

SUPPLEMENT TO “EQUILIBRIUM EFFECTS OF FOOD LABELING POLICIES”
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NANO BARAHONA

Department of Economics, University of California, Berkeley

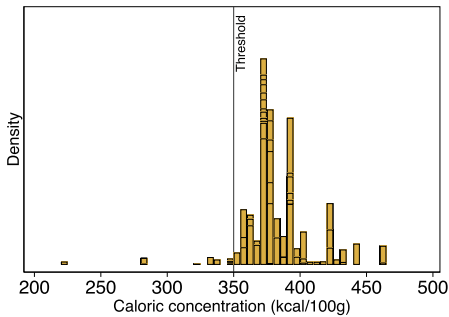
CRISTÓBAL OTERO

Department of Economics, University of California, Berkeley

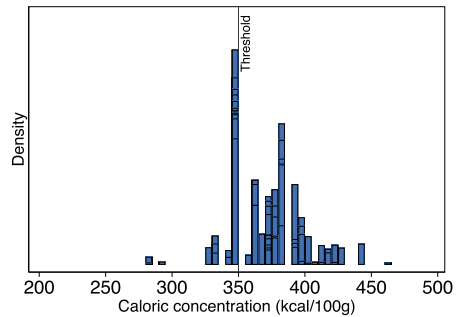
SEBASTIÁN OTERO

Haas School of Business, University of California, Berkeley

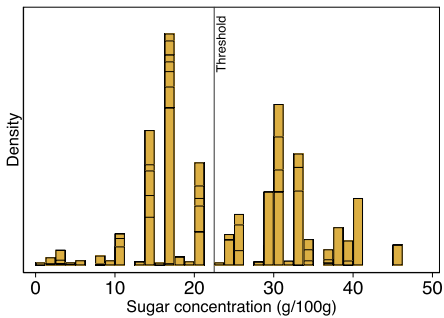
APPENDIX A: ADDITIONAL FIGURES AND TABLES



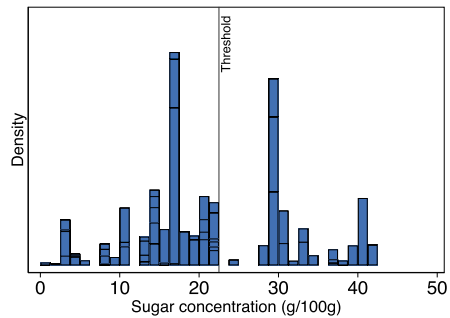
(a) Distribution of calorie content in 2016



(b) Distribution of calorie content in 2018



(c) Distribution of sugar content in 2016



(d) Distribution of sugar content in 2018

FIGURE A.1.—Distribution of caloric and sugar concentration pre- and post-legislation. *Notes:* This figure plots the distribution of calories and sugar per 100g for cereal products before and after the policy implementation. Horizontal black lines inside the bars identify different products. Observations are weighted by pre-policy revenue. We exclude oatmeal products, which do not have artificially added critical nutrients, as they are exempted from the regulation and do not reformulate their products.

Nano Barahona: nanobk@berkeley.edu

Cristóbal Otero: cotero@berkeley.edu

Sebastián Otero: seb.otero@berkeley.edu

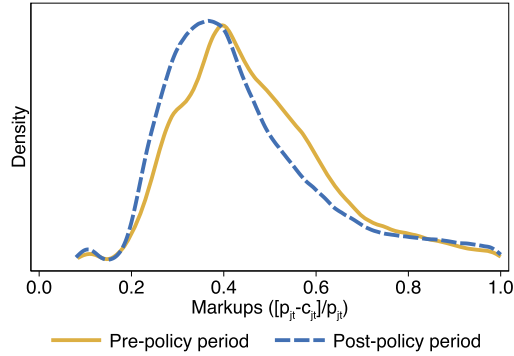


FIGURE A.2.—Distribution of markups. *Notes:* This figure shows the distribution of markups—defined as the ratio of price minus marginal cost to price—across products and markets before and after the policy implementation.

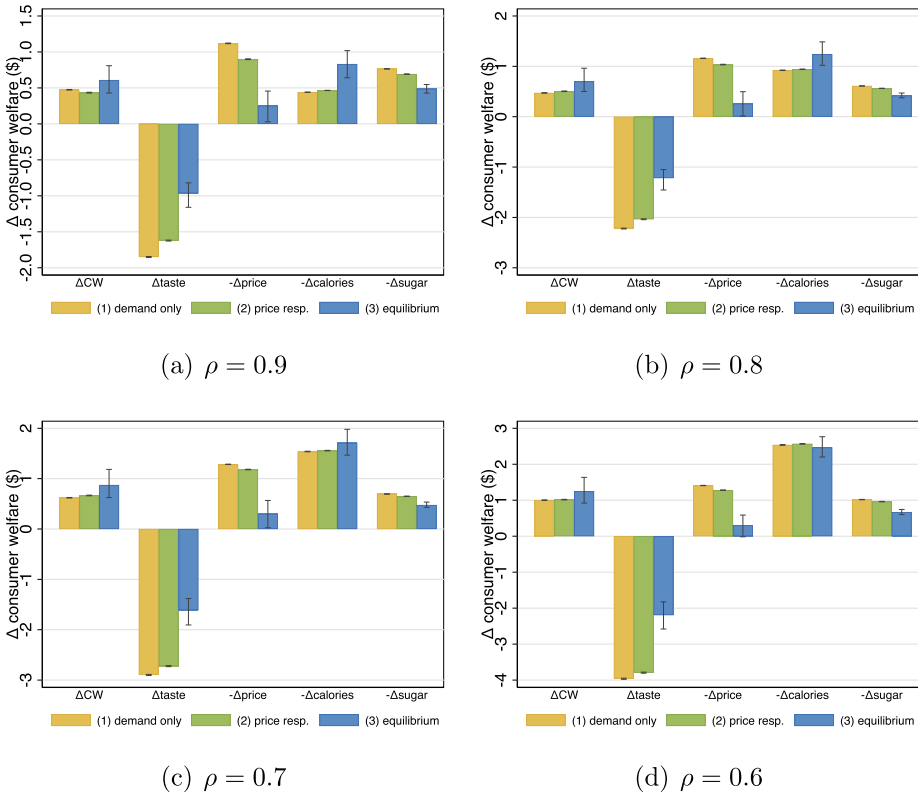


FIGURE A.3.—Changes in consumer welfare under different values of ρ . *Notes:* This figure replicates the findings from Figure 6 by imposing different values of ρ . For each panel, we fix ρ at 0.9, 0.8, 0.7, and 0.6, respectively. For each value of ρ , we estimate all other parameters from the demand and supply models presented in Sections 4 and 5. We then run our main counterfactuals and calculate the changes in consumer welfare under the different parameters. We show that our main results are qualitatively similar when we assume lower values of ρ .

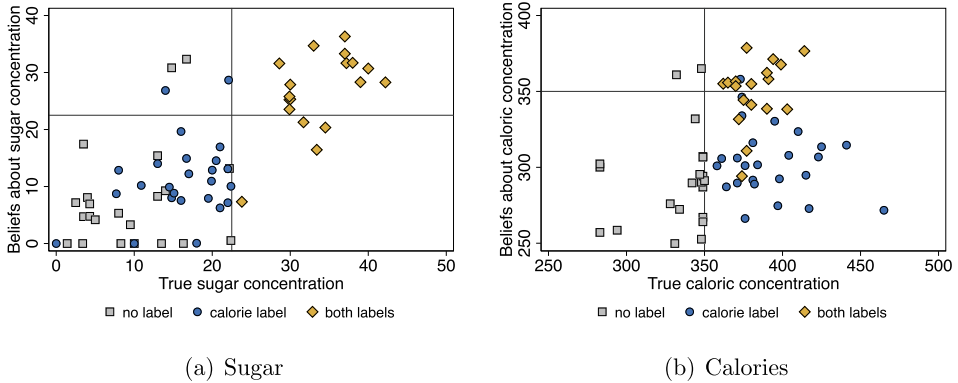


FIGURE A.4.—Beliefs about nutritional content versus true post-policy nutritional content. *Notes:* This figure shows the estimated average belief (between low- and high-SES consumers) about each product’s nutritional content against the true post-policy period nutritional content. Vertical and horizontal lines correspond to the value of the policy threshold in both spaces. Gray-square products did not receive any label, blue-circle products received a high-in-calorie label, and yellow-diamond products received a high-in-calorie and a high-in-sugar label. We exclude products that do not show up in the pre-policy period or are exempt from the policy.

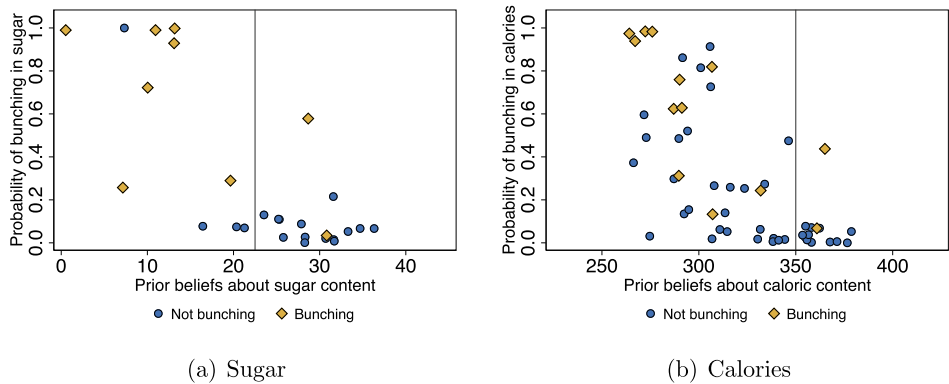


FIGURE A.5.—Predicted probability of bunching as a function of prior beliefs. *Notes:* The figure shows the predicted probability of each product bunching in sugar and calories as a function of the average prior belief about their nutritional content. In Panel (a), we focus on sugar content. Products in yellow diamonds are products that bunched in the data and crossed the sugar policy threshold. Products in blue circles are products that did not bunch and received a “high-in-sugar” label. In Panel (b), we focus on caloric content. Products in yellow diamonds are products that bunched in the data and crossed the calorie policy threshold. Products in blue circles are products that did not bunch and received a “high-in-calorie” label.

TABLE A.1
MEDIAN PRICE ELASTICITIES.

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

Note: The first column reports the median market share of each product across all 2704 markets. For the rest of the table, cell entries j, k —where j indexes rows and k columns—give the percent change in market share of product j with a 1% increase in the price of product k . Each entry represents the median of the elasticities from all markets. Note that the cross-price elasticities within a subcategory are relatively constant. We do not observe product characteristics that vary within subcategories, which limits our ability to include preference heterogeneity to recover more flexible substitution patterns.

APPENDIX B: CHANGES IN PRICES, PRODUCT ASSORTMENT, AND PACKAGE SIZE

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

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

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

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

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

These results are in contrast to those in Pachali, Kotschedoff, van Lin, Bronnenberg, and van Herpen (2022), who concluded that warning labels lead to higher prices of labeled cereals due to changes in product differentiation. The differences seem to be driven by differences in the sample. While we use scanner data from Walmart, they used household panel data from Kantar World-panel Chile. Moreover, of the 94 products in our sample, they focused on 14, of which only three are unlabeled. When repeating the analysis in our

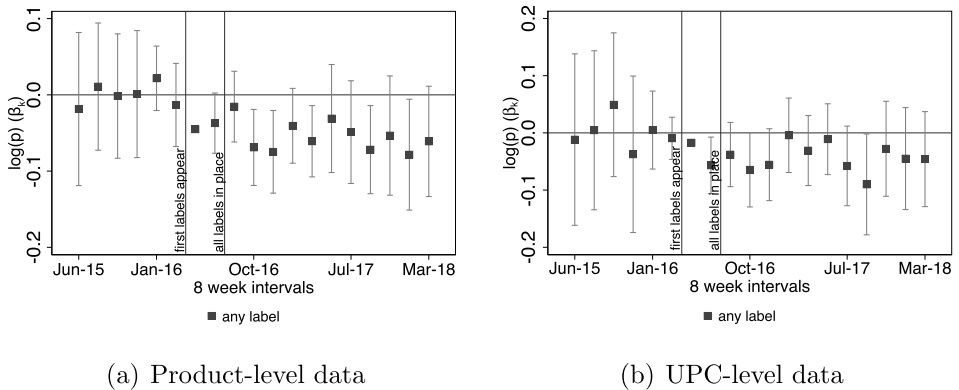


FIGURE B.1.—Event study for cereal prices. *Notes:* This figure presents the β_k coefficients of our event study regression for prices from Equation (B.1). Vertical segments delimit the 95% confidence intervals. Panel (a) uses product-level data and is estimated on the sample of 68 ready-to-eat cereals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

data but restricting it to the 14 products in their sample, we find no significant differences in price changes between labeled and unlabeled products.

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

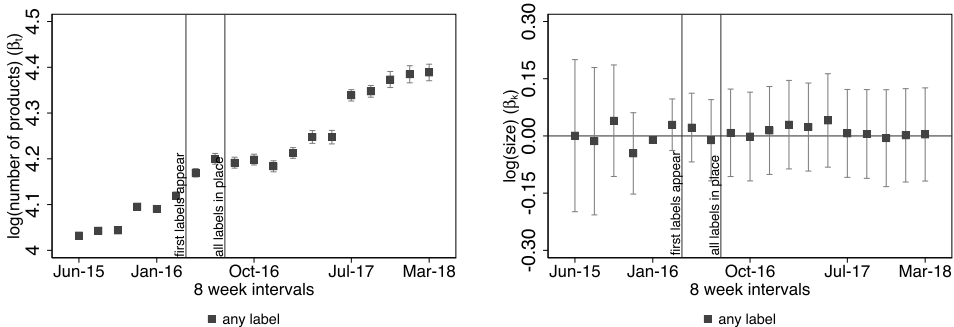
$$\log(N_{st}) = \beta_t + \delta_s + \varepsilon_{st}, \quad (\text{B.2})$$

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

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

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

where size_{ist} is the size of the package for product j 's UPC i in store s in period t . All other variables and details are defined as in Equation (1), and observations are at the UPC level. Results are presented in Figure B.2, Panel (b). We find that once the policy is implemented, there is no significant change in the average size of product packages.



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

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

APPENDIX C: DEMAND MODEL DISCUSSION

C.1. *Stockpiling*

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

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

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

$$y_{it} = \beta \text{sale}_{it} + \delta_i + \epsilon_{it},$$

where sale_{it} takes the value of 1 if household i purchases a cereal product in period t that was on sale. Coefficients δ_i control for household fixed effects. We test for the following implications under stockpiling behavior:

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

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

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

To test for the third implication, we define the outcome variable to take the value 1 if household i 's cereal purchase before buying cereal again in period t was of cereal products that were not on sale. Under stockpiling, we expect β to be *negative*. In Table C.1, column

TABLE C.1
STOCKPILING TESTS.

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

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

(3), we find that $\beta = -0.0633$, implying a 7.7% decrease in the probability that the last purchase was a non-sale purchase. This number is negative but smaller in magnitude than those in [Hendel and Nevo \(2006b\)](#), who found a 16.7% and 13.5% decrease in the market for yogurt and soft drinks, respectively.

Our results are in line with [O'Connell and Smith \(2021\)](#), who performed similar tests in the soft-drinks market in the United Kingdom and found that the sign of these tests is consistent with stockpiling but very small in magnitude.

C.2. *Salience Effects*

In this subsection, we investigate the potential salience effects of food labels in the cereal market. Salience refers to a situation in which an attribute of an item attracts more attention, and subsequently receives more weight when making decisions. In Section 3.1, we argue that labels shift consumer demand because they provide consumers with information about the true nutritional content of a product. However, labels may also make the unhealthiness of products more salient to consumers. In other words, labels may induce consumers to pay more attention to the role of sugar and calories in the decision-making process. Hence, if labels were only impacting demand through salience, we should expect the reduction in equilibrium quantities documented in Figure 1(a) to be stronger for those products with higher concentrations of critical nutrients.

To investigate this hypothesis, we follow the same empirical design implemented in Section 3.1. We split our sample of labeled products into two groups: products below the median in the caloric concentration distribution (20 products) and products above the median in the caloric concentration distribution (21 products). We use indicator dummies for each of these groups (denoted by Low_j^c and $High_j^c$) and estimate the following equation:

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

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

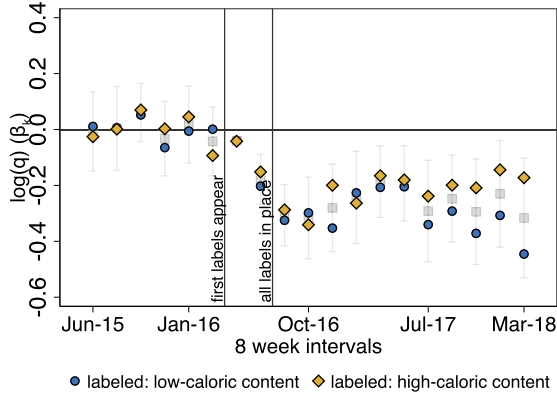


FIGURE C.1.—Changes in equilibrium quantities by caloric concentration. *Notes:* This figure displays the coefficients from Equation (C.1). Coefficients in blue circles and yellow diamonds denote β_k^l , β_k^h , respectively. Gray squares denote the β_k coefficients from Equation (1) and the vertical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

Results from Equation (C.1) are shown in Figure C.1. Coefficients in blue and yellow denote β_k^l and β_k^h estimates, respectively. Coefficients in light gray denote β_k coefficients from Equation (1). Products with low caloric concentration (blue dots) and high caloric concentration (yellow diamonds) saw a similar reduction in equilibrium quantities.^{S1} If anything, high-calorie products seem to experience lower reductions in demand, as opposed to what we would expect under strong salience effects.

C.3. Invariant Taste

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

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

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

The main and most important difference between this model and the model in the main article lies in the parameterization of the experience/taste aspect of the utility. In

^{S1}Splitting products according to sugar concentration is less interesting. Because sugar concentration is highly correlated with beliefs about caloric concentration, results are similar to Figure 1(b). Labeled products with high sugar concentration experienced lower changes in equilibrium quantities than labeled products with low sugar concentration. This, again, rejects important salience effects.

this section, we will allow δ_{ijt} to vary with w_{jt} . In particular, we assume that

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

Consumers' decision utility in this model is then given by

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

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

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

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

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

We present the results in Table C.2. The parameter estimates show that higher concentrations of sugar and calories do not imply higher taste, thus rejecting the hypothesis that reformulated products substantially decreased their taste. This is consistent with

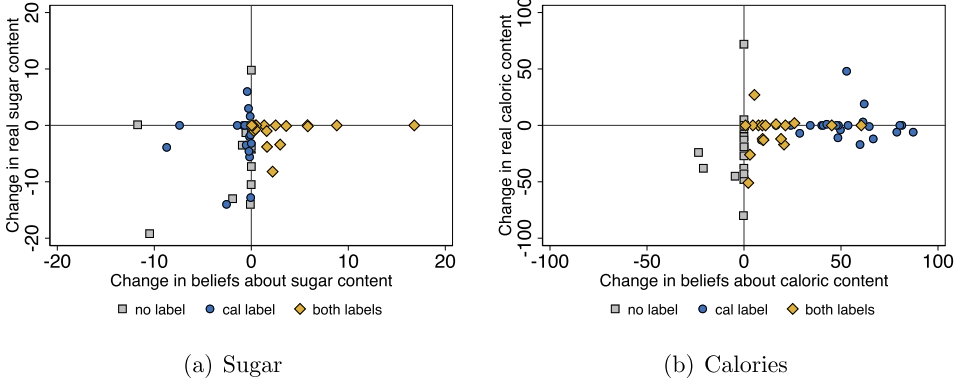


FIGURE C.2.—Changes in beliefs versus changes in real nutritional content. *Notes:* The figure shows changes in beliefs about nutritional content versus changes in real nutritional content. To calculate changes in beliefs about nutritional content, we subtract the estimates of $\mathbb{E}_b[w_{ji}|L_{ji}]$ from before and after the policy implementation. We calculate changes in real nutritional content directly from the data. Gray squares are products that did not receive any label, blue circles are products that received a high-in-calorie label, and yellow diamonds are products that received both a high-in-calorie and a high-in-sugar label. Panel (a) shows results for sugar and Panel (b) shows results for calories.

the evidence provided in Supplemental Material Appendix D.2, in which we explain that the reformulation process took place with the explicit goal of not affecting the product's taste. More surprisingly, we find that $\gamma_b^c < 0$, which implies that reducing caloric content increases the taste of the product. We believe this finding is driven by measurement error in the change in beliefs shown in Figure C.2. Products that, on average, were believed to be low in calories and reformulated calories to avoid receiving the label should see no changes in beliefs, according to our model. However, some consumers may be learn-

TABLE C.2
ESTIMATED DEMAND PARAMETERS WITH VARIABLE TASTE.

Panel A: Preferences for price and healthiness (α_b)									
low-SES			high-SES						
Price (α_b)	α_l	0.2759 (0.0200)	$\bar{\alpha}_h$	0.2086 (0.0221)					
Panel B: Preferences for healthiness and taste (ϕ_b, γ_b)									
		Sugar				Calories			
		low-SES		high-SES		low-SES		high-SES	
Healthiness (ϕ_b)	ϕ_l^s	0.0054 (0.0028)	ϕ_h^s	0.0045 (0.0031)	ϕ_l^c	0.0387 (0.0034)	ϕ_h^c	0.0369 (0.0042)	
Taste (γ_b)	γ_l^s	-0.0033 (0.0029)	γ_h^s	0.0010 (0.0036)	γ_l^c	-0.0176 (0.0057)	γ_h^c	-0.0221 (0.0071)	

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

ing from the labels regardless, which can induce increases in demand for those products despite reducing their calories.

C.4. Advertising

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

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

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

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

where A_{jt} is a measure of advertising intensity for product j in market t , and all other variables are the same as in the model from Section 4 in the main article.^{S2} We measure advertising intensity as the average daily number of ads shown on each TV channel for each product.^{S3} Since we only have two snapshots of advertising intensity, we follow the same strategy used for reformulation and changes in beliefs, and assume that all changes happened at the time of the policy implementation. We present the results in Table C.3.

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

^{S2}We estimate the model following the same methodology as in Section 4, including A_{jt} interacted with consumer type dummies as additional instruments.

^{S3}Our results are robust to other measures of advertising, such as average daily ad minutes per channel and average daily minutes times rating points per channel.

TABLE C.3
ESTIMATED DEMAND PARAMETERS WITH ADVERTISING.

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

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

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

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

APPENDIX D: SUPPLY MODEL DISCUSSION

D.1. Timing of Firms' Choices

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

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

and logit demand, in which firms set marginal cost first and then choose prices, it is also an equilibrium for all firms to choose the minimum cost. Let the profit function of a single-product firm be given by $\pi_j(\mathbf{p}, c_j) = (p_j - c_j)s_j(\mathbf{p})$, where $s_j(\mathbf{p}) = \frac{\exp(-\alpha p_j + \delta_j)}{1 + \sum_k \exp(-\alpha p_k + \delta_k)}$. In the first stage of the sequential model, firms choose $c_j \geq \underline{c}_j$. In the second stage, after marginal costs are realized, firms choose p_j .

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

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

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

From the first-order conditions of firm k , we have that $s_k(\mathbf{p}') \geq s_k(\mathbf{p}^*)$. It is also straightforward from the logit demand formula that $s_0(\mathbf{p}') \geq s_0(\mathbf{p}^*)$, where $s_0(\cdot)$ is the market share of the outside option. Because market shares add up to 1, we have then that $s_j(\mathbf{p}') \leq s_j(\mathbf{p}^*)$. Finally, with logit demand, lower market shares imply lower markups. Thus, we have that $\pi_j(\mathbf{p}', c'_j) \leq \pi_j(\mathbf{p}^*, \underline{c}_j)$, which proves that firm j has no incentive to deviate.

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

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

D.2. Reformulation Process

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

There are two potential ways firms may reformulate their products. In one way, firms may choose to sacrifice taste for healthiness by removing some of the critical nutrients from their products. In the other way, firms may choose to replace critical nutrients with

alternative, potentially more expensive, ingredients without compromising taste, mouth-feel, shelf life, and other attributes to ensure that consumers will continue to buy their products.

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

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

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

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