that maximizes consumer welfare 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.

consumer welfare by up to \$0.38 when the threshold is set at 4g/100g. 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 welfare.[49] On the other hand, equilibrium prices are higher due to reformulation. At the same threshold of 4g/100g, increases in prices decrease consumer welfare by \$0.2. 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).[50] Most sugar taxes are structured as a per-ounce tax on any product with added sugar. However, Allcott et al. (2019b) recommend using tax designs that depend on the amount of sugar instead of the amount of product, to encourage consumers to switch to lower-sugar products, and producers to reduce sugar content. We follow this tax structure 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, as sales taxes are not observed by consumers in Chile. We use ψ to denote the marginal value of public funds. To calculate consumer welfare, we distribute the tax money to consumers through a lump sum transfer (i.e. $\psi = 1$).

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

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

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, ν_j, and reduce the nutritional content of their

[49] We show changes in consumer welfare for $\lambda = 1.5$ in Supplementary Material I, Figure I.10.

[50] The main focus of these taxes is on sugar-sweetened beverages, with some cases of implementation among solid food products in some countries.

products to pay lower taxes. Moreover, the price equation has an additional term given by the tax, which is proportional to the sugar content, and gets passed on to consumers through higher prices.

In Figure 8(b), we present gains in consumer welfare at different tax values. The optimal sugar tax (i.e. the tax that maximizes consumer welfare) is set at 0.27¢ per gram of sugar. This is not far from the value of sugar taxes implemented in some American cities.[51] Gains in consumer welfare with optimal sugar taxes are 12.5% larger than under food labels at the optimal policy threshold.

Figure A.3 of the online Appendix shows the change in sugar intake and dollars spent induced by the policy. Taxes turn out to be more effective at reducing sugar intake than food labels. However, they do this at a greater direct financial cost to consumers. Under the optimal tax level, consumers spend 2.4 additional dollars a year in taxes, equivalent to 7% of the total expenditure on cereal. Because taxes collected are relatively high, our results are sensitive to the choice of ψ, the marginal value of public funds.[52]

Note that, in contrast to food labels, sugar taxes are granular instruments, which are levied more heavily on products with higher levels of sugar. This is important for two reasons. First, sugar taxes have the potential to incentivize firms to reformulate all 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 misinformation analyzed in this

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

[52] In Supplementary Material I, Figure I.10 we set $\psi = 0.95$. Gains in consumer welfare under optimal taxes become 43% lower than under food labels at the optimal policy threshold.

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 variety of policies targeted at adults in the United States have marginal values of public funds that range from $\psi = 0.7$ to $\psi = 1.1$.[53]

In Figure 9, 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 regarding w_{jt}. Taxes, however, impose a large burden on consumers who end up spending up to 7% more on cereal. If the marginal value of public funds ψ is small, the resources collected through taxes will not contribute much to the total welfare. The smaller the value of ψ, the less effective taxes will be.

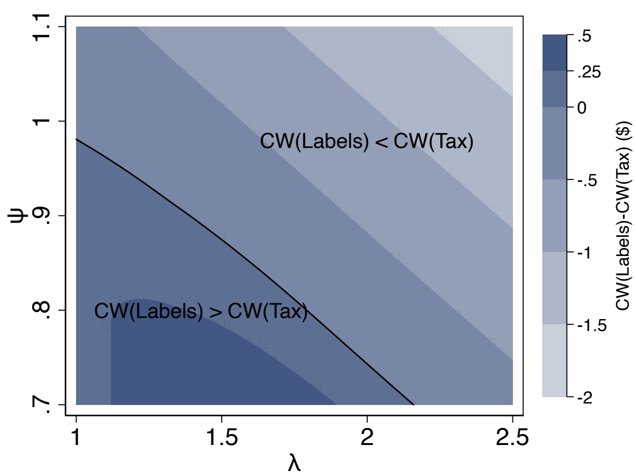


Figure 9: Differences in consumer welfare under different values of λ and ψ

Notes: This figure shows a contour plot that represents the difference in gains in consumer welfare between a food labeling policy and sugar taxes as a function of λ, the parameter that accounts for additional market imperfections, and ψ, the marginal value of public funds. For each value of λ and ψ, we choose policy thresholds (for labels) and tax values that maximize consumer welfare. In the bottom-left zone, food labels are more effective than taxes at increasing consumer welfare. In the top-right zone taxes are more effective than food labels.

[53] 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 reach up to $\psi = 43.6$ in the case of the Perry Preschool project, for example. For these values, sugar taxes become strictly better than food labels.

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 this 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 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, food labels will only affect the decisions of uninformed individuals and not those of consumers who are informed and were already making optimal choices ex-ante, even when the instrument is not itself targeted. 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 Supplementary Material I, Figure I.12, and show that, in this simple model, sugar taxes are 50% less efficient when they cannot 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 determining the incidence of each policy.

The first parameter is the extent to which low-SES consumers are more or less inclined than high-SES consumers to prefer products that are high in sugar. While food labels improve consumer welfare by providing information about the healthiness of products, taxes correct consumer behavior by inflating the prices of products that are high in sugar. If low-SES consumers prefer high-in-sugar products more than high-SES consumers do, then they will be charged disproportionately higher taxes. Depending how the tax revenue is spent by the government, sugar taxes can benefit high-SES consumers relatively more. In the United States, for example, consumers with household incomes below $10,000 purchase 25% more grams of added sugar per calorie than do households with incomes above $100,000 (Allcott et al., 2019).[54] Sugar taxes are therefore more likely to be regressive than food labels.

[54] Allcott et al. (2019a) also document that households in the U.S. with annual incomes below $10,000 consume twice as many sugar-sweetened drinks as households with incomes 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 Supplementary Material VI.2, Table VI.1).

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 uninformed population. In the absence of equilibrium effects, food labels mainly affect the behavior of uninformed consumers, while taxes distort the 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 by low- and high-SES consumers in the absence of government regulation. A value of 1.2, for example, means that low-SES customers consume 20% more sugar for every dollar spent than do high-SES customers. In our model, we vary the sugar-income gradient by differentially changing the relationship between preferences over products' taste, 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.[55]

Figure A.4 from the online Appendix A shows the main results. Panel (a) shows the average gains in consumer welfare for low- and high-SES consumers from moving from the *no intervention* counterfactual, (0), to the *equilibrium* counterfactual, (3), under the policy threshold that maximizes total consumer welfare for different values of the sugar-income gradient. We find that gains in consumer welfare are similar for the two groups and stable across different values of the sugar-income gradient. Panel (b) shows the gains in consumer welfare from moving from the *no intervention* counterfactual, (0), to the *sugar tax* counterfactual under the tax level that maximizes total consumer welfare for different values of the sugar-income gradient. We find that gains in consumer welfare 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 inequalities.

[55]From the estimation results in 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 Supplementary Material XI.

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.[56] In our model, we vary the misinformation-income gradient by differentially changing the relationship between beliefs over products' nutritional contents, 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.[57]

Figure A.5 from the online Appendix A shows the main results of this exercise. Panel (a) shows the average gains in consumer welfare for low- and high-SES consumers from moving from the *no intervention* counterfactual, (0), to the *equilibrium* counterfactual, (3), under the policy threshold that maximizes total consumer welfare for different values of the misinformation-income gradient. Intuitively, gains in consumer welfare are larger for low-SES individuals when they are relatively less informed about the nutritional content of products pre-policy. Gains in consumer welfare for high-SES individuals, on the other hand, is constant across specifications. Panel (b) shows the gains in consumer welfare from moving from the *no intervention* counterfactual, (0), to the *sugar tax* counterfactual under the tax level that maximizes total consumer welfare for different values of the misinformation-income gradient. Unlike in the case of food labels, gains in consumer welfare 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, which disproportionally benefits high-SES individuals through redistribution.

7. Policy discussion: Beyond cereal

So far, we have 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 may 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

[56] 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.

[57] From the estimation results in 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 Supplementary Material XI.

that are perceived to be healthy but are 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 soft drinks category, for example, consumer beliefs about sugar concentration are relatively accurate (see Supplementary Material III, Figure III.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 in equilibrium quantities sold between labeled and unlabeled products is half that for products in the breakfast cereal category (see Supplementary Material V).

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 more incentive 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 Supplementary Material V, 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 product taste, almost all products exhibit bunching at the regulatory 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 product 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 for categories where 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 across all categories. 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., the United Kingdom's traffic light labeling system). 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 at 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 suggests, 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 contents, 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 higher taxes on categories in which non-informational biases are larger, and lower taxes in categories in which the sugar-income gradient is larger.[58]

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 welfare. 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

[58] In Supplementary Material I, Figure I.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 welfare that are 30% larger relative to using each instrument by itself.

the products' true nutritional content, allowing them to make better-informed purchasing decisions. In the absence of supply-side responses, labels increase average consumer welfare by \$0.74 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 140% and increase gains in consumer welfare by 30%.

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. (2011). What would we eat if we knew more: The implications of a large-scale change in nutrition labeling. *Massachusetts Institute of Technology Working Paper*.

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*.

Allais, O., F. Etilé, and S. Lecocq (2015). Mandatory labels, taxes and market forces: An empirical evaluation of fat policies. *Journal of Health Economics 43*, 27–44.

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.

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.

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.

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.

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 suboptimal 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.

Online Appendix for:
Equilibrium Effects of Food Labeling Policies

Nano Barahona   Cristóbal Otero   Sebastián Otero   Joshua Kim

March 31, 2021

Appendix A: Additional Figures

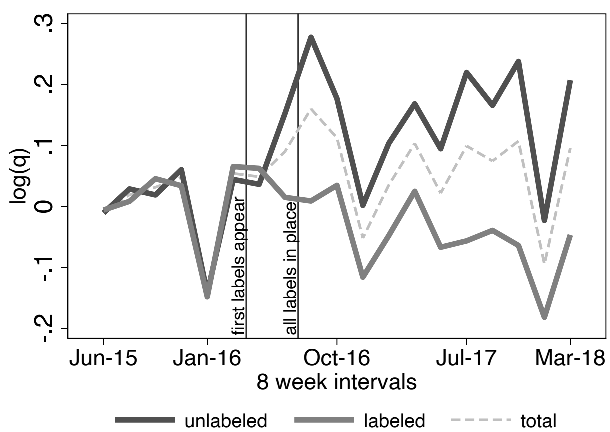
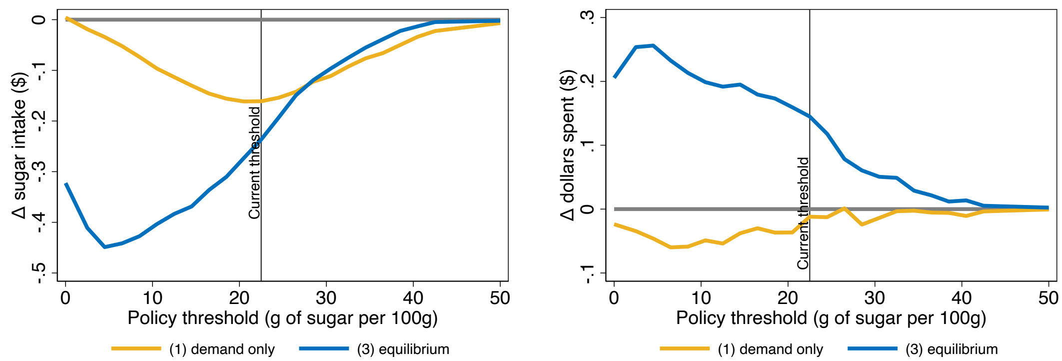


Figure A.1: Log-quantities of labeled and unlabeled ready-to-eat-cereal

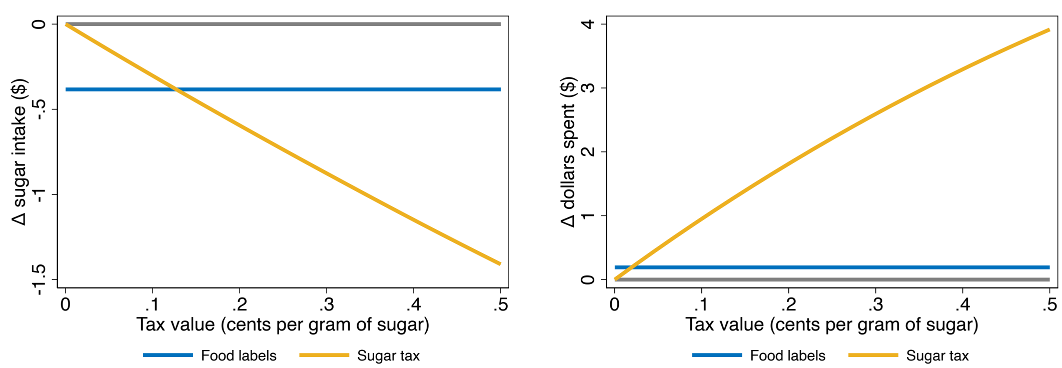
Notes: This figure compares the normalized log-quantities of labeled and unlabeled products sold over time. One observation is the log total grams of cereal purchased across labeled and unlabeled products over eight consecutive weeks. The y-axis is normalized such that the average value for the two groups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



(a) Sugar intake (b) Dollars spent

Figure A.2: Changes in sugar intake and dollars spent under different policy thresholds

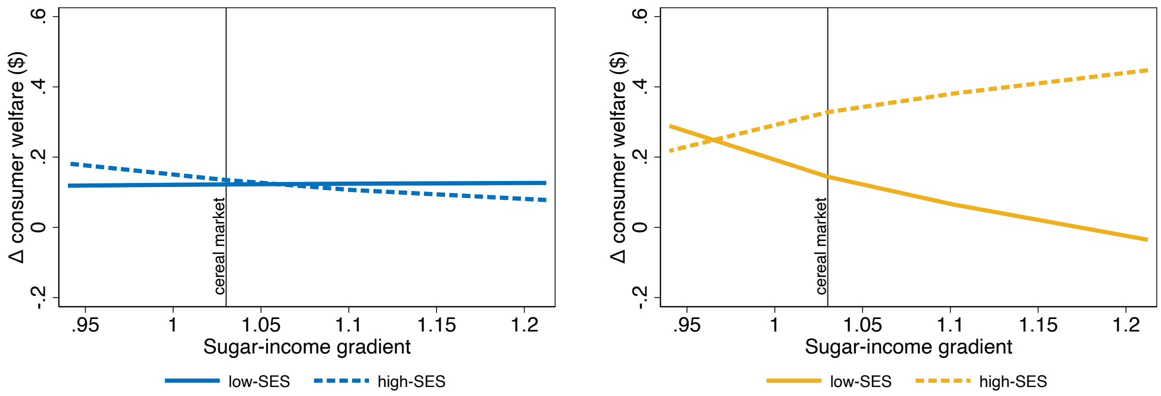
Notes: The figure plots average outcomes of interest under different regulatory thresholds under counterfactuals (1) and (3) relative to counterfactual (0). Panel (a) shows changes in sugar intake converted to dollars using the parameters of the utility function, and panel (b) shows changes in dollars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



(a) Sugar intake (b) Dollars spent

Figure A.3: Changes in sugar intake and dollars spent under different tax levels

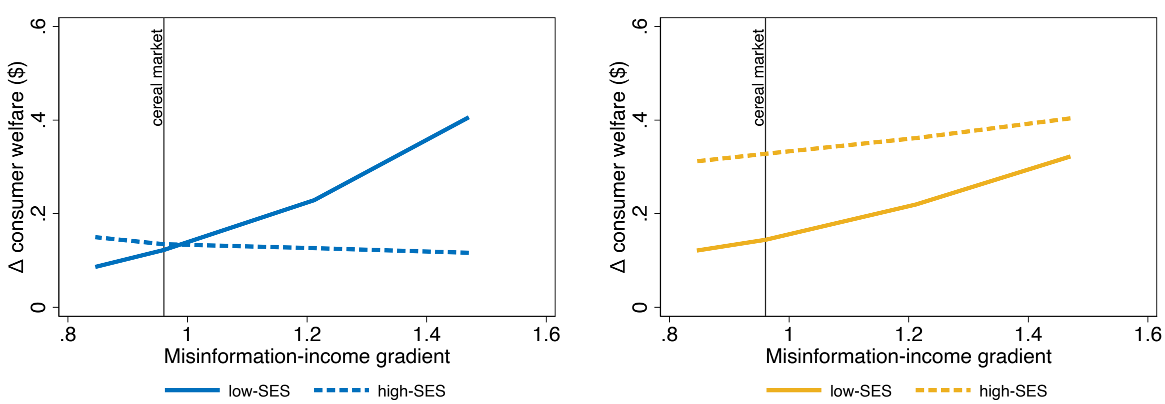
Notes: The figure plots average outcomes of interest under different tax values. Panel (a) shows changes in sugar intake converted to dollars using the parameters of the utility function, and panel (b) shows changes in dollars spent. The blue lines correspond to outcomes under food labels at the regulatory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



(a) Food labels (b) Sugar tax

Figure A.4: Sugar-income gradient

Notes: This figure shows the average gains in consumer welfare for low- and high-SES individuals from implementing food label and sugar tax policies 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 welfare. Panel (b) shows values for a sugar tax policy where the tax value is set to maximize total gains in consumer welfare. In Panel (b), tax money is returned to consumers in proportion to their baseline expenditure in the absence of the policy.



(a) Food labels (b) Sugar tax

Figure A.5: Misinformation-income gradient

Notes: This figure shows the average gains in consumer welfare for low- and high-SES individuals from implementing food label and sugar tax policies 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 welfare. Panel (b) shows values for a sugar tax policy where the tax value is set to maximize total gains in consumer welfare. In Panel (b), tax money is returned to consumers in proportion to their baseline expenditure in the absence of the policy.

Appendix B: Model Discussion

In this section, we discuss additional results implied by the model as well as its potential limitations.

B.1. *Theoretical results*

In Supplementary Material VIII 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 welfare 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 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 welfare become ambiguous. These results highlight the importance of taking the model to the data to test the effectiveness of food labeling policies.

B.2. *Limitations*

The model abstracts from reality in different ways that we discuss below.

B.2.1. *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 Supplementary Material IX.1.

B.2.2. *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 Supplementary Material IX.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.

B.2.3. *Advertising*: Our model does not account for potential changes in advertising due to the labeling policy. In Supplementary Material IX.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.

B.2.4. *Invariant taste*: : We assume that taste is invariant to reformulation. This assumption simplifies the firm's problem of choosing w_{jt}. As explained in Supplementary Material VII, this assumption is consistent with industry participants' descriptions of the way that reformulation took place. Moreover, in Supplementary Material X.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.

B.2.5. *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.

B.2.6. *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 Supplementary Material VII, 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.

B.2.7. *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.

Appendix C: Identification and Estimation of Demand

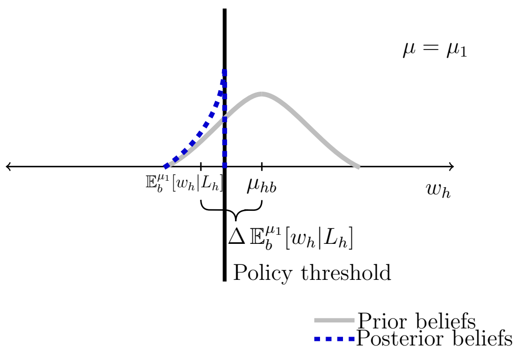
C.1. *Identification*

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).[1]

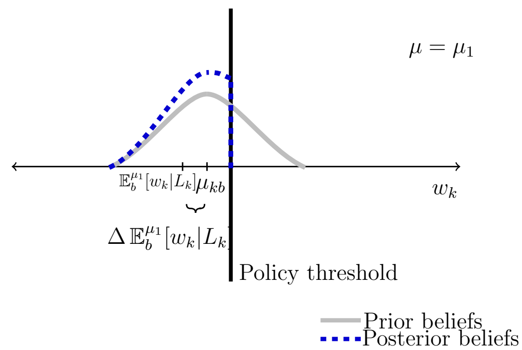
The identification of ϕ_b, the preferences over the perceived health consequences of consuming sugar and calories, and μ, the parameter that shifts the value of consumer beliefs elicited in the survey, is more difficult. First, note that if $\mathbb{E}_b[w_{jt}|L_{jt}]$ were observed in the data, we 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 C.1 and C.2 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 $\tilde{\mu}_{hb} > \tilde{\mu}_{kb}$)

[1] In Supplementary Material X.7, we show that, once we control for all fixed effects, prices do not correlate with market-specific 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.

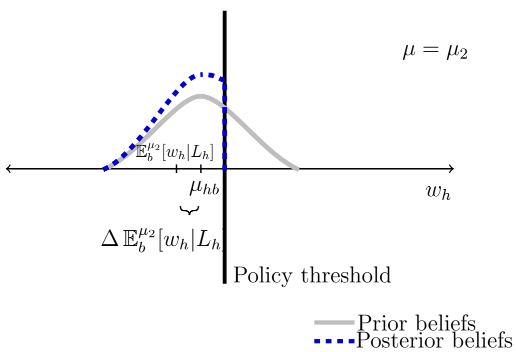
at two different parameter values, $\mu = \mu_1$ and $\mu = \mu_2$ (with $\mu_1 > \mu_2$).



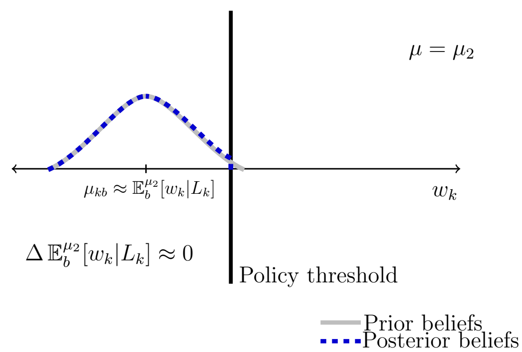
(a) Change in beliefs about product h when $\mu = \mu_1$



(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 C.1: 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 $\mu = \mu_2$.

In Figure C.1, 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 C.2 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 solid line corresponds to $\mu = \mu_1$ and the dashed line to $\mu = \mu_2$. Different values of μ have different implications for the relative difference between the change in expected utility of products h and k. For large values of μ, the increase in expected utility from consuming product h will be larger than that from consuming product k. For small values of μ, the increase in expected utility will be small and similar for the two products.

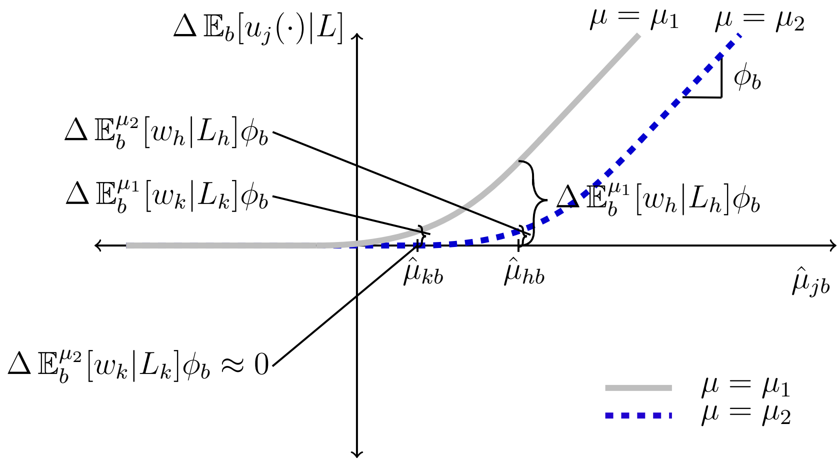


Figure C.2: Model-implied change in expected utility for product h and k at different values of μ

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 C.2. 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.[2]

Finally, we identify ρ, the intra-nest correlation of the logit error, using variation in

[2]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.

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.

C.2. *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 C.1, 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 C.2, 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 C.2 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 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.

Appendix D: Model fit

D.1. *Demand model fit*

To visualize how our model interacts with the raw data, in Figure D.1, 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:

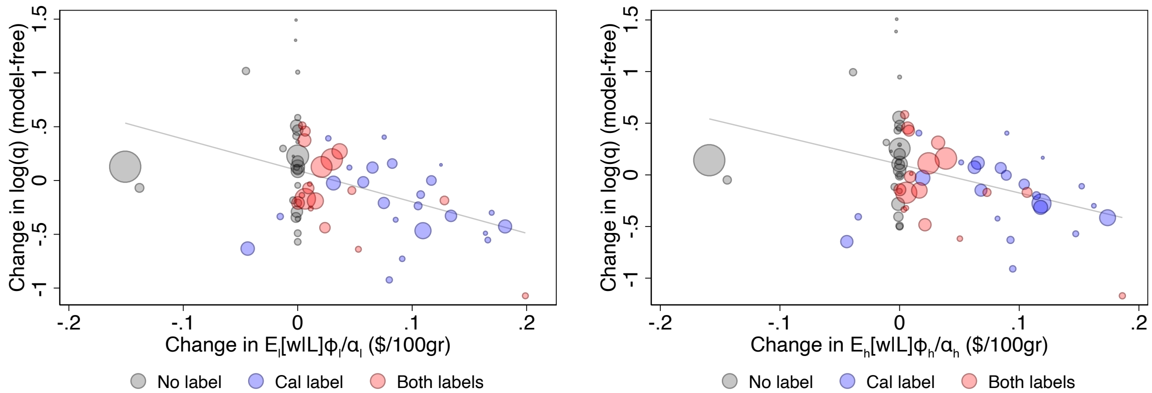
$$\log(q_{bjst}) \quad = \quad \beta_{jb} \cdot \text{Post}_t + \gamma_b \cdot p_{jst} + \delta_{jsb} + \delta_{tb} + \varepsilon_{jstb} \tag{D.1}$$

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.

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 4(b).

D.2. *Supply 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



(a) Low-SES households

(b) High-SES households

Figure D.1: 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 (D.1).

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:

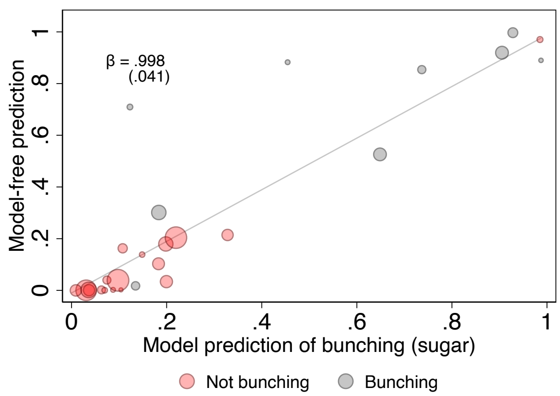
$$c_{jt}(w^*_{jt}) = \beta \cdot B_j \cdot Post_t + \delta_{js} + \delta_t + \varepsilon_{jt}$$

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 2.8¢ per 100gr, slightly smaller than the 4¢ per 100gr estimated with the parametric model-based approach above.

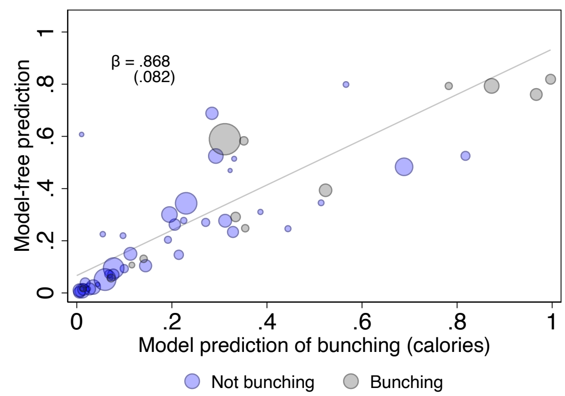
We also compare the model-based predicted probability of each product bunching in a given nutrient, with a reduced-form prediction based only on pre-policy nutritional content values and the first moment of consumers' prior beliefs. We use a logistic regression model of the form:

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

where $f(\cdot)$ is a second order polynomial. We present the model-based and reduced-form predictions for sugar and calories in Figure D.2.



(a) Bunching in sugar



(b) Bunching in calories

Figure D.2: 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.