CENTRO DE ECONOMÍA APLICADA

INGENIERÍA INDUSTRIAL • UNIVERSIDAD DE CHILE

DOCUMENTOS DE TRABAJO

Serie Economía

Nº 339

IDENTIFYING FOOD LABELING EFFECTS ON CONSUMER BEHAVIOR

SEBASTIÁN ARAYA, ANDRÉS ELBERG, CARLOS NOTON Y DANIEL SCHWARTZ

FACULTAD DE CIENCIAS FÍSICAS Y MATEMÁTICAS UNIVERSIDAD DE CHILE

diseases- and dietary habits has mounted, the World Health Organization (WHO) has forcefully advocated the use of nutrition labeling schemes and the provision of nutritional information as leading strategies to improve healthy food choice (WHO (2004)). In line with the WHO's recommendations, many countries have required sellers to disclose calorie and nutritional content information (Hawkes (2004), WHO (2004))

Despite its importance, identifying the impact of food labeling on consumer behavior has proved elusive to date. Bleich et al. (2017), for instance, review 53 studies on the impact of calorie labeling on consumer behavior and conclude that the lack of statistical power and poor designs challenge any reliable conclusion about the effects of calorie labels.[3] Moreover, regulations implemented at a single point in time pose a formidable challenge to the identification of the labeling effect as the typical before-after estimation requires the unobserved components of consumer behavior being time-invariant (Ippolito & Mathios (1995), Dumanovsky et al. (2011)). Alternatively, using other geographic locations as control group requires the absence of market-specific unobservables (e.g., Elbel et al. (2009), Bollinger et al. (2011), Finkelstein et al. (2011)).

We take advantage of the gradual implementation of a comprehensive and mandatory food labeling regulation recently introduced in Chile to identify its effects on consumer behavior. The regulation was prominently featured in a recent article in the New York Times which regarded the measures adopted in Chile 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" (NYT (2018)). The regulation established that products exceeding given thresholds of critical nutrients should display mandatory warning labels by the end of June 2016. However, food suppliers gradually introduced the warning labels in different stores a few months before the regulation came into force. During this period, supermarkets began selling labeled products driven by stock availability in each store. We collected daily data on whether specific products (at the Universal Product Code (UPC)-level) displayed the new warning labels, and find substantial variation in labeled and non-labeled products across time and stores, allowing us to avoid the identification problems present in previous literature.

We use individual-level data from a big-box supermarket chain and estimate a demand model for differentiated products in which a food label indicator identifies the potential disutility of the label warning of the potentially unhealthy content of a given product. We focus on four product categories which were especially hard hit by the regulation: breakfast cereals, chocolates & candies, juices, and cookies.[4] Our transactional scan-data come from the loyalty card records of the retailer, containing 478,711 consumers and representing nearly 80 percent of total sales. The variation in product-specific information across stores allows us to identify the warning label effect while including product and time fixed effects.

[3] See Kiszko et al. (2014) and Harnack & French (2008) for additional systematic reviews.

[4] Soft drinks is another relevant category. However, the gradual implementation of the label for this category started several weeks before we began collecting data on whether products displayed the new label.

We find heterogeneous effects across the four product categories we study. In the breakfast cereal category, the new warning label reduces the probability that a product is chosen by 11.0 percent whereas we observe a sizable 23.8 percent reduction in the probability of choosing a labeled product in the juice category. In contrast, we find no effects of the regulation on chocolates & candies and cookies. This result is consistent with research on information disclosure that indicates that effectiveness of information provision depends on whether it provides new insights into the previous agent's information set (Loewenstein et al. (2014)). In our case, consumers may respond to labeled products which were unexpectedly unhealthy, such as breakfast cereals and juices, while they may not change their behavior in categories such as chocolates and candies, in which the warning labels did not provide additional information on products' healthfulness. We also explore heterogeneous treatment effects and find that high-expenditure households reduce more their purchases of labeled products than do low-expenditure households. This result is consistent with prior literature which suggests that higher-income, more educated individuals tend to be more sensitive to nutritional labels (Kim et al. (2001), Drichoutis et al. (2005), Bollinger et al. (2011).)

As a way of comparison, we further estimate the effect of the food labeling regulation using the standard pre and post analysis. In this case, the estimates of the label effect almost double, stressing the fact that unobservable time components can severely bias the results. We also conduct a placebo robustness test, in which we simulate the same gradual introduction of warning label but in a period without any actual warning label. We find no warning labeling effect in this case, reducing the chance of spurious factors affecting our results.

We also overcome the potential complication of consumers' misunderstanding and neglecting the information presented to them (Rotfeld (2009)). Our study takes advantage of a highly advertised regulation as confirmed by a survey to more than 3,000 customers at the exit of supermarket stores which indicates that 73 percent of consumers identified products with the new food labeling before the law came into force (CERET (2016)).

Our paper contributes to vast literature studying the impact of food labeling on consumer behavior. Similar to our work, Bollinger et al. (2011) estimate the effect of a mandatory nutrition labeling policy on purchase decisions of consumers in the actual market. They use transaction data from Starbucks to study the consequences of a law first implemented in New York City, which mandated the posting of calories on menus in chain restaurants. Bollinger et al. (2011) estimate the impact of the law by comparing the behavior of New York customers with those of other cities (Boston and Philadelphia) not affected by the regulation. They find that mandatory calorie posting causes average calories to decrease by 6 percent.

Kiesel & Villas-Boas (2013) and Downs et al. (2009) also study consumer responses to the provision of nutritional information in real market environments. Kiesel & Villas-Boas (2013) conduct a supermarket-level field experiment in which they manipulate the information content of nutritional shelf labels in one product category (microwave popcorn) across five treatment stores selected by the supermarket chain. While the experimental setting allows the authors a proper identification, the selection on unobservables of their specific product category and particular outlets remains a potential issue.[5] Our study solves this potential problem, and it adds to this research by considering several food categories and representative stores. Downs et al. (2009) summarize the results from two field experiments in which treated consumers receive different calorie information mimicking recent regulations. They find that the effects of calorie information provision are small and that the provision of calorie information may induce higher calorie consumption among dieters. In both field experiments consumers are aware of their participation in a study, potentially driving their attention to the new nutritional information. Our natural market setting with massive and detailed transactional data avoids potential biases from surveys and laboratory experiments as it captures the normal shopping behavior of consumers after the introduction of an exogenous change in information.

Finally, our paper contributes to the public debate on mandatory information disclosure and its potentially heterogeneous effect across different segments of the population (Cawley et al. (2016)). Policy makers aim at improving the choice of less wealthy households. Nevertheless, our results show that the high-income consumers are most likely to substitute away from unhealthy items given the new and straightforward information.

The remainder of this paper is organized as follows. Section 2 describes the regulation we study, institutional details and summary statistics of our supermarket data. Section 3 presents our demand model and econometric approach while Section 4 presents the results and robustness checks. Section 5 concludes.

2 Data and Institutional Background

2.1 The Nutritional Labeling Law and its gradual implementation

Over the last few years, Chile introduced groundbreaking changes to its legislation regulating nutritional food labeling. The new regulatory framework put in place by the Chilean authorities broadly aimed at improving point-of-sale nutritional information using simple interpretive front-of-package labeling.[6] Under the new regulations, pre-packaged food products whose contents of four critical nutrients –sugar, sodium, saturated fats, and calories[7] exceeds certain thresholds

[5] Kiesel & Villas-Boas (2013) randomly assigned tag labels attached to the prices placed on the shelf of microwave popcorn (e.g., "low calorie" vs. "low fat" and "low calorie"). Authors were only allowed to tag products in the low calorie, low fat and low trans-fat categories in five stores selected by the supermarket chain. The authors use a synthetic control group to ameliorate the store selection, as the supermarket chain did not provide information on how they selected the five treated stores.

[6] The law only affects packaged products and not bulk goods and unpackaged food such as bread.

[7] While calories are not, strictly speaking, a nutrient, we refer hereafter to all four food components regulated by the law (i.e., sugar, sodium, saturated fats and, calories) as nutrients for expositional convenience.

must display standardized black labels warning that the product contains excessive levels of one or more of these critical nutrients.[8]

The warning labels take the form of front-of-pack octagons, resembling a black stop sign, displaying the legend *High in* followed by the name of the critical nutrient being exceeded.[9] Figure 1 displays the labels introduced by the law.

The regulation is very specific about the size of the warning labels and the position they must occupy to ensure saliency to the public. For instance, according to the regulation, a product which exceeds a critical nutrient limit and whose front pack exceeds 300 square centimeters (approximately 0.32 square feet) must include a warning label of dimensions 3.5 by 3.5 centimeters (approximately 1.38 by 1.38 inches). The law divided products into solids and liquids and specified the thresholds for labeling a product in terms of a fixed quantity of the product (100 grams for solids and 100 ml. for liquids).

The legislation established a three-stage process over which products would be progressively labeled as "High in" a critical nutrient. The initial phase began on June 26 of 2016, one year after the official order specifying the details of the new regulation was published in the Official Gazette.[10] More stringent thresholds were mandated to be gradually introduced in June 2018 and June 2019. In this paper, we focus on the impact of the nutritional labels introduced during the first phase of the process.[11]

The changes in the regulatory environment caused significant controversy, especially among food manufacturers and retailers. An especially controversial aspect of the regulation was the choice of defining thresholds for critical nutrients based on a standardized fixed quantity of the product (100 grams or 100 ml.) instead of defining them based on serving size. One argument against the use of a rule based on a fixed quantity is that some products would be labeled in spite of the fact that the typical serving size is substantially smaller than 100 grams or 100 ml of the product (e.g., "crackers"). If a potential consumer exposed to the labeled product ignores that the tagging criterion is based on 100 grams of the product, his or her purchase decisions may be misled by the presence of the warning labels. The issue of whether to use a fixed quantity or a serving size criterion for establishing the thresholds was not resolved until a later stage in the parliamentary discussion. In the end, the authorities favored the use of a fixed quantity over a rule based on serving sizes presumably because of the potential manipulation of serving size by food manufacturers. Corvalán et al. (2013) discuss advantages and disadvantages of different elements

[8]In addition, the new legislation regulated advertising of the labeled products and their sales in schools. Specifically, advertising of unhealthy tagged products targeting children under age 14 years was prohibited as was the sale of these products in or within 100 meters of a school.

[9]Inclusion of the name of an institution backing the nutritional message has been found to enhance its credibility (Feunekes et al. (2008)).

[10]Decree No. 13 of the Ministry of Health which modified the Sanitary Food Regulation.

[11]The thresholds for solid (liquid) products over the initial phase were defined as: 350 (100) for calories; 800 (100) for sodium; 22.5 (6) for sugars; and 6 (3) for saturated fats.

of the law on nutrition labeling.[12]

An international comparison puts Chile among the early adopters of a mandatory front-of-pack nutrition labeling law, an ambitious policy intervention that is being increasingly considered by other countries worldwide (Hawkes (2010), NYT (2018)). For example, Canada has begun discussing the adoption of a mandatory front-of-pack nutrition labeling system which, according to the initial specifications set by the Canadian Ministry of Health, would include several elements contained in the Chilean law.[13] Also, Australia, New Zealand as well as several European countries have put in place graphical nutrition labeling systems. Among the countries that have already implemented mandatory front-of-pack nutrition labeling systems are Bolivia, Ecuador, Peru, and Mexico.[14]

The actual implementation of the new regulation plays a crucial role in our empirical strategy. The law mandating the introduction of the warning labels was approved in June 2012, but its implementation required the completion of several administrative and legal procedures.[15] The legislation was finally promulgated in April 2015 and entered into force on June 26th of 2016.

There was an initial period of confusion about whether the stock of unlabeled products exceeding the limits of critical nutrients would be allowed after the June 2016 deadline. The authorities ruled that all products "high in" some nutrient would have to display the warning labels by June 26th of 2016 regardless of their manufacturing date. Stores that failed to comply with the new regulations by the deadline would be subject to fines. This clarification prompted large retailers to demand delivery of labeled products several months in advance of the legal deadline. This process resulted in some products simultaneously being delivered displaying the black warning label(s) in some stores but not in others.

Our empirical strategy exploits this gradual implementation of the law. Since retail stores received labeled products before the deadline set by the law, we can observe at a given point in time a product displaying a warning label in one store while the same product in a similar outlet being traded without the warning label.[16] This overlap of labeled and unlabeled products

[12] Another point made by the detractors of the law was that it might adversely affect the international trade of packaged products as it would force foreign companies to incur the cost of adding warning labels to products shipped to Chile and would force local exporters to use different packaging for products sold in foreign countries.

[13] In a recent stakeholder engagement meeting organized by Health Canada, the authority required stakeholders to submit possible front-of-package nutrition symbols which complied with three criteria included in the Chilean law. The three principles are: (1) follow the "high-in" approach; (2) focus on the three nutrients of public health concern (sugars, sodium, and saturated fats); and use only black and white colors (HC (2017)).

[14] In other nations graphical nutrition labeling schemes are applied on a voluntary basis. A pioneering intervention along these lines is the traffic light system implemented in the UK. The system was born as an initiative of the industry and has replicated by some retailers in France and Portugal (Hawkes (2010)).

[15] The final required modifications of the Sanitary Regulations of Food, which included the actual limits on critical nutrients and the precise specifications on the size and location of the warning labels. The finally, the Ministry of Health promulgated the Decree No. 13 of in April of 2015 and published in the Official Gazette on June 26th of 2015, establishing their implementation one year after.

[16] We identify a product based on its Universal Product Code, UPC.

changing over time, coupled with observations of purchasing behavior at the UPC-store level, allows us to measure the impact of the food labeling on consumer behavior.

The assignment of labeled products to retail outlets was unlikely to have been manipulated by manufacturers, and it can be considered exogenous to consumers. Consistently, from several interviews we conducted with large suppliers of products directly affected by the regulations, we learned that it was logistically impractical for them to determine which specific stores would end up receiving the labeled products. We discuss the observed implementation in the next Subsection below.

2.2 Data Description

We partnered with a large chain of supermarkets in Chile to study the impact of the nutrition labeling law on purchasing behavior. We were able to measure whether specific UPCs displayed warning labels on the shelves of six supermarket stores located in three major Chilean cities (Santiago, Valparaíso, and Viña del Mar) over a period of gradual introduction of warning labels in the supermarket stores. Our team of research assistants visited the stores before the legal deadline, over May and June 2016, and recorded whether a given UPC displayed the new nutritional label and the type of warning label presented by the UPC. On average, each store was visited 40 times over the period in which the intervened product was exhibited with and without the black warning label(s) on the supermarket shelves.[17]

We focus on four product categories which were primarily affected by the regulation: Fruit juices, breakfast cereals, chocolates & candies and cookies. Figure 2 shows the evolution of warning labels per category over the period of analysis in the six stores included in our sample. As expected, there is an upward trend in the number of labeled UPCs over time across all stores and categories. We combine our collected data on the presence of warning labels with consumer-level point-of-sale data which include all items in consumers' shopping baskets, the prices paid for each item and the date and time of the transaction. We identify individual consumers using customer membership in the retailer loyalty card program. According to the retailer, purchases made through its loyalty program account for about 80 percent of its total revenues. The retailer also provided us with cardholders' demographic information including their gender, age, and socio-economic group classification.

We observe considerable variation in the food labeling implementation across products, stores and time. Figure 3 shows the number of days in advance of the legal deadline the warning labels were implemented for each of the top 30 products in a category. For each product in a category, the figure displays the average number of days ahead of the deadline the warning label was introduced in across stores (blue dots) and its standard deviation. Within a category, products are ordered based on their market shares with product 1 being the top market share product and

[17] Our data include transactions between June 26 and July 22, 2016, when the law was already in place.

product 30 the one exhibiting the tiniest market share. Importantly, the charts in Figure 3 do not suggest any clear pattern linking market shares with the timing of the introduction of warning labels across stores. Notice that for the juice category only four out of the 30 products are eventually labeled. For instance, product 9 in the top-left panel (breakfast cereal), was labeled on average 36.8 days in advance of the deadline (SD = 6.9), but it exhibited a warning label 43 days in advance in the first store, while the last store introduced the warning label 24 days before the deadline.

Our consumer-level data comes from the loyalty card records which contain all purchases made in the participating supermarket stores by registered consumers. In addition, our dataset includes historical data extending back to early 2015 with purchases made by the same set of customers in our main dataset as well as demographic data on these consumers. We use data from May to July 2015 and from May to July 2016.

Our final sample contains 125,485 consumers, who made 210,819 eligible transactions in different categories.[18] To ensure mutually exclusive choices, we define as an eligible transaction those with no more than one item in the selected categories: cereal, juice, chocolates & candies, and cookies. The indicator variable is one for the bought UPC, and zero for all other products in the same category. Since not all the top 30 products were available in every store, the average choice set contains 25.91 products, implying 5,463,587 observations in total. Table 1 provide more details on the number of transactions and choices per category.

Table 2 presents summary statistics for our transactional dataset. Our typical consumer spent, on average, approximately \$6 and purchased, on average, 2.5 items per visit.[19] There is little variation in the size of the shopping basket and expenditure per visit across stores. A store in our sample generated, on average, approximately 2,300 daily transactions (including a product from one of the four categories we analyze). Variation in the total number of transactions and revenue across stores mainly reflects differences in store size and location.

3 Demand Model

To identify the impact of the food-labeling regulation on consumer behavior, we estimate a random utility model that includes a distaste parameter for warning labels. In the standard linear utility, we add an indicator variable that equals one when the unhealthy product displays the warning label. This fixed effect acts as a "utility shifter" decreasing the utility of the tagged product. Hence, we assume that the warning label is an additional attribute to be considered for the consumer and it may yield a disutility that is constant across products within the same category.

In our application, we observe transaction records of many stores over several weeks which

[18] We consider consumers from the percentiles 10 to 90 in the total expenditure distribution to focus on household purchases.

[19] Amounts in American Dollars, using the average conversion rate during the implementation period

we use to estimate the impact of the warning labels in each category separately. Importantly, as seen in the previous Section, the presence of warning labels vary over time and across stores for the same product.

We assume an alternative-specific conditional logit model (McFadden (1974)), in which the utility of consumer $i = \{1, .., N\}$ for food product $j = \{1, .., J\}$ in store $s = \{1, .., S\}$ at week $t = \{1, .., T\}$ is given by:

$$u_{ijst} = \alpha(y_i - p_{jst}) + \beta' x_{jt} + \gamma L_{jst} + \varepsilon_{ijst}$$

where y_i is consumer's income, p_{jst} is the price and x_{jt} is the vector of product dummies and their interaction with time dummies. Particularly important in our setting is the label dummy, L_{jst}, which equals one if product j displays a warning label in a given (s, t) combination, and zero otherwise. ε_{ijst} is an iid random term with a Type I extreme value distribution function.

Typically, demand estimations are concern about the potential endogeneity of prices. Prices are identical for those individuals in the same store and exogenous to consumers. However, if the retailer is setting prices based on unobservables (to the researcher), we still may observe price endogeneity. We resolve the problem by using weekly brand intercepts to control for weekly brand-specific characteristics, as suggested in Chintagunta et al. (2005).

The parameter γ is the coefficient that captures the disutility of purchasing unhealthy products displaying the warning label; α is the marginal utility of income, and β is a vector of taste coefficients. Denote by $\theta = (\alpha, \beta, \gamma)$ the vector containing all the parameters of the model that are identical across individuals and time invariant.

We estimate the model using detailed panel data on all transactions for each consumer in the supermarket. Denote by $y_{ist} = \{1, .., J\}$ when individual i chooses product j in store s at time t. Therefore, the probability of purchasing product j is the integral over shocks ε that ensures that product j is the one that maximizes the utility given the choice set in the market. Using the distribution of ε, we obtain a closed-form solution for the individual probability s_{ijst} of purchasing product j. Formally:

$$s_{ijst}(\theta) \equiv \mathbb{P}(y_{ist} = j \mid \theta) = \mathbb{P}(u_{ijst} > u_{ikst}\ , \forall k \neq j) = \frac{\exp(-\alpha p_{jst} + \beta x_{jt} + \gamma L_{jst})}{\sum_{h=1}^{J} \exp(-\alpha p_{hst} + \beta x_{ht} + \gamma L_{hst})} \quad (1)$$

Importantly, explanatory variables that are not product specific (such as consumer's income y_i or potential store fixed effects) cancel out in the utility comparisons and thus, play no role in the purchasing probabilities.

We estimate the model via maximum likelihood (MLE) that solves the following program:

$$\widehat{\theta}_{MLE} = \arg\max_{\theta \in \Theta} \ln L(\theta) = \arg\max_{\theta \in \Theta} \sum_{i=1}^{N} \sum_{j=1}^{J} \sum_{s=1}^{S} \sum_{t=1}^{T} y_{ijst} \ln(s_{ijst}(\theta))$$

where the dummy y_{ijst} is one if individual i chose product j in the store s at time t, and zero otherwise.

3.1 Identification

Our data offer unusual features that are suitable for the identification of the warning labels on consumer behavior. Most research on the effects of food-labeling on consumer behavior cannot separately identify time effects from the labeling effect as the implementation of the regulation takes place simultaneously in all products and stores.

Our identification of parameter γ relies on warning-labels being tagged to the same product in different stores at different moments in time. In fact, this rich variation in the data allows us to identify the effect of labeling on purchasing behavior. For a given product at a given time, we have stores in which the product displays the warning-label and some other stores in which the same products do not. The differences in consumer purchasing probabilities between the two stores allow us to identify the warning-label effect.[20]

The parameter β contains product fixed effects and the interaction between product and time fixed effects. Our product fixed effects will capture all the product characteristics that are time-invariant. Our product-week interacted fixed effects will capture national marketing campaigns and any other activity that product-time specific but common across stores. For example, we can control for the massive advertisement for a particular brand of Easter eggs, and still identify the warning-label effects in that weekend as long as we have stores with and without the regulated packaging.

Identification of the price coefficient, α, relies on the standard price variation across time and products in the data. In fact, we observe price promotions (i.e., temporary price reductions) that differ across products and sometimes across stores.

4 Results

We estimate the discrete choice model laid out in the previous section using data for the four product categories in our sample which were targeted by the regulation. We use data from the same days in May to July 2015 that those days that we have labeling information from May to July 2016. For computational reasons, we limit the analysis to the top 30 UPCs within each category regarding market share.[21] The rest of the UPCs exhibit market shares smaller than one percent within their category.

[20]See Subsection 2.2 for a detailed description of the observed variation in the data.

[21]In ranking products by market share, we considered purchases from both 2015 and 2016. The reason for including the latter period is that some UPCs improved their ranking substantially between the two periods and hence excluding them would have implied leaving out some UPCs which are relevant in consumers' choice decisions.

Table 3 presents the estimation results for each category. Namely, we have breakfast cereals in Panel A, juices in Panel B, chocolates & candies in Panel C; and cookies in Panel D. We include as controls the UPC's price, a set of product dummies and the interaction between product dummies and all the variables that are not product-specific. We report our estimates both pooling across all customers and for two subsamples of interest: high- and low-expenditure customers. We use total expenditure as a proxy for customers' income levels.[22]

Breaking down the analysis by expenditure level is interesting for at least two reasons. First, some prior literature suggests that higher-income, more educated individuals, tend to respond to a greater extent to the presence of front-of-pack labels (Kim et al. (2001), Drichoutis et al. (2005)).[23] Second, as obesity is a more prevalent problem among lower-income groups it is relevant from a policy perspective to determine whether the policy is having an impact on these groups' decision making processes. All estimations in Table 3 include product, store and time fixed effects.

Column (1) in Table 3 presents our estimates for the effects of prices and warning labels on choice probabilities pooling across all customers who bought a UPC in the respective category. Estimated price coefficients are negative and statistically significant across all categories which is consistent with expected demand behavior. Estimates of the parameter of interest (i.e., the coefficient associated to the warning label dummy variable) vary greatly across categories. We find evidence of a strong negative effect of the warning label on the choice probability of a given brand in breakfast cereals and juices. The implied marginal effects of the warning label dummies indicate that the presence of a warning label decreases the probability of choosing a brand by 0.11 in breakfast cereals and 0.24 in juices as shown in Table 4. These estimates are statistically significant at the 5 percent level. In contrast, we cannot reject the null hypothesis that choice probabilities are not affected by the warning labels in the remaining two categories –Chocolates & Candies and Cookies in Panel C and D, respectively.

Turning to the estimates for the high and low-expenditure subsamples, we observe stronger warning labels effects in the case of higher-income customers.[24] In the Cereal category, high-expenditure individuals' choice probabilities are approximately 0.12 lower when the UPC displays a warning label, with the effect being statistically significant at the 5 percent level. In contrast, we do not find a statistically significant coefficient for the low-expenditure customers in the Cereal category. We see that choice probabilities of both low-expenditure and high-expenditure customers are negatively affected by the presence of the warning label in the Juice category with the

[22]To classify consumer type, we use the median of the total expenditure in all categories. Not surprisingly, high-expenditure consumers are over-represented among the transactions in the four selected categories. For computational reasons of the standard errors, we have to consider 15 and 8 products in the estimations reducing the sample size of the low-expenditure.

[23]Kim et al. (2001) find that females are more likely to use labels, that label usage decreases with age and that it increases with income. Similarly,Drichoutis et al. (2005) find that consumers with lower income and education are more likely to report poor nutritional knowledge and label use.

[24]Due to the small sample size of the low-expenditure subsample, the estimations for this subgroup include a lower number of UPCs (15 UPCs for the Cereals, Juices, and Chocolates & Candies categories; and 8 UPCs for Cookies).

effect being slightly stronger in the case of high-expenditure individuals. The presence of a warning label reduces the probability of choosing a UPC from the Juice category by approximately 0.25 in the case of high-expenditure individuals and about 0.23 in the case of low-expenditure individuals.

4.1 Placebo Tests

We conduct a placebo test using the same discrete choice model from Section 3, but using data that predates the implementation of the warning label. In particular, instead of using the previous two months before the law came into force, we "manually introduced" the warning label in the period January 2016-February 2016.[25] In the data, we imposed the same gradual introduction of the warning label, product by product, but in a period in which consumers did not see any label. Table 5 shows the results of this analysis for each category. All coefficients are not significantly different from zero, indicating that there is no effect of the placebo warning label for any of the categories. Therefore, the effects of the warning label from Section 4 are unlikely caused by spurious factors.

4.2 Gradual Implementation versus Before-After

Our identification strategy relies on the gradual implementation of the warning label over time and over stores allowing for time-specific unobservables. In this section, we quantify how sensitive are the results to these set of potential unobservables.

We compare our main estimates relative to two alternative approaches that do not exploit the gradual implementation of the warning labels. The two alternative approaches are i) Using the entire dataset but mistakenly assuming that the labels were implemented at the legal deadline; ii) Using the data before and after the regulation (July 2015 and July 2016 respectively) without exploiting the gradual implementation feature.

We obtain substantial distortions in our estimates that highlight the importance of exploiting the gradual implementation of the food labeling law in three of the studied categories.[26]

The first approach assumes no implemented label before the deadline and that all the warning labels were in place by the limit day. Using few days before and few days after the time limit on June 26th, this estimation resembles a discontinuity regression. The regression discontinuity design in this application assumes that all unobservables are identical before and after the deadline date.

[25] Some manufacturers began the implementation of the warning label in their products in March 2016. The supermarket chain confirmed this, and also it is illustrated in local news at the time (Mostrador (2016)).

[26] Since all products in the Cookie category are labeled after the legal deadline, then the proposed alternative approaches cannot estimate the alternative-specific conditional logit model because the warning labels are no longer alternative specific in the period after the regulation.

The second approach assumes the absence of product-year specific unobservables. The primary source of identification of this approach is that the non-labeled products identify the year effect and the labeled products identify the sum of the label and year effect. If unobservable factors affect a particular UPC in a given year (for example, different marketing campaigns, a different set of competitors, different allocations of supermarket stores shelf space, etc.), then the warning label estimates would be biased.

Table 7 compares the estimates when exploiting the gradual implementation of the regulation versus the two alternative before-after approaches. Column (1) contains the main estimates presented in this paper (Gradual Implementation). Column (2) presents the results when assuming that the implementation only took place at the legal deadline (Deadline Implementation). Column (1) and (2) consider the same dates from May to July 2015 and from May to July 2016. They only differ in the label information. Column (3) presents the estimates when considering two periods of the different regimes: one episode with no warning labels (July 2015) and another episode with full implementation of the warning labels (July 2016) (Column (3) considers the same days of July in both years). We observe *sizable* changes in the results, stressing the quantitative importance of allowing product-time-specific unobservables in the estimation.[27]

5 Conclusions

Providing consumers with interpretative nutritional information is an increasingly favored policy option to induce healthier food choices (Hawkes (2010)). In this paper, we study the effects of a comprehensive nutrition labeling law recently enacted in Chile which mandated the introduction of front-of-pack labels warning of the high levels of calories, sugars, sodium and saturated fats contained in frequently-bought packaged goods. A distinctive feature of our empirical setting is the rich variation we observe in the display of warning labels by narrowly defined products at a given point in time. This variation allows us to overcome a traditional challenge afflicting studies attempting to identify the effects of nutrition labeling policies using a before-after approach, namely the difficulty of disentangling the actual impact of the regulation from time-specific unobservables.

Our estimates from four product categories especially hard hit by the new regulation reveal critical cross-category differences in the response of consumers to new interpretative nutritional information. While consumers tend not to substitute away from products displaying the warning labels in the chocolates & candies and cookies categories, we find evidence of substantial substitution from labeled products in the breakfast cereals and juices products. These results are consistent with interpretative nutritional information affecting consumer decisions when they provide decision-makers with novel information regarding the nutritional content of foods. Furthermore, we find that the effects are primarily driven by high-income consumers suggesting that decisions

[27] See Table 6 for the main estimates and Table 8 for marginal effects in Appendix Section.

on healthful eating by high socioeconomic groups are more susceptible to be modified by the provision of interpretative nutritional information. This finding is highly relevant from a policy perspective as a declared goal of proponents of this type of interventions is to help modify the eating habits of lower-income, less educated segments of the population, who are at higher risk of developing obesity and its associated chronic diseases.

While our empirical approach allows us to improve the identification power of prior work studying consumer responses to nutrition labeling in natural market environments, we are mindful of some of its limitations. First, an issue shared with previous research such as Kiesel & Villas-Boas (2013) and Bollinger et al. (2011), is that our study focuses on a single retail chain. To the extent that purchasing behavior and, in particular, the response to interpretative nutritional information is different from that of consumers served by other retailers our results cannot be extrapolated to the population at large. We should emphasize, however, that the focus on one retail chain in no way compromises the internal validity of our findings. Another limitation is that we quantify the impact of the intervention over the first few months of its introduction. We are unable to capture learning effects that may be taking place over a longer time horizon.

Finally, our focus in this paper is on purchase incidence. Our future research agenda involves investigating other aspects of the consumer response to this type of intervention such as the frequency and quantities of purchase and the amount of aggregate calories that consumers buy. Similarly, we plan to examine cross-category effects of the warning labels and, in particular, the way food categories of “healthy” products (i.e., categories not including labeled products) were affected by the regulation. The estimation of nutrition labeling effects on the purchases of households with children, a key group targeted by the regulation, is also at the top of our list.

References

Bleich, S., Economos, C., Spiker, M., Vercammen, K., VanEpps, E., Block, J., Elbel, B., Story, M. & Roberto, C. (2017), 'A systematic review of calorie labeling and modified calorie labeling interventions: Impact on consumer and restaurant behavior.', *Obesity* **25**(12), 2018–2044.

Bollinger, B., Leslie, P. & Sorensen, A. (2011), 'Calorie posting in chain restaurants', *American Economic Journal: Economic Policy* **3**(1), 91.

Cawley, J. (2015), 'An economy of scales: A selective review of obesity's economic causes, consequences, and solutions', *Journal of Health Economics* **43**, 244–268.

Cawley, J., Hanks, A. S., Just, D. R., Wansink, B. et al. (2016), 'Incentivizing nutritious diets: A field experiment of relative price changes and how they are framed', *NBER Working Paper 21929* .

CERET (2016), 'Medicion de calidad de servicio en la industria del retail supermercados', *Centro de Estudios del Retail (CERET), Depto Ing Industrial, U de Chile.* .
URL: *http://www.ceret.cl/wp-content/uploads/2016/09/Etiquetado-08292016.pdf*

Chintagunta, P., Dubé, J.-P. & Goh, K. Y. (2005), 'Beyond the endogeneity bias: The effect of unmeasured brand characteristics on household-level brand choice models', *Management Science* **51**(5), 832–849.

Corvalán, C., Reyes, M., Garmendia, M. L. & Uauy, R. (2013), 'Structural responses to the obesity and non-communicable diseases epidemic: the chilean law of food labeling and advertising', *Obesity Reviews* **14**(S2), 79–87.

Downs, J. S., Loewenstein, G. & Wisdom, J. (2009), 'Strategies for promoting healthier food choices', *The American Economic Review Papers and Procedings* **99**(2), 159–164.

Drichoutis, A. C., Lazaridis, P. & Nayga, R. M. (2005), 'Nutrition knowledge and consumer use of nutritional food labels', *European Review of Agricultural Economics* **32**(1), 93–118.

Dumanovsky, T., Huang, C. Y., Nonas, C. A., Matte, T. D., Bassett, M. T. & Silver, L. D. (2011), 'Changes in energy content of lunchtime purchases from fast food restaurants after introduction of calorie labelling: cross sectional customer surveys', *The British Medical Journal* **343**, d4464.

Elbel, B., Kersh, R., Brescoll, V. L. & Dixon, L. B. (2009), 'Calorie labeling and food choices: a first look at the effects on low-income people in new york city', *Health Affairs* **28**(6), w1110–w1121.

Feunekes, G. I., Gortemaker, I. A., Willems, A. A., Lion, R. & Van Den Kommer, M. (2008), 'Front-of-pack nutrition labelling: testing effectiveness of different nutrition labelling formats front-of-pack in four european countries', *Appetite* **50**(1), 57–70.

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

Harnack, L. J. & French, S. A. (2008), 'Effect of point-of-purchase calorie labeling on restaurant and cafeteria food choices: A review of the literature', *International Journal of Behavioral Nutrition and Physical Activity* **5**(1), 51.

Hawkes, C. (2004), Nutrition labels and health claims: the global regulatory environment, *in* 'Nutrition Labels and Health Claims: the Global Regulatory Environment', WHO.

Hawkes, C. (2010), *Government and Voluntary Policies on Nutrition Labelling: A Global Overview*, The Food and Agriculture Organization of the United Nations and Woodhead Publishing Series in Food Science, Technology and Nutrition, chapter 4, pp. 37–58.

HC (2017), 'Front-of-package nutrition labelling: September 18, 2017 Stakeholder Engagement Meeting', *Ministry of Health, Canada* .
URL: *https://www.canada.ca/en/services/health/publications/food-nutrition/labelling-stakeholder-engagement-meeting-september-2017.html*

IHME (2013), 'The global burden of disease: Generating evidence, guiding, policy', *Institute for Health Metrics and Evaluation* .
URL: *http://www.ceret.cl/wp-content/uploads/2016/09/Etiquetado-08292016.pdf*

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

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

Kim, S.-Y., Nayga, R. M. & Capps, O. (2001), 'Food label use, self-selectivity, and diet quality', *Journal of Consumer Affairs* **35**(2), 346–363.

Kiszko, K. M., Martinez, O. D., Abrams, C. & Elbel, B. (2014), 'The influence of calorie labeling on food orders and consumption: A review of the literature', *Journal of Community Health* **39**(6), 1248–1269.

Loewenstein, G., Sunstein, C. R. & Golman, R. (2014), 'Disclosure: Psychology changes everything', *Annual Review of Economics* **6**, 391–419.

Malnick, S. D. & Knobler, H. (2006), 'The medical complications of obesity', *Journal of the Association of Physicians* **99**(9), 565–579.

McFadden, D. L. (1974), Conditional logit analysis of qualitative choice behavior, *in* P. Zarembka, ed., 'Frontiers in Econometrics', Academic Press, New York, NY, pp. 105–142.

Mostrador (2016), 'Ley de etiquetados de alimentos', *Diario El Mostrador* .
URL: *http://www.elmostrador.cl/noticias/opinion/2016/03/15/ley-de-etiquetado-de-alimentos/*

NYT (2018), 'In sweeping war on obesity, Chile slays Tony the tiger', *New York Times* .
URL: *https://nyti.ms/2BhlLWv*

Rotfeld, H. J. (2009), 'Health information consumers can't or don't want to use', *The Journal of Consumer Affairs* **43**(2), 373–377.

WHO (2004), 'Global strategy on diet, physical activity and health', *World Health Organization Report* .

6 Figures

Figure 1: *Warning Labels in Chile*

Notes: From left to right: High in Sugar, High in Calories, High in Saturated Fats and High in Sodium. At the bottom of each label it states Ministry of Health.

7 Tables

Table 1: Sample size of Transactions and Choices

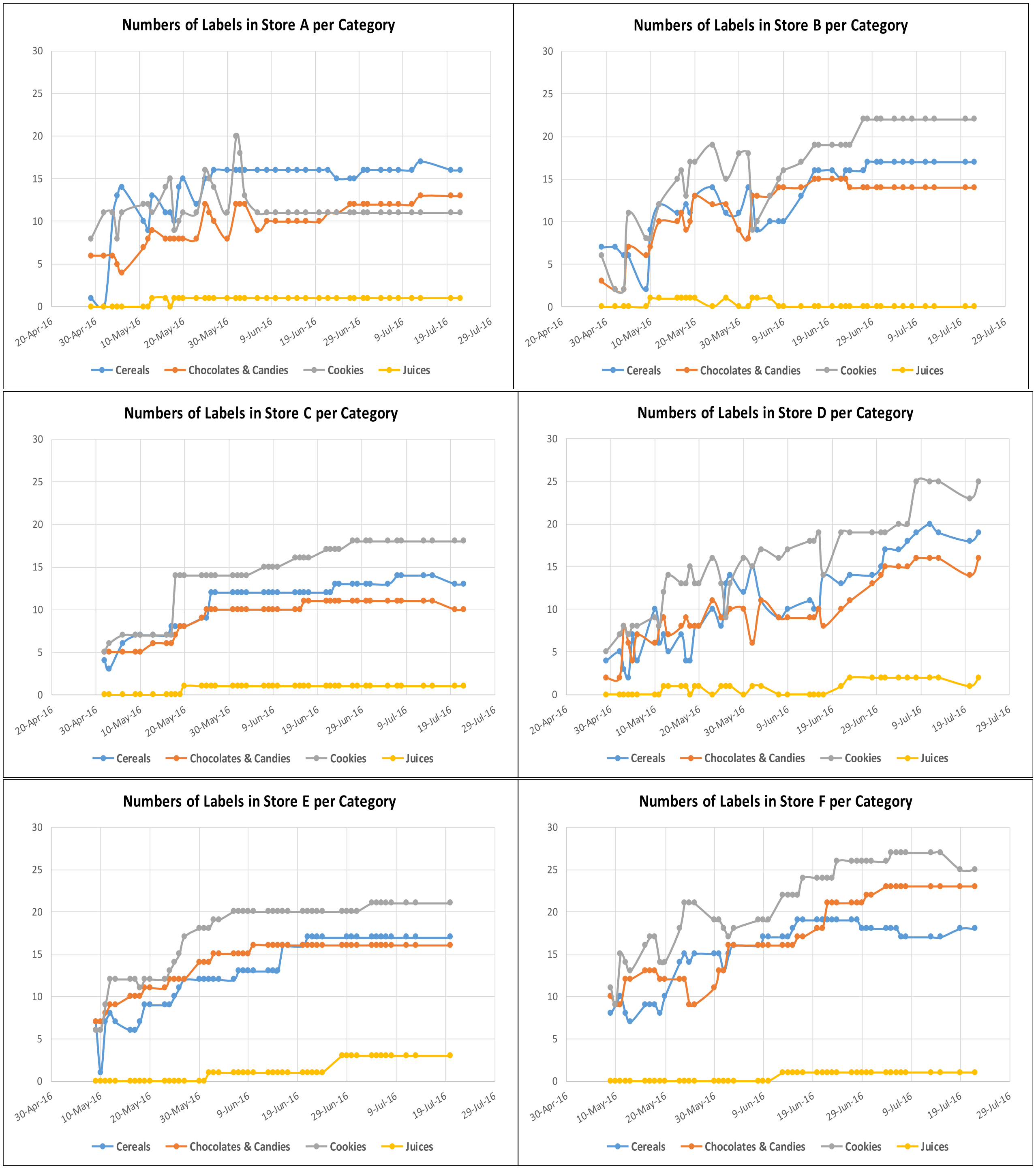
Categories	# Transactions	# Top 30 Choice Set	# Obs.
Cereals	36,797	26.17	962,855
Juice	41,553	26.53	1,102,341
Chocolates & Candies	75,528	24.93	1,882,824
Cookies	56,941	26.62	1,515,567

Table 2: Summary Statistics of Transactions

Store	Average weekly transactions per store	Average weekly revenue per store	Average number of items per transaction	Average amount of dollars per transaction
Local A	3,413	22,678	2.7	6.6
Local B	3,076	14,965	2.1	4.9
Local C	2,879	19,566	2.6	6.8
Local D	2,066	14,182	2.8	6.9
Local E	1,178	4,953	2.2	4.2
Local F	1,554	8,775	2.6	5.6

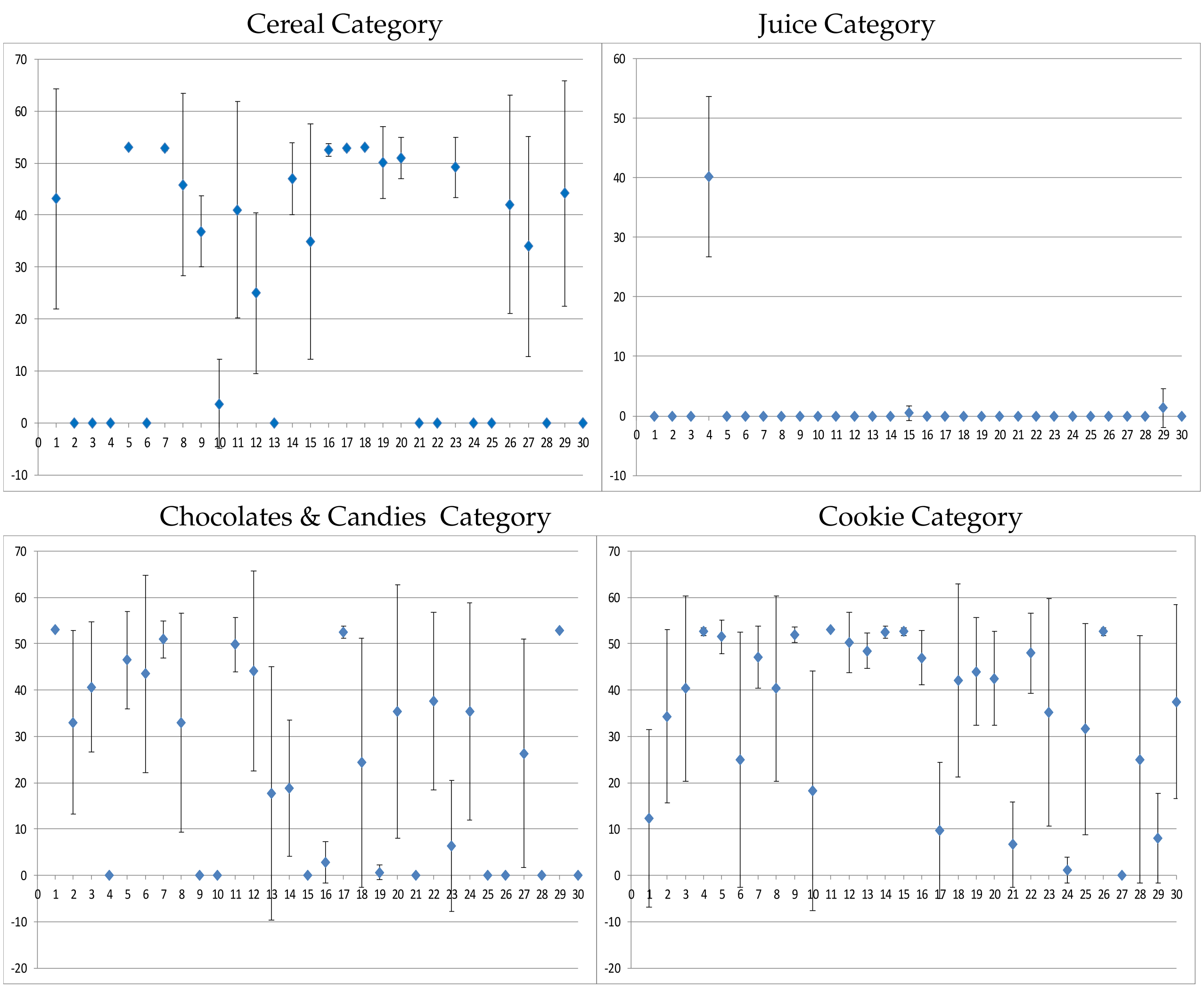
Note: We consider household purchases those made by the consumers from the percentiles 10 to 90 in the total expenditure distribution. To ensure mutually exclusive choices, we define as an eligible transaction those with no more than one item among the top 30 in the selected categories: cereal, juice, chocolates & candies, and cookies. The indicator variable is one for the bought UPC, and zero for all other products in the same category. The final sample size of consumers is 125,485, who made 210,819 eligible transactions in different categories. Since not all the top 30 products were available in every store, the average choice set contains 25.91 products, implying 5,463,587 observations in total.

Figure 2: Evolution of the Number of Labeled products per store over time



Notes: Y-axis is the number of labeled products, X-axis is the time line in weeks. Light blue Line: Breakfast Cereals, Orange Line: Chocolates & Candies, Grey Line: Cookies, Yellow Line: Juices.

Figure 3: Variation of the Time in Advance of the Warning Label Implementation



Notes: X-axis displays each of the top 30 products considered in each category. Y-axis is the number of days in advance of the actual implementation of the warning labels before the legal deadline. The blue dot represents the mean of the number of days in advance across stores for each product, and the error bars represent the corresponding variation (using the standard deviation). Dots at Y=0 correspond to unlabeled (healthy) products. Products are sorted by market share, being product 1 the largest market share and product 30 the tiniest market share among the selected products.

Table 3: Demand Model Estimates for Price and Warning Label Coefficients

	(1)	(2)	(3)
Panel A: Cereals	Full Sample	High Expenditure	Low Expenditure^{+}
log(Price)	-1.676**	-1.549**	-2.248**
	(0.146)	(0.149)	(0.224)
Warning Label Indicator	-0.122**	-0.131**	-0.0476
	(0.0368)	(0.0342)	(0.0866)
Number of Choices	36,797	30,991	3,906
Number of Obs	962,855	811,600	51,954
Panel B: Juices	Full Sample	High Expenditure	Low Expenditure^{+}
log(Price)	-0.105**	-0.0348	-0.270*
	(0.0320)	(0.0448)	(0.113)
Warning Label Indicator	-0.285*	-0.302*	-0.278*
	(0.120)	(0.120)	(0.142)
Number of Choices	41,553	34,110	4,846
Number of Obs	1,102,341	906,826	62,630
Panel C: Chocolates and Candies	Full Sample	High Expenditure	Low Expenditure^{+}
log(Price)	-1.550**	-1.608**	-1.366**
	(0.342)	(0.348)	(0.351)
Warning Label Indicator	0.115	0.124	0.0933
	(0.0979)	(0.0997)	(0.113)
Number of Choices	75,528	57,594	14,066
Number of Obs	1,882,824	1,440,349	201,051
Panel D: Cookies	Full Sample	High Expenditure	Low Expenditure^{++}
log(Price)	-0.547**	-0.576**	-0.0524
	(0.191)	(0.199)	(0.227)
Warning Label Indicator	0.0176	0.0114	-0.0758
	(0.0679)	(0.0628)	(0.179)
Number of Choices	56,941	44,682	4,699
Number of Obs	1,515,567	1,192,169	34,879

Note: $*p < 0.1, **p < 0.05, ***p < 0.01$, (Standard errors in parentheses). To classify consumer type, we use the median of the total expenditure in all categories. More high-expenditure consumers purchase transactions with a single item from the four selected categories. For computational reasons of the standard errors, we have to consider 15 and 8 products in the estimations (marked with superscripts $+$ and $++$ respectively), reducing the sample size of the low-expenditure. We consider data from May to July 2015 and from May to July 2016.

Table 4: Marginal Effects of the Warning Label on Purchase Probabilities

Marginal Effects	(1) **Cereals**	(2) **Juices**	(3) **Chocolates & Candies**	(4) **Cookies**
Full Sample	-11.0% **	-23.8% **	11.2%	1.7%
High Expenditure	-11.8% **	-25.0% *	12.3%	1.1%
Low Expenditure	-4.2%	-22.3% *	8.2%	-5.9%

Note 1: Reported marginal effects on purchase probabilities are computed as a market-share weighted average of the marginal effects for individual products in a category. These are obtained as the difference between the choice probability when the warning label takes the value of one, and the choice probability when the choice probability takes the value of zero while keeping the remaining independent variables at their sample mean values.
Note 2: The estimates significance is denoted by $*p < 0.1$ and $**\, p < 0.05$. Columns (3) and (4) are based on non-significant coefficients.

Table 5: Placebo Test Estimates

	(1) Cereals	(2) Juices	(3) Chocolates & Candies	(4) Cookies
log(Price)	-0.802*** (0.163)	-0.140*** (0.0238)	-0.948 (0.114)	-1.201*** (0.197)
Warning Label Indicator	0,018 (0.0278)	0.191 (0.190)	0.00821 (0.0223)	-0.0188 (0.0622)
Number of Choices	21,959	29,070	41,040	34,607
Number of Obs	571,168	778,791	1,025,034	939,283

Note 1: The placebo sample uses transactions in January-February in 2015 and 2016. No warning label was in place before March 2016.
Note: The estimates significance is denoted by $*p < 0.1$ and $**\, p < 0.05$.

Table 6: Demand Model Estimates assuming Deadline Implementation

Panel A: Cereals	(1) Full Sample	(2) High Expenditure	(3) Low Expenditure
log(Price)	-1.681***	-1.555***	-2.245***
	(0.152)	(0.155)	(0.223)
Warning Label Indicator	-0.268	-0.292*	-0.716
	(0.166)	(0.172)	(1.122)
Number of Choices	36,797	30,991	3,906
Number of Obs	962,855	811,600	51,954

Panel B: Juices	(1) Full Sample	(2) High Expenditure	(3) Low Expenditure
log(Price)	-0.104***	-0.0341	-0.269**
	(0.0323)	(0.0451)	(0.113)
Warning Label Indicator	0.344	0.357	0.376
	(0.285)	(0.274)	(0.251)
Number of Choices	41,553	34,110	4,846
Number of Obs	1,102,341	906,826	62,630

Panel C: Chocolates & Candies	(1) Full Sample	(2) High Expenditure	(3) Low Expenditure
log(Price)	-1.552***	-1.610***	-1.365***
	(0.340)	(0.346)	(0.348)
Warning Label Indicator	0.133	-0.0211	0.278***
	(0.270)	(0.275)	(0.101)
Number of Choices	75,528	57,594	14,066
Number of Obs	1,882,824	1,440,349	201,051

Note: $*p < 0.1, **p < 0.05, ***p < 0.01$, (Standard errors in parentheses). Due to sample size, we consider top 15 products only in the low-expenditure estimations.

Table 7: Estimates Comparison between Gradual Implementation vs Before-After

Cereals	(1) Gradual Implementation	(2) Deadline Implementation	(3) July 2015 -July 2016
log(Price)	-1.676**	-1.681**	-1.761**
	(0.146)	(0.152)	(0.274)
Label	-0.122**	-0.268	-0.190**
	(0.0368)	(0.166)	(0.0893)
Number of Choices	36,797	36,797	7,872
Number of Obs	962,855	962,855	211,291

Juices	(1) Gradual Implementation	(2) Deadline Implementation	(3) July 2015 -July 2016
log(Price)	-0.105**	-0.104**	-0.174***
	(0.0320)	(0.0323)	(0.0436)
Label	-0.285*	0.344	0.0659
	(0.120)	(0.285)	(0.133)
Number of Choices	41,553	41,553	8,965
Number of Obs	1,102,341	1,102,341	237,139

Chocolates & Candies	(1) Gradual Implementation	(2) Deadline Implementation	(3) July 2015 -July 2016
log(Price)	-1.550**	-1.552**	-2.315**
	(0.342)	(0.340)	(0.293)
Label	0.115	0.133	-0.365**
	(0.0979)	(0.270)	(0.120)
Number of Choices	75,528	75,528	16,393
Number of Obs.	1,882,824	1,882,824	408,830

Note 1: Column (1) shows the estimates of Gradual Implementation (Table 3) and Column (2) shows the estimates of Deadline implementation considering data from May-Jul 2015 and May-Jul 2016. Column (3) presents the before and after analysis using data from Jul 2015 and Jul 2016. All cookies are labeled in July 2016; hence conditional logit cannot be estimated as the warning labels are no longer alternative specific.
Note 2: Standard errors are in parentheses and the estimates significance is denoted by $*p < 0.1, **p < 0.05, ***p < 0.01$.

Table 8: Marginal Effects assuming Deadline Implementation

Marginal Effects	(1) **Cereals**	(2) **Juices**	(3) **Chocolates & Candies**
Full Sample	-22.7%	38.1%	13.0%
High Expenditure	-24.5% *	39.7%	-2.0%
Low Expenditure	-48.3%	39.3%	26.2% ***

Note 1: This table shows the marginal effects in the before and after analysis using data from Jul 2015 and Jul 2016. Reported marginal effects on purchase probabilities are computed as a market-share weighted average of the marginal effects for individual products in a category. These are obtained as the difference between the choice probability when the warning label takes the value of one, and the choice probability when the choice probability takes the value of zero while keeping the remaining independent variables at their sample mean values. All cookies are labeled in July 2016; hence conditional logit cannot be estimated as the warning labels are no longer alternative specific.
Note 2: Standard errors are in parentheses and the estimates significance is denoted by $*p < 0.1, **p < 0.05, ***p < 0.01$.

Centro de Economía Aplicada
Departamento de Ingeniería Industrial
Universidad de Chile

2018

339. Identifying Food Labeling Effects on Consumer Behavior
Sebastián Araya, Andrés Elberg, Carlos Noton y Daniel Schwartz

338. Cooperatives vs Traditional Banks: The impact of Interbank Market Exclusion
Raphael Bergoeing y Facundo Piguillem

337. Sorting On-line and On-time
Stefano Banfi, Sekyu Choi y Benjamín Villena-Roldán

336. Investment Opportunities and Corporate Credit Risk
Eugenia Andreasen, Patricio Valenzuela

2017

335. Efectos de la Reforma del Código de Aguas
Ronald Fischer

334. Returns to Higher Education: Vocational Education vs College
Ana Maria Montoya, Carlos Noton y Alex Solis

333. Group strategy-proof stable mechanisms in priority-based resource allocation under multi-unit demand: a note
Antonio Romero-Medina y Matteo Triossi

332. (Group) Strategy-proofness and stability in many-to-many matching markets
Antonio Romero-Medina y Matteo Triossi

331. Longevity, Human Capital and Domestic Investment
Francisco Parro y Francisco Szederkenyi y Patricio Valenzuela

330. The Inequality-Credit Nexus
Ronald Fischer, Diego Huerta y Patricio Valenzuela

329. Inequality, Finance, and Growth
Matías Braun, Francisco Parro y Patricio Valenzuela

328. Take-it-or-leave-it contracts in many-to-many matching markets
Antonio Romero-Medina y Matteo Triossi

2016

327. Do High-Wage Jobs Attract more Applicants?
Directed Search Evidence from the Online Labor Market
Stefano Banfi y Benjamín Villena-Roldán

326. Economic Performance, Wealth Distribution and Credit Restrictions with Continuous Investment
Ronald Fischer y Diego Huerta

325. Motivating with Simple Contracts
Juan F. Escobar y Carlos Pulgar

324. Gone with the wind: demographic transitions and domestic saving
Eduardo Cavallo, Gabriel Sánchez y Patricio Valenzuela

2015

323. Colaboración Público-Privada en infraestructuras: Reforma del sistema concesional español de autopistas de peaje
Eduardo Engel, Ronald Fischer, Alexander Galetovic y Ginés de Rus

322. The Joy of Flying: Efficient Airport PPP contracts
Eduardo Engel, Ronald Fischer y Alexander Galetovic

321. On the welfare cost of bank concentration
Sofía Bauducco y Alexandre Janiak

320. Banking Competition and Economic Stability
Ronald Fischer, Nicolás Inostroza y Felipe J. Ramírez

319. Persistent Inequality, Corruption, and Factor Productivity
Elton Dusha

318. Reputational Concerns in Directed Search Markets with Adverse Selection
Elton Dusha

317. Soft Budgets and Renegotiations in Public-Private Partnerships: Theory and Evidence
Eduardo Engel Ronald Fischer Alexander Galetovic

316. Inequality and Private Credit
Diego Huerta, Ronald Fischer y Patricio Valenzuela

315. Financial Openness, Domestic Financial Development and Credit Ratings
Eugenia Andreasen y Patricio Valenzuela

314. The Whole is Greater than the Sum of Its Parts: Complementary Reforms to Address Microeconomic Distortions
(Por aparecer en The World Bank Economic Review)
Raphael Bergoeing, Norman V. Loayza y Facundo Piguillem

313. Economic Performance, Wealth Distribution and Credit Restrictions under variable investment: The open economy
Ronald Fischer y Diego Huerta

312. Destructive Creation: School Turnover and Educational Attainment
Nicolás Grau, Daniel Hojman y Alejandra Mizala

311. Cooperation Dynamic in Repeated Games of Adverse Selection
Juan F. Escobar y Gastón Llanes

310. Pre-service Elementary School Teachers' Expectations about Student Performance: How their Beliefs are affected by Mathematics Anxiety and Student Gender
Francisco Martínez, Salomé Martínez y Alejandra Mizala

309. The impact of the minimum wage on capital accumulation and employment in a large-firm framework
Sofía Bauducco y Alexandre Janiak

2014

306. Assessing the extent of democratic failures. A 99%-Condorcet's Jury Theorem.
Matteo Triossi

2013

305. The African Financial Development and Financial Inclusion Gaps
Franklin Allen, Elena Carletti, Robert Cull, Jun "Qj" Qian, Lemma Senbet y Patricio Valenzuela

304. Revealing Bargaining Power through Actual Wholesale Prices
Carlos Noton y Andrés Elberg

303. Structural Estimation of Price Adjustment Costs in the European Car Market
Carlos Noton

302. Remedies for Sick Insurance
Daniel McFadden, Carlos Noton y Pau Olivella

301. Minimum Coverage Regulation in Insurance Markets
Daniel McFadden, Carlos Noton y Pau Olivella

300. Rollover risk and corporate bond spreads
Patricio Valenzuela

299. Sovereign Ceilings "Lite"? The Impact of Sovereign Ratings on Corporate Ratings
Eduardo Borensztein, Kevin Cowan y Patricio Valenzuela

298. Improving Access to Banking: Evidence from Kenya
F. Allen, E. Carletti, R. Cull, J."Qj" Qian, L. Senbet y P. Valenzuela

297. Financial Openness, Market Structure and Private Credit: An Empirical Investigation
Ronald Fischer y Patricio Valenzuela

296. Banking Competition and Economic Stability
Ronald Fischer, Nicolás Inostroza y Felipe J. Ramírez

295. Trust in Cohesive Communities
Felipe Balmaceda y Juan F. Escobar

294. A Spatial Model of Voting with Endogenous Proposals: Theory and Evidence from Chilean Senate
Matteo Triossi, Patricio Valdivieso y Benjamín Villena-Roldán

2012

293. Participation in Organizations, Trust, and Social Capital Formation: Evidence from Chile
Patricio Valdivieso - Benjamín Villena-Roldán

292. Neutral Mergers Between Bilateral Markets
Antonio Romero-Medina y Matteo Triossi

291. On the Optimality of One-size-fits-all Contracts: The Limited Liability Case
Felipe Balmaceda

290. Self Governance in Social Networks of Information Transmission
Felipe Balmaceda y Juan F. Escobar

289. Efficiency in Games with Markovian Private Information
Juan F. Escobar y Juuso Toikka

288. EPL and capital-labor ratios
Alexandre Janiak y Etienne Wasmer

287. Minimum wages strike back: the effects on capital and labor demands in a large-firm framework
Alexandre Janiak y Sofía Bauducco

286. Comments on Donahue and Zeckhauser: Collaborative Governance
Ronald Fischer

285. Causal Effects of Maternal Time-Investment on Children
Cecilia Ríos-Aguilar y Benjamín Villena-Roldan

284. Towards a quantitative theory of automatic stabilizers: the role of demographics
Alexandre Janiak y Paulo Santos Monteiro

283. Investment and Environmental Regulation: Evidence on the Role of Cash Flow
Evangelina Dardati y Julio Riutort

282. Teachers' Salaries in Latin America. How Much are They (under or over) Paid?
Alejandra Mizala y Hugo Ñopo

281. Acyclicity and Singleton Cores in Matching Markets
Antonio Romero-Medina y Matteo Triossi

280. Games with Capacity Manipulation: Incentives and Nash Equilibria
Antonio Romero-Medina y Matteo Triossi

279. Job Design and Incentives
Felipe Balmaceda

278. Unemployment, Participation and Worker Flows Over the Life Cycle
Sekyu Choi, Alexandre Janiak y Benjamín Villena-Roldán

277. Public-Private Partnerships and Infrastructure Provision in the United States
Eduardo Engel, Ronald Fischer y Alexander Galetovic

276. The economics of infrastructure finance: Public-private partnerships versus public provision
Eduardo Engel, Ronald Fischer y Alexander Galetovic

* Para ver listado de números anteriores ir a http://www.cea-uchile.cl/.