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Competitive Effects of Front-of-Package Nutrition Labeling Adoption on Nutritional Quality: Evidence from Facts Up Front–Style Labels

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Abstract

"Facts Up Front" nutrition labels are a front-of-package (FOP) nutrition labeling system that presents key nutrient information on the front of packaged food and beverage products in an easy-to-read format. The authors conduct a large-scale empirical study to examine the effect of adoption of FOP labeling on products' nutritional quality. The authors assemble a unique data set on packaged food products in the United States across 44 categories over 16 years. By using a difference-in-differences estimator, the authors find that FOP adoption in a product category leads to an improvement in the nutritional quality of other products in that category. This competitive response is stronger for premium brands and brands with narrower product line breadth as well as for categories involving unhealthy products and those that are more competitive in nature. The authors offer evidence regarding the role of nutrition information salience as the underlying mechanism; they also perform supplementary analyses to rule out potential self-selection issues and conduct a battery of robustness checks and falsification tests. The authors discuss the implications of the findings for public policy makers, consumers, manufacturers, and food retailers.

Keywords

competition, difference-in-differences, Facts Up Front, front-of-package nutrition labeling, nutritional quality, public policy and marketing

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According to estimates from the Centers for Disease Control and Prevention (2018), more than one-third of U.S. adults are obese. Childhood and adolescent obesity rates have also skyrocketed in the last 30 years, with one in five school-aged children considered obese. To combat this disconcerting trend, public policy makers, food manufacturers, and grocery retailers have made efforts over time to design nutrition labels that can educate consumers about the nutritional value of the foods they purchase and help consumers make healthier choices. Recently, the U.S. Food and Drug Administration (FDA), in an attempt to promote healthy food choices among consumers, announced a new Nutrition Facts label for packaged food products that reflects new scientific information, highlighting the link between diet and obesity-related chronic diseases.[1]

The packaged food industry has also voluntarily taken steps to inform consumers about the nutritional value of food products so that consumers can make better choices; one such initiative undertaken by food manufacturers is the Facts Up Front front-of-package (FOP[2]) nutrition labeling. Such

[1] See https://www.fda.gov/Food/GuidanceRegulation/GuidanceDocumentsRegulatoryInformation/LabelingNutrition/ucm385663.htm (accessed June 22, 2017).

[2] We use "FOP" to refer to front-of-package and/or front-of-package nutrition labels. We also use the terms "FOP adoption" and "FOP label adoption" interchangeably.

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Figure 1. Facts Up Front–style front-of-package nutrition labels.

nutrition labels are *voluntarily* adopted by food manufacturers and provide nutrient information on the front of food packaging in a clear, simple, and easy-to-read format. The standardized labels present the key information listed on the Nutrition Facts Panel (NFP; displayed on the back or side of food packages) more concisely, and the information often includes calorie content and the amounts of key nutrients to limit (e.g., saturated fat, sugar, and sodium per serving) (see Figure 1).

Front-of-package labels can be effective in stimulating positive outcomes both on the demand and the supply sides. On the demand side, such easy-to-read labeling systems can help time-starved consumers make healthier choices at the point of purchase and help overcome disadvantages of the mandatory nutrition label (the NFP), which is difficult to read and understand (Nikolova and Inman 2015). Multiple recent studies showed a positive effect of FOP labels on consumers' perceptions of foods' healthiness (for a recent meta-analysis of studies on FOP labels, see Ikonen et al. [2020]) and consumer choice at the point of purchase (Dubois et al. 2020; Zhu et al. 2016). In addition, FOP labels can help mitigate the negative effects of front-of-package nutrient content claims (e.g., "Low Fat") that may serve as a food marketing tool rather than promote health (Emrich et al. 2013). Whereas nutrient content claims can selectively highlight certain nutrients to make the product look healthier and lead to halo effects such that consumers infer that the entire product is healthy from information about only a selected nutrient (Roe, Levy, and Derby 1999), FOP labels provide exact nutrient information. On the supply side, FOP labels can help stimulate product innovation and lead to nutritionally better products. Although the demand effects of FOP labels have generated much interest in recent research, with consensus emerging that FOP labels help consumers identify healthy products (Ikonen et al. 2020), the supply-side implications of FOP labels have not been systematically examined. This study is an attempt to fill this critical research gap in the areas of health and nutrition, public policy, and marketing.

The first objective of our study is to conduct a systematic empirical examination of the effect of adoption of FOP nutrition labels in a product category on the nutritional quality of the food products in the category. Our second objective is to examine the moderating effects of brand and category characteristics. Our central thesis is that adoption of FOP makes product nutrition information more salient, and as consumers' preference for healthier products increases, food manufacturers respond by enhancing the nutritional quality of their products. In accordance with recent studies that suggest conducting mechanism checks as a way of validating claims of causal inference (Goldfarb and Tucker 2014), our final objective is to establish the role of nutritional information salience in consumers' choice of food products as the underlying mechanism that drives food manufacturers to improve the nutritional quality of their products.

To accomplish our objectives, we undertook a comprehensive data collection effort and examined packaging and nutrient information of packaged food and beverage products (21,096 products, 9,083 brands, and 4,408 firms across 44 food and beverage categories) in the United States over a 16-year period. In this study, we focus on a class of FOP labels (commonly known as "Facts Up Front" FOP nutrition labels) that have a standardized and neutral form in which key nutrient information is presented on the front of the package as clear and easy-to-read icons (see examples of the Facts Up Front–style FOP nutrition label in Figure 1). We use a quasi-experimental study design to examine the effects of FOP adoption in a product category on the nutritional quality of the products in the category. We exploit temporal variation in adoption of FOP at the product category level and cast our model in the difference-in-differences (DD) modeling framework built on panel data that helps us compare changes in the nutritional quality of products during the pre- and post-FOP adoption periods across product categories that are exposed to FOP adoption (the treatment categories) and product categories that are not exposed to FOP adoption (the control categories).

We report four sets of findings. First, we find that the adoption of FOP nutrition labeling in a product category results in a considerable improvement in the nutritional quality of food products in that category. Second, heterogeneity analyses suggest that the effect of FOP adoption is stronger for premium (high-priced) brands and brands with a narrower product line breadth. Third, we find that the FOP adoption effect is stronger for unhealthy categories and categories with a higher competitive intensity. Fourth, we find that manufacturers increase the nutritional quality of products by reducing the calorie content and the levels of nutrients to limit, for example, sugar, sodium, and saturated fat. This result helps us shed light on the underlying mechanism. If FOP adoption increases the salience of nutritional information, we argue that this would incentivize food manufacturers to improve products' nutritional quality by limiting the calories and the levels of other nutrients to limit that are actually displayed on the FOP label.

This study advances the understanding of FOP labels from the theoretical and practical perspectives. From the theoretical perspective, we tackle the issue of FOP labels from the supply side and answer the recent call by scholars to help understand the relationship between FOP labels and product nutritional quality (Dubois et al. 2020; Ikonen et al. 2020). We also present evidence of a "nutritional information clearinghouse effect" of FOP labels, whereby such labels increase the salience of nutritional information of products. From the practical perspective, these results will help inform public policy, as well as manufacturers, retailers, and consumers. From the public policy perspective, because the NFP has not been effective in changing consumer choice behavior (Kiesel, McCluskey, and Villas-Boas 2011), the FDA has encouraged food manufacturers to adopt voluntary initiatives that highlight key nutrients on the front of food packages to serve the dual purpose of increasing consumer access to nutritional information and improving product quality. The present results help inform public policy makers that FOP labels, which display key nutrient information on the front of the package in a standardized and a uniform format, help increase products' nutritional quality. Thus, such labels should be promoted. The study's findings specifically help unpack the role of key brand and category characteristics that moderate the effectiveness of FOP adoption suggesting the specific categories and brands in which FOP label adoption can provide the greatest benefits by enhancing product nutritional quality. We believe retailers can benefit from the study by encouraging FOP label adoption in categories that need help in improving nutritional quality.

Facts Up Front FOP Nutrition Labeling Initiative

In 1994, under the Nutrition Labeling and Education Act (NLEA), the FDA mandated food manufacturers to display the NFP on the back (or sometimes on the side) of food packages. Since then, several studies have questioned the effectiveness of the NFP in consumer decision making at the point of purchase. Much of this has been attributed to the high costs of processing information that shoppers face at the time of purchase (Kiesel, McCluskey, and Villas-Boas 2011). In recent years, FOP nutrition labels have gained widespread popularity because they provide information on calories and a set of selective nutrients in the form of easy-to-read icons on the front of food packages. Over the past few years, many different types of FOP nutrition labels have been developed and introduced in the market. In 2009, the FDA commissioner declared in an open letter to the food industry that FOP nutrition labeling would be the agency's top priority and encouraged food manufacturers and retailers to design a standardized, science-based FOP nutrition labeling system that would comply with FDA regulations (Hamburg 2010). Subsequently, two of the leading food industry trade organizations in the United States—the Grocery Manufacturers Association and the Food Marketing Institute—officially announced the voluntary FOP nutrition labeling scheme called the "Facts Up Front" FOP labeling initiative (Sophos 2017). According to the initiative, food manufacturers present the nutritional content of their products in an easy-to-read "callout" format that is based on the Guideline Daily Amounts. Food packages are required to carry four basic icons—for calories (per serving), saturated fat (in grams and Percent Daily Value [%DV]), sodium (in milligrams and %DV), and sugar (in grams)—as a default format.[3]

In this study, for the following reasons, we focus on all of the FOP labels that meet the Facts Up Front guidelines. First, these labels are the most commonly used and standardized FOP nutrition labels. All food manufacturers follow the same format for the shape of the icons and the presentation of information about key nutrients. The format has been accepted and encouraged by the Grocery Manufacturers Association. The FOP labels that we examine also have the support of several agencies, such as the Food Marketing Institute and the FDA

[3] Detailed information about Facts Up Front can be accessed at http://www.aeb.org/images/PDFs/Retail/facts-up-front-style-guide.pdf (accessed October 18, 2018).

(FoodNavigator-USA 2012). In a thorough examination of food product packaging over nearly two decades and across 44 categories, we found that this has been the most common standardized format (this helped us rule out format-related differences that may affect outcomes). Second, the Facts Up Front–style FOP format lists the presence of nutrients in Guideline Daily Amounts. In particular, the levels of nutrients such as saturated fat and sodium presented as a %DV per serving can help consumers choose a balanced food product (see Figure 1). Third, we would like to emphasize that the FOP labels that we study are not nutrient claims (e.g., "25% less saturated fat"). Unlike claims that highlight improvement in selected nutrients of a product, the Facts Up Front–style FOP labels simply present the key nutrient information from the NFP (on the back of a product package) on the front of the package. Moreover, although nutrient claims such as "25% less sugar" may imply a healthier product based on a single nutrient (but not necessarily overall nutrition), Facts Up Front–style FOP labels bring the critical nutrient information from the back panel to the front, which creates the opportunity to focus on the improved *overall* nutritional profile. Figure 1 presents examples of food products with the Facts Up Front–style FOP nutrition labels examined in this study.

Hypotheses

Adoption of FOP Labels Leads to Improvement in Nutritional Quality

Prior research in marketing and economics literature has suggested that consumers often do not have complete information about product attributes (Moorman 1998; Salop 1976), and the resulting costly search process has a profound effect on consumer behavior and competitive behavior (Stigler 1961). In the context of nutrition information, research suggests that consumers face three main types of costs in collecting and assimilating information: (1) collection cost, which comprises the time and effort spent in acquiring nutrition information; (2) computational cost, which includes the effort combining the relevant information into an overall evaluation; and (3) comprehension cost, which captures the effort needed to understand the nutritional information (Russo et al. 1986). Nikolova and Inman (2015) show that a simplified nutrition scoring system at the point of sale reduces all three types of costs, thus motivating consumers to switch to higher-scoring products that are healthier.

Front-of-package labels make key nutrient information salient through their prominent display on the front of the package. A product attribute is deemed salient "when it stands out among the good's attributes relative to that attribute's average level in the choice set" (Bordalo, Gennaioli, and Shleifer 2013, p. 803). Research suggests that consumers give more weight to information that is salient (Bordalo, Gennaioli, and Shleifer 2013; Wu, Swait, and Chen 2019). Therefore, we argue that adoption of FOP labels makes nutritional information more salient and reduces nutritional search and information costs. Indeed, Zhu et al. (2016) calibrate a model based on household purchase–level data and find that the use of FOP labeling increases the weight of the healthiness attribute in consumers' product choices.

Building on these findings, we argue that FOP adoption makes nutritional information more salient, reducing consumers' overall search costs for nutritional information at the point of purchase which, in turn, influences consumer decision making. This change in consumer behavior has important implications for food manufacturers. Game theoretical models and empirical studies suggest that any market mechanism that helps reduce consumers' price search costs—"information clearinghouse" (e.g., the internet price comparison site)—would intensify price competition between firms (Salop and Stiglitz 1977). Following this argument, we suggest that adoption of FOP in a product category serves as a source of "nutritional information clearinghouse" and spurs nutrition competition among food manufacturers. Because consumers favor healthier options, food manufacturers would compete by improving the nutritional quality of products. In summary, FOP adoption in a product category increases salience of nutrition information on the demand side, leading to increased consumer preference for healthier products; on the supply side, food manufacturers respond by offering nutritionally better products in the category. Thus, we propose the following hypothesis:

> **H_1:** Adoption of FOP in a product category has a positive effect on the nutritional quality of products in the category.

In the following subsections, we propose that the effect of FOP adoption in a product category on the improvement in the nutritional quality of products is moderated by brand and category characteristics. We focus on brand characteristics (specifically, price premium and product line breadth) that provide a greater incentive for brands to respond to competitive changes in a product category. For category characteristics, we focus on factors (specifically, category healthiness and competitive intensity) that present a greater opportunity for food manufacturers to improve products' nutritional quality.

The Moderating Effect of Brand Characteristics

Although price competition is a common strategy in the grocery market, many brands compete on perceived quality and command a price premium. Prior research has suggested that brands' price premium is a critical lower-funnel shopper marketing instrument that influences consumers' decision making at the point of purchase (Lamey et al. 2018). Because premium brands target a price-insensitive consumer segment and charge a price premium over competing lower-tier brands in a category, they face constant pressure to differentiate their products and justify their higher prices. Researchers have identified health and nutrition information as one of the key associations consumers make with a brand that can drive their willingness to pay for grocery products (Balcombe, Fraser, and Di Falco 2010; Bauer, Heinrich, and Schäfer 2013; Drichoutis, Lazaridis, and Nayga 2009). Studies also suggest that consumers who are less sensitive to price are more likely to focus on the nutritional aspects of products and nutrition labels

(Drichoutis, Lazaridis, and Nayga 2005) and that the introduction of a point-of-sale nutrition scoring system can decrease shoppers' price sensitivity (Nikolova and Inman 2015). Taken together, these arguments suggest that premium brands are more likely to invest in product innovation and offer nutritionally better products to continue to justify the price premium they command over nonpremium brands. From the demand perspective, given the price point of premium brands, consumers are also more likely to pay greater attention to the nutritional content of high-priced products. Thus, premium brands benefit from improving their products. From the supply side, premium brands may also have greater resources to invest in product innovation, leading to products with higher nutritional quality, which is aligned with changing consumer preferences for nutritionally better products. Therefore, we expect the effect of FOP adoption on nutritional quality to be greater for premium brands in a product category and propose the following hypothesis:

> **H_{2a}:** The effect of FOP adoption on the nutritional quality of products is stronger for premium brands.

The second brand characteristic we consider is the breadth of a brand's product line. The product mix is an important part of a brand's overall competitive strategy. In grocery retailing, beyond the price dimension, brands compete in nonprice dimensions and constantly innovate and introduce new products to expand product lines and gain market share (Gielens 2012). Research has shown that although broader product lines can help increase demand and prices, they can also increase costs related to product design and development (Bayus and Putsis 1999). In a similar vein, brands with broader product lines might impose additional resource constraints in such a way that brands with narrower product lines might have an edge in reformulating products and engaging in product innovation by improving the nutritional profile of their products. Although brands with a broader product line breadth could have more market power and greater potential to innovate, we argue that brands with narrower product lines are better positioned to change the products' nutrition level. This is because, on the demand side, consumers face lower nutrition information search costs for brands with narrower product lines. Consumers may also be able to compare a brand's nutritional profile within and across categories more easily for brands with a smaller product portfolio, thus effectively motivating these brands to leverage their focused product portfolio and actively engage in improving their products. Thus, we expect that the effect of FOP is greater for brands with a narrower product line breadth across categories. Thus, we present the following hypothesis:

> **H_{2b}:** The effect of FOP adoption on the nutritional quality of products is stronger for brands with narrower product line breadth.

The Moderating Effect of Category Characteristics

As consumers process nutritional information of products and search for healthier options, the marginal benefit of searching for healthier options is lower in healthy categories compared with unhealthy categories. Moorman (1996) finds that following the enactment of the NLEA, a negative relationship exists between category healthiness and the amount of information consumers obtain in a product category, suggesting that consumers may need more information in unhealthy categories. This finding, applied to the present study context, suggests that introduction of FOP labeling would make nutrition information more salient in less healthy categories. From the demand-side perspective, Cadario and Chandon (2020) argue that healthy eating nudge interventions (including nutrition labeling) are more effective in reducing unhealthy eating than increasing healthy eating. On the supply side, given that unhealthy categories have low nutritional quality, the opportunity to improve the nutritional quality of products is also higher in unhealthy categories. Thus, food manufacturers in unhealthy categories have a greater incentive to invest in product innovation and to appeal to consumers who search for relatively healthier or less unhealthy options even in inherently unhealthy categories. Moorman, Ferraro, and Huber (2012) find that after the NLEA was enacted, firms in unhealthy categories improved the nutritional quality of their products more than those in healthy categories. We posit the following hypothesis:

> **H_{3a}:** The effect of FOP adoption on the nutritional quality of products is stronger for unhealthy categories.

Consumers face higher search costs for product attributes when shopping in product categories with higher competitive intensity compared with less competitive categories. Extant research suggests that price dispersion can be higher in more competitive markets (Borenstein and Rose 1994; Chandra and Tappata 2011). In such markets, consumers may face higher search costs, and firms have an incentive to take actions to reduce consumers' search costs so that the products can enter consumers' consideration sets (Pires 2018). Thus, on the demand side, consumers may face high price dispersion and high search costs in highly competitive categories. On the supply side, food manufacturers in more competitive categories have more incentives to innovate to reduce consumers' search costs so that their products can enter consumers' consideration sets. Stated differently, firms have a greater incentive to differentiate themselves by investing in improving the nutritional quality of their products in more competitive categories. Thus, we propose the following hypothesis:

> **H_{3b}:** The effect of FOP adoption on the nutritional quality of products is stronger for categories with greater competitive intensity.

Methods

Data

The primary data source is the Mintel Global New Products Database (GNPD), which is considered the industry standard in reporting new product launches, trends, and innovations in the packaged food and beverage product industry. The database provides nutritional information, photographs of the package, price, package size, number of units in a multipack product, and so on. In addition to these product attributes, the database has information about brands, manufacturers, categories, and published dates. We accessed the database and collected the aforementioned information for all food and beverage products across 44 product categories in the United States over 16 years (from 1996 to 2011), including existing and new product launches. By manually examining the photographs of the packages of all the products released during the period, we identified products with FOP labels and recorded when the FOP-labeled products were introduced in each product category. To assemble the estimation data set, we removed outliers (based on a boxplot of nutrient levels) and products with missing nutrient information. Next, we separated the data into two sets, the calibration data set (from 1996 to 2002) and the estimation data set (from 2003 to 2011). We used the calibration data to construct the moderating variables.[4] This ensured that brand and category classifications did not confound with the estimation period and helped us interpret the effect of moderating variables (Rishika et al. 2013). The final estimation data set consists of 21,096 products, 9,083 brands, and 4,408 firms in 44 food and beverage categories.

Nutritional Quality Measurement

To measure products' nutritional quality level, we used the Nutrient Profiling (NP) model that was developed by the United Kingdom Food Standard Agency and the British Heart Foundation Health Promotion Research Group at Oxford University (Rayner, Scarborough, and Lobstein 2009). The NP model has been widely used in marketing (André, Chandon, and Haws 2019; Dubois et al. 2020), economics (Wang, Rojas, and Bauner 2015), public health (Scarborough et al. 2007), and nutrition (Julia et al. 2015) literature. The NP score is calculated in a way to offset calories (kJ)[5] and the nutrients to limit—including saturated fat (g), sugar (g), and sodium (mg)—by the nutrients to encourage, including fruit, vegetable, and nut (FVN) content (%); fiber (g); and protein (g). Specifically, based on the content of the aforementioned nutritional elements in a 100 g or 100 mL food or beverage product, 0 to 10 points are assigned to each negative element, and 0 to 5 are assigned to each positive element. The total points for positive elements are subtracted from the total points for negative elements to calculate the NP score. Based on calories, five nutrients (saturated fat, sodium, sugar, fiber, and protein), and the FVN content,[6] the NP model generates a single score that ranges between -15 (the most healthy) and 40 (the least healthy).

Several unique characteristics of the NP model deserve mention. First, the NP score is a serving size–free index—because it measures the nutritional quality based on the amount of each nutrient in 100 g or 100 mL of a food or beverage product—and thus measures the nutritional quality independent of individual-specific food consumption patterns and enables comparison of the nutritional quality of various products across brands and categories. Second, the NP score is a standardized score that helps classify food and beverage products as "healthy" or "less healthy." A food product is classified as "less healthy" if the NP score is more than or equal to 4, and a beverage product is classified as "less healthy" if the NP score is more than or equal to 1 (Rayner, Scarborough, and Lobstein 2009). Table 1 provides the summary statistics of the NP score across the product categories that we analyze.

Research Design and Identification Strategy

Before we present our proposed econometric model, we discuss issues related to the research design and identification strategy. We take a quasi-experimental approach with the (first-time) adoption of FOP by a brand in a category as the treatment and examine the effect on the nutritional quality of products of other brands in the same category. As we mentioned previously, our estimation data spans 2003 to 2011 (referred to as the "focal time period"). Using the adoption of FOP by all the brands in all of the product categories during the focal time period, we classify the product categories into two types: the treatment group (categories in which we observe the introduction of a FOP-labeled product during the focal time period) and the control group (categories in which we do not observe the introduction of a FOP-labeled product during the focal time period). In other words, the timing of FOP adoption is the only criterion that we use to classify categories into the treatment and control groups. One might be concerned about the effect of category characteristics on group assignment. However, in line with the arguments presented in Hwang and Park (2016), we contend that category factors (e.g., healthiness) that can potentially induce self-selection bias are not time varying. Thus, the group assignment—based solely on the timing of FOP adoption—ensures that there are no systematic differences between the treatment and control categories. The empirical modeling approach, DD, accounts for time-invariant brand-, firm-, and category-specific characteristics. We also confirm that there is no statistically significant correlation between the timing of FOP adoption and category healthiness.[7]

[4] We refer readers to the "Heterogeneity Across Brands: The Role of Price and Product Line Breadth" and "Heterogeneity Across Categories: The Role of Healthiness and Competitive Intensity" subsections of the "Methods" section.

[5] In the GNPD, because the calorie content is given in kilocalories (kcal), we converted the calorie metric from kilocalories to kilojoules (kJ).

[6] We note that the GNPD does not have detailed information on the FVN content levels. Following Griffith et al. (2018), we classify the food/beverage categories into two groups, categories with 0% FVN and categories with 100% FVN. Among the 44 product categories, Nuts, Salad, and Vegetables are included in the latter group, and all other categories are included in the former group. We note that although some categories (e.g., sauces, spreads, soups) contain FVNs of more than 40% (but less than 100%), Griffith et al. (2018) still assigned zero points for FVN content in calculating NP scores.

[7] We rule out selection issues in the "Self-Selection Challenges" subsection of the "Validation Analyses" section.

Table 1. Summary Statistics of Product Categories.

Index	Category	Food/ Beverage	Treatment/ Control Category	Summary Statistics of Nutrient Profiling Score				
				Mean	Mdn	SD	Min	Max
1	Baking Ingredients & Mixes	Food	Treatment	14.27	16.00	7.80	−8	35
2	Bread	Food	Treatment	4.24	2.00	6.64	−7	27
3	Cakes, Pastries & Sweet Goods	Food	Treatment	14.42	16.00	6.82	−5	32
4	Caramel & Cream Spreads	Food	Control	18.57	18.00	6.25	7	35
5	Carbonated Soft Drinks	Beverage	Treatment	1.53	2.00	.96	0	3
6	Chocolate Confectionery	Food	Treatment	19.08	21.00	7.14	0	32
7	Chocolate Spreads	Food	Control	19.37	20.00	4.11	12	26
8	Cold Cereal	Food	Treatment	9.11	9.00	6.77	−8	34
9	Confiture & Fruit Spreads	Food	Treatment	9.93	11.00	4.95	−4	26
10	Corn-Based Snacks	Food	Control	10.43	11.00	6.95	−3	31
11	Creamers	Food	Treatment	12.15	10.50	7.42	0	30
12	Dairy-Based Frozen Products (Ice Cream)	Food	Treatment	11.51	13.00	5.98	−9	29
13	Eggs & Egg Products	Food	Treatment	1.41	−1.50	7.07	−5	23
14	Energy Bar	Food	Treatment	12.99	13.00	5.19	−6	35
15	Energy Drinks	Beverage	Treatment	−.21	.00	2.04	−5	3
16	Fish Products	Food	Treatment	2.74	1.00	5.67	−5	21
17	Hot Cereal	Food	Treatment	3.23	1.00	6.97	−6	20
18	Juice	Beverage	Treatment	1.66	2.00	1.42	−5	13
19	Margarine	Food	Control	22.03	24.50	6.61	0	28
20	Mayonnaise	Food	Treatment	19.82	23.00	6.22	0	28
21	Meat Snacks	Food	Control	17.51	17.00	5.98	0	28
22	Milk	Beverage	Treatment	1.29	.00	4.91	−2	22
23	Nuts	Food	Treatment	2.64	3.00	4.44	−10	21
24	Nut Spreads	Food	Treatment	13.65	15.00	4.54	0	23
25	Pasta	Food	Treatment	−1.17	−3.00	4.97	−7	16
26	Pasta Sauce	Food	Treatment	5.04	3.00	5.51	−5	29
27	Pizza	Food	Treatment	8.43	10.00	5.37	−4	28
28	Popcorn	Food	Treatment	14.18	16.00	7.92	−6	27
29	Potato Products	Food	Treatment	4.41	4.00	5.05	−6	25
30	Potato Snacks	Food	Treatment	13.87	13.00	5.41	−4	34
31	Poultry Products	Food	Treatment	5.54	4.00	5.84	−6	24
32	Prepared Meals	Food	Treatment	2.04	1.00	4.01	−6	27
33	Ready-to-Drink Iced Tea	Beverage	Treatment	.84	1.00	.85	−1	3
34	Rice	Food	Treatment	2.33	.00	6.11	−7	18
35	Salad	Food	Control	5.62	4.00	6.16	−3	35
36	Salad Dressings	Food	Treatment	14.73	16.00	6.81	−1	31
37	Savory Biscuits/Crackers	Food	Treatment	12.39	14.00	7.27	−6	40
38	Soup	Food	Treatment	2.95	2.00	3.47	−7	27
39	Sports Drinks	Beverage	Treatment	4.52	1.00	8.04	−3	23
40	Sweet Biscuits/Cookie	Food	Treatment	18.95	20.00	5.57	−7	40
41	Syrup	Food	Control	12.12	13.00	3.27	−1	17
42	Table Sauces	Food	Treatment	9.95	10.00	6.35	−3	40
43	Vegetables	Food	Treatment	−5.66	−6.00	3.48	−14	10
44	Yogurt	Food	Treatment	.62	1.00	2.69	−5	13

Notes: Categories are presented in alphabetical order. The smaller the Nutrient Profiling (NP) score, the better the nutritional quality. For a food product, the NP score that is more than or equal to 4 indicates "less healthy." For a beverage product, the NP score that is more than or equal to 1 indicates "less healthy."

Our research design involves the treatment effect of adoption of FOP in a product category by a brand (referred to as the "first adopter") on the change in nutritional quality of products of other (competing) brands in the same product category. Regarding the first adopter brand in any given category, one can argue that it has higher nutritional quality and is more likely to adopt FOP. To ensure that the first adopter brand does not contaminate the results, and to facilitate a cleaner interpretation of the effect of FOP adoption (by the first adopter brand) on the nutritional quality of other competing brands, we removed the "first adopter" brands (and firms) from the analysis. As FOP nutrition labeling is voluntary, and because we removed the first adopters from the analysis, the timing of the adoption of FOP by the first adopter in a product category is unlikely to be correlated with the nutritional quality of other brands in the same product category. In summary, we treat FOP adoption (by the first adopter brand) in a category as an exogenous shock to other brands in the category and investigate whether FOP adoption acts as a catalyst for other brands to improve the nutritional profile of their product portfolios.

Following this research design, we cast our analyses in the DD modeling framework to estimate the treatment effect (adoption of FOP in a product category) on the outcome variable (overall nutritional quality of food and beverage products; Meyer 1995). By comparing the nutritional quality of products of brands in a product category before and after FOP adoption, and between the treatment group and the control group categories, we not only account for temporal factors that affect both groups simultaneously but also control for innate differences between the two groups. The "double differencing" helps identify the causal effect of FOP category adoption on nutritional quality of products (Angrist and Pischke 2009). We remind readers that we work with observational data. Thus, we acknowledge that any causal interpretation is valid within the assumptions of the DD model. Given the absence of full randomization, we further conduct a series of robustness checks and falsification tests to validate our DD modeling strategy that are discussed in subsequent sections.

Main Effect of FOP Adoption on Products' Nutritional Quality

The key dependent variable of interest is the NP score of a product in the set of packaged food and beverage product categories. Given the range of the NP score across the diverse set of categories (ranging between −14 and 40 in our study), to facilitate an intuitive interpretation, we use the min-max scaling procedure (Jain and Bhandare 2014) and rescale the NP scores on a new scale ranging from 1 (the least healthy) to 100 (the most healthy). We refer to the rescaled NP score as the Nutrient Profiling Index (NPI)[8] and use the score as our focal dependent variable in the DD models. The unit of analysis is the product–brand level.[9] We employ the DD modeling framework to examine the effect of adoption of FOP in a category on the nutritional quality of products in the category (H_1) as follows:

$$\text{Nutritional quality}_{pbfct} = \alpha_1 \text{FOP}_{pbfct} + \alpha_2 \text{Time trend}_t + \phi_b + \omega_f + \nu_c + \sigma_t + \tau_{ct} + \epsilon_{pbfct}. \quad (1)$$

In Equation 1, $\text{Nutritional quality}_{pbfct}$ represents the NPI score of product p by brand b that belongs to firm f in category c at time t. FOP_{pbfct} is the focal independent variable that is equal to 1 for all products in a treatment category in the post-FOP period, and 0 for all products in a treatment category during the pre-FOP period and for those in a control category. The time trend variable (Time trend_t) helps control for linear trend in nutritional quality across all food products over time. As there are different categories, the inclusion of category-specific time trend effects (τ_{ct}) helps further control trend in nutritional quality across all food products within a category. The inclusion of year fixed effects (σ_t) not only helps control for changes in nutritional quality in a given year due to supply-side factors (e.g., manufacturing capabilities) and demand-side factors (e.g., consumers' preference for healthier products) but also helps control for any other year-specific omitted variables. The brand (ϕ_b), firm (ω_f), and category (ν_c) fixed effects help account for baseline differences in nutritional quality across brands, firms, and categories, respectively. ϵ_{pbfct} is the error term. The focal coefficient of interest is α_1 (the DD estimate), which captures the average effect of adoption of FOP in a category on the NPI of products in the treatment categories relative to those in the control categories in the post-FOP period (compared with the pre-FOP period).

Heterogeneity Across Brands: The Role of Price and Product Line Breadth

Premium brands versus nonpremium brands. Following the arguments presented in recent marketing literature using DD models (Janakiraman, Lim, and Rishika 2018; Tucker, Zhang, and Zhu 2013), we use the median split of the brand-specific mean price to classify the brands into premium and nonpremium brands.[10] We focused on brands that exist in both the calibration and estimation periods and used data from the calibration period (1996 to 2002) to compute a set of brand-specific mean prices of the products. This helps ensure that the brand classification does not confound with the estimation time period and allows for easy interpretation of the moderating effects of brands (Janakiraman, Lim, and Rishika 2018; Rishika et al. 2013). To empirically examine the effect of premium brand (H_{2a}), following recent studies (Goldfarb and Tucker 2011), we extend our DD model to the difference-in-difference-in-differences (DDD) modeling framework by interacting FOP_{pbfct} (presented in Equation 1) with the focal moderating variable, an indicator variable associated with premium brands. The proposed DDD model is as follows:

$$\text{Nutritional quality}_{pbfct} = \beta_1 \text{FOP}_{pbfct} \times \text{Premium}_b + \beta_2 \text{FOP}_{pbfct} + \beta_3 \text{Time trend}_t + \phi_b + \omega_f + \nu_c + \sigma_t + \tau_{ct} + \epsilon_{pbfct}. \quad (2)$$

In Equation 2, Premium_b takes a value of 1 if brand b is a premium brand, and 0 otherwise. All other variables and fixed effects in Equation 2 are identical to those in Equation 1. In Equation 2, the main coefficient of interest is β_1 (the DDD

[8] The min-max normalization-based rescaling procedure is used to fit the desired or target range, and the procedure allows for easy interpretation of the model results. Moreover, this normalization preserves the information of the NP scores and relationship between the original data values (Jain and Bhandare 2014).

[9] We use the term "product" to differentiate between the two products—for example, Kellogg's Cinnamon Frosted Flakes and Frosted Flakes with Marshmallows—by the brand Frosted Flakes, which belongs to the firm Kellogg's.

[10] Our models replicate the results using continuous moderating variables (see the "Robustness Checks" subsection of the "Validation Analyses" section).

estimate) that captures the effect of FOP adoption in a category on the nutritional quality of products of the premium brands (relative to the nonpremium brands) in the treatment categories (relative to the control categories) in the post-FOP period (compared with the pre-FOP period).

Wider product line breadth brands versus narrower product line breadth brands. To measure the level of product line breadth of brands, we focused on brands that exist in both the calibration and estimation periods and calculated the total number of products of each brand in the calibration period. Drawing on the median split of the brand-specific total number of products, we classify the brands into two types: brands with a wider product line breadth and those with a narrower product line breadth. Similar to the DDD model presented in Equation 2, we estimate a DDD model of nutritional quality to examine the differential effect of FOP adoption between brands with a wider product line breadth and those with a narrower product line breadth (H_{2b}). The model is as follows[11]:

$$\begin{aligned}\text{Nutritional quality}_{\text{pbfct}} = {} & \beta_1 \text{FOP}_{\text{pbfct}} \times \text{Product line breadth}_{\text{b}} \\ & + \beta_2 \text{FOP}_{\text{pbfct}} + \beta_3 \text{Time trend}_{\text{t}} + \phi_{\text{b}} \\ & + \omega_{\text{f}} + \nu_{\text{c}} + \sigma_{\text{t}} + \tau_{\text{ct}} + \epsilon_{\text{pbfct}}.\end{aligned} \tag{3}$$

In Equation 3, Product line breadth_b takes a value of 1 if brand b is a brand with a wider product line breadth (i.e., a brand with a larger number of products), and 0 otherwise. All other variables and fixed effects in Equation 3 are identical to those in Equations 1 and 2.

Heterogeneity Across Categories: The Role of Healthiness and Competitive Intensity

H_{3a} and H_{3b} examine the variation in the effects of introduction of FOP across categories based on healthiness and competitive intensity, respectively. As stated previously, and following precedence (Rayner, Scarborough, and Lobstein 2009), we classify a food product as "less healthy" if the NP score is more than or equal to 4, and we classify a beverage product as "less healthy" if the NP score is more than or equal to 1. Drawing on the average NP score of all products (from the calibration period data) in a category, we classified the 44 categories into healthy and unhealthy groups (see Table W1 in the Web Appendix). Following previous industrial organization literature (Borenstein and Rose 1994; Chandra and Tappata 2011), we operationalize competitive intensity by price dispersion as measured by the coefficient of variation. The coefficient of variation[12] is a unit-free measure of relative dispersion that helps compare price dispersion across categories where products are sold at different price levels (Sorensen 2000). This measure has been widely used in the economics and management literature (Borenstein and Rose 1994; Sorensen 2000; Zhao 2006). The larger the coefficient of variation, the more dispersed the price, and the greater the competitive intensity (Borenstein and Rose 1994; Zhao 2006). As discussed previously, we use data from the calibration period, and based on the median split of the category-specific coefficients of variation, we classify the categories into high versus low levels of competitive intensity (see Table W1 in the Web Appendix).

To test H_{3a} and H_{3b}, we propose the following DDD model:

$$\begin{aligned}\text{Nutritional quality}_{\text{pbfct}} = {} & \gamma_1 \text{FOP}_{\text{pbfct}} \times \text{Healthy}_{\text{c}} + \gamma_2 \text{FOP}_{\text{pbfct}} \\ & \times \text{Competitive intensity}_{\text{c}} + \gamma_3 \text{FOP}_{\text{pbfct}} \\ & + \gamma_4 \text{Time trend}_{\text{t}} + \phi_{\text{b}} + \omega_{\text{f}} + \nu_{\text{c}} + \sigma_{\text{t}} \\ & + \tau_{\text{ct}} + \epsilon_{\text{pbfct}}.\end{aligned} \tag{4}$$

In Equation 4, Healthy_c and Competitive $\text{intensity}_\text{c}$ are the indicator variables that take a value of 1 if category c is determined to be a healthy and more competitive category, respectively, and 0 otherwise. All other variables and fixed effects in Equation 4 are the same as those in Equations 1–3.[13] The DDD estimates (γ_1 and γ_2) help us examine how the effect of FOP adoption varies across the category characteristics.

Results

Effect of FOP Category Adoption on Overall Nutritional Quality of Products

In Column 1 of Table 2, we present the results of the DD model shown in Equation 1. We note that the standard errors reported in the table are clustered at the category level and are heteroskedasticity robust. The DD estimate (α_1) is positive and statistically significant which suggests that the adoption of FOP in a category leads to improvement in nutritional quality of products in the category. We thus find support for H_1.

To better understand the effect size of the adoption of FOP labels at the product category level, we estimated the DD model (in Equation 1) with the original NP score as the dependent variable, and based on the DD estimate, we find that the introduction of FOP reduces calorie levels by approximately 42.21 kcal[14] in 100 g of food or 100 mL of beverage product

[11] Because the samples for the DDD models in Equations 2 and 3 are different due to missing brand information (e.g., price) during the calibration time period, we estimate the DDD models including the different moderating variables one at a time.

[12] Because the distribution of prices is skewed to the right and lognormally distributed, we use the following formula of coefficient of variation for a more precise estimate: $\sqrt{e^{s^2} - 1}$, where s is a sample standard deviation of the price after a natural log transformation (Koopmans, Owen, and Rosenblatt 1964).

[13] Unlike the DDD models for brand-level moderating effects presented in Equations 2 and 3, the sample is common across the category-level moderating effects analyses, and thus all the interaction terms are in one DDD model.

[14] For a one-unit increase in the NP score, the upper limits of the calories, saturated fat, sugar, and sodium increase by 335 kJ (= 80.07 kcal), 1 g, 4.5 g, and 90 mg, respectively (Rayner, Scarborough, and Lobstein 2009). Thus, the calorie decrease attributable to FOP can be calculated with the following formula: 80.07 kcal × −.5272 (DD estimate).

Table 2. Effect of FOP Nutrition Labeling on Nutritional Quality.

		Dependent Variable: Nutritional quality			
		(1)	**(2)**	**(3)**	**(4)**
Main effect	**FOP**	**.9490**** **(.3713)**	.2527 (.9653)	−.1082 (.8838)	.1067 (.6446)
Brand-level moderating effects	**FOP × Premium**	—	**1.3967**** **(.5899)**	—	—
	FOP × Product line breadth	—	—	**−1.2605**** **(.6080)**	—
Category-level moderating effects	**FOP × Healthy**	—	—	—	**−1.3930**** **(.5745)**
	FOP × Competitive intensity	—	—	—	**1.5193**** **(.6081)**
Time trend		−.0633* (.0360)	−.1067*** (.0404)	−.0882** (.0362)	−.0473* (.0274)
Brand fixed effects		Yes	Yes	Yes	Yes
Firm fixed effects		Yes	Yes	Yes	Yes
Category fixed effects		Yes	Yes	Yes	Yes
Year fixed effects		Yes	Yes	Yes	Yes
Category-specific time trends		Yes	Yes	Yes	Yes
Observations		21,096	5,811	8,376	21,096
R^2		.8189	.6952	.7145	.8190

*$p < .10$.
**$p < .05$.
***$p < .01$.
Notes: The focal variable of interest and its coefficient estimate (i.e., DD and DDD estimate) that is statistically significant is highlighted in bold. Robust standard errors that are clustered at the category level are in parentheses.

when there is no change in other nutritional contents and decreases saturated fat, sugar, and sodium by approximately .53 g, 2.37 g, and 47.45 mg, respectively. Drawing on the entire set of products in the treatment categories in the post-FOP period, we find that FOP adoption leads to a reduction in calories (−12.50%), saturated fat (−12.97%), sugar (−12.62%), and sodium (−3.74%; see Table 3). To evaluate the effect size for an individual product in a more realistic setting, we identified a set of packaged food products outside the sample. Based on their actual nutritional information and serving sizes, we calculated the marginal effect of the introduction of FOP on the nutritional quality of the selected products (see Table 3).

Moderating Effects of Brand Characteristics

H_{2a} and H_{2b} refer to the variation in the proposed effects of FOP labels across brands based on premium brands and product line breadth. The positive and statistically significant DDD estimate (β_1 in Equation 2) suggests that the effect of FOP category adoption is stronger for premium brands (see Column 2 of Table 2). In addition, the negative and statistically significant DDD estimate (β_1 in Equation 3) indicates that the FOP effect is stronger for brands with a narrower product line breadth (see Column 3 of Table 2). The spotlight analyses presented in Figure 2 (Panels A and B) illustrate that, following the adoption of FOP at the product category level, the difference between the treated and control categories in nutritional quality is larger for premium brands and brands with a narrower product line breadth. We thus find support for both H_{2a} and H_{2b}.

Moderating Effects of Category Characteristics

In H_{3a} and H_{3b}, we proposed that the FOP effect varies across categories depending on healthiness and competitive intensity. The results suggest that the effect of FOP introduction is greater for unhealthy (vs. healthy) and for more competitive (vs. less competitive) categories (see Column 4 of Table 2). Figure 2 (Panels C and D) provides support for the hypotheses for the category-specific moderating effects, H_{3a} and H_{3b}. In addition, we confirm the robustness of the DDD estimates in Equations 2, 3, and 4 to the inclusion of the interaction terms between the linear time trend and the moderators (see Table W2 in the Web Appendix), continuous measures of the moderating variables and a comprehensive DDD model specification that includes all of the moderating variables (in both discrete and continuous forms) in a single model (for details, see the “Robustness Checks” subsection of the “Validation Analyses” section). In summary, we find support for all proposed moderating effect hypotheses.

Mechanism Check: The Role of Information Salience

To test for the role of information salience as the underlying mechanism that drives the effect of FOP adoption, we conduct the following empirical analyses.

Table 3. Effect Size of FOP Adoption for Selected Products.

		Calories and Nutrient Amounts in an Original Packaged Food				FOP Effect (%)			
Product	**g/mL per Serving**	**Calories (kcal)**	**Saturated Fat (g)**	**Sugar (g)**	**Sodium (mg)**	**Calories**	**Saturated Fat**	**Sugar**	**Sodium**
All products in the treatment categories	—[a]	337.61[b]	4.09	18.79	1,268.31	−12.50	−12.97	−12.62	−3.74
Whole Grain Oats Breakfast Cereal	28 g	100	.50	1	140	−11.82	−29.52	−66.43	−9.49
Chocolate Peanut Butter Breakfast Cereal	30 g	120	1	8	190	−10.55	−15.82	−8.90	−7.49
Butter Bread	45 g	120	.50	4	210	−15.83	−47.45	−26.69	−10.17
Honey Wheat Bread	49 g	140	1	6	180	−14.77	−25.83	−19.37	−12.92
Four Cheese Thin Crispy Crust Pizza	226 g	530	9	10	870	−18.00	−13.24	−53.62	−12.33
Four Cheese Traditional Crust Pizza	261 g	690	13	13	1,160	−15.97	−10.58	−47.63	−10.68
French Vanilla Ice Cream	99 g	210	7	19	60	−19.90	−7.46	−12.36	−78.29
Buttered Pecan Ice Cream	99 g	250	7	20	100	−16.72	−7.46	−11.74	−46.97
Lightly Salted Microwave Popcorn	31 g	130	2	0	300	−10.07	−8.17	—[c]	−4.90
Movie Theater Butter Microwave Popcorn	33 g	180	4.50	0	330	−7.74	−3.87	—	−4.74
Regular Chocolate Sandwich Cookies	34 g	160	2	14	135	−8.97	−8.96	−5.76	−11.95
Extra Creme Chocolate Sandwich Cookies	36 g	180	3	18	90	−8.44	−6.33	−4.74	−18.98

[a]The level of calories and amount of each nutrient of all products are standardized to a 100 g/mL in our data, and thus serving sizes are not needed to calculate the average effect size.
[b]Average calories across all products in the treatment categories.
[c]The effect size cannot be calculated because the sugar amount of the original product is zero.
Notes: Our calculations in change of the nutrient levels are based on the DD estimate (−.5272) from the model. We assume other nutrients are held constant when we calculate the effect of change of a nutrient.

Do firms improve nutritional quality by increasing the nutrients to encourage or decreasing the nutrients to limit? Although food products have nutrients to encourage (e.g., fiber) and nutrients to avoid (e.g., saturated fat), as shown in Figure 1, Facts Up Front–style FOP labels are required to carry four basic icons for calories, saturated fat, sodium, and sugar (nutrients to limit) as the default format. Given this, our main argument that FOP adoption leads to salience of nutritional information on the part of consumers which, in turn, spurs food manufacturers to increase the nutritional quality of products suggests that FOP adoption has a greater impact on calorie content and the nutrient levels that are actually displayed on the FOP labels. To empirically examine this, we estimate a series of DD models of levels of calories and individual nutrients. The results in Table 4 show that FOP adoption leads to reductions in the calorie content and in sugar, sodium, and saturated fat—information displayed on FOP labels as the default format. However, we do not find a statistically significant effect of FOP adoption on the fiber, protein, and unsaturated fat levels—information that is not required to be displayed. From a theoretical perspective, these results support our argument that salience of nutritional information is the mechanism that drives the effect of FOP adoption. These results suggest that food manufacturers improve the nutritional quality of their products by decreasing the content of nutrients to limit.

Do FOP adopter brands improve nutritional quality more than non-FOP adopter brands? Following the adoption of FOP for the first time in a category, some brands adopted the FOP nutrition labeling, and others did not. We leverage this phenomenon and examine how the effect of the introduction of FOP in a category differs across adopter versus nonadopter brands. If our argument that increased salience of nutritional information due to FOP adoption is valid, we would expect FOP adopter brands to improve the nutritional quality of their products more than non-FOP adopter brands, because the nutritional information of the products of the FOP adopter brands would be more noticeable to consumers. To empirically test this, we examined photographs of the product packaging thoroughly to identify brands that launched products with FOP after the first introduction of FOP in a category. Then, we estimated a model (in the form of Equation 2) to examine the variation in the effect of FOP across these two types of brands, FOP adopters and non-FOP adopters.

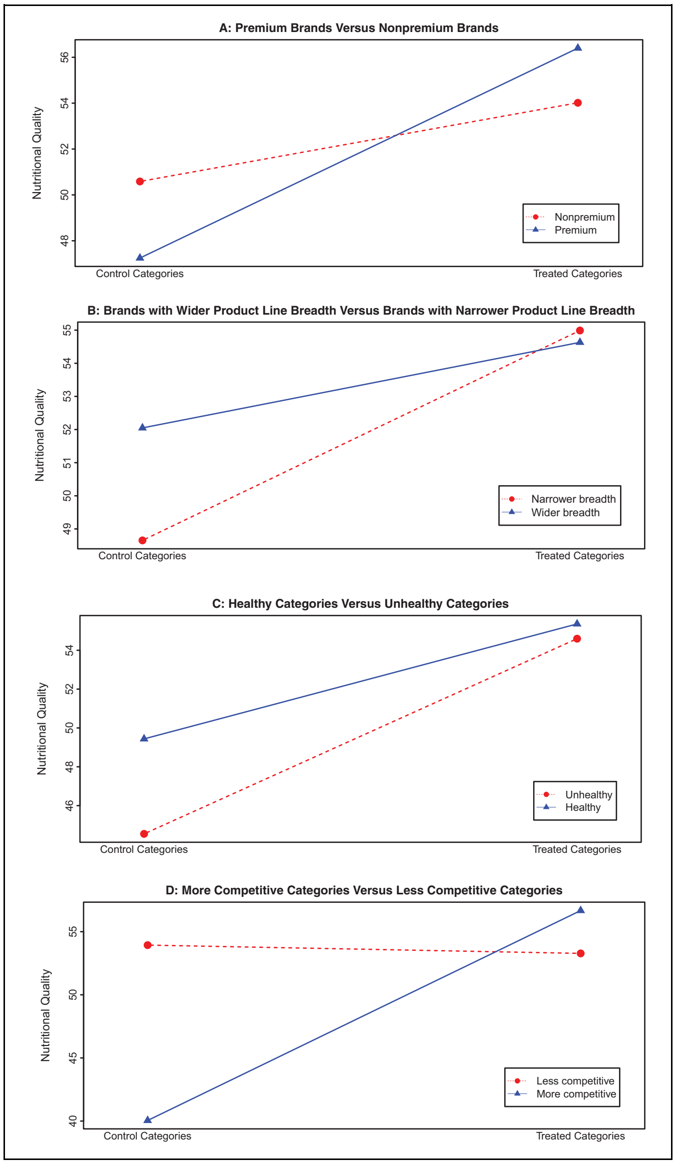

Figure 2. Spotlight analyses for the moderating effects of the brand and category characteristics.

The result suggests that the FOP effect is stronger for FOP adopter brands (see Table W3 in the Web Appendix). This result provides further support for our argument that salience of nutritional information is the mechanism behind the effect of FOP adoption.

Validation Analyses

In this section, we present the validation analyses that we conducted to confirm robustness of our results, address potential self-selection issues, test the identifying assumptions of our DD modeling strategy, and rule out effects due to spurious correlation and/or model misspecification. Table 5 summarizes our validation analyses.

Robustness Checks

In this section, we discuss a series of tests we conducted to verify the robustness of the results.

Alternative measures of nutritional quality. As an alternative measure of the nutritional quality of food and beverage products, following Moorman, Ferraro, and Huber (2012), we compute a nutrition score based on the %DVs of individual nutrients.[15] We compute the overall nutrition score of a product by adding the %DVs of positive elements (fiber and protein) and (100 − %DVs) of negative elements (fat, saturated fat, cholesterol, sodium, and sugar) and dividing by the number of nutrients (seven). The larger the overall nutrition score, the better the nutritional quality. In addition, we compute the weighted overall nutrition scores by using the category-specific mean and variance of each nutrient's %DV as weights. This helps account for the role of a nutrient in a certain category in terms of amount and variability. The estimation results of the DD models (see Table W4 in the Web Appendix) are in agreement with the main set of results and confirm the robustness of the main results to the alternative measures of nutritional quality.

Continuous moderating variables. To check whether the moderating analyses results are robust to continuous moderating variables, we reestimate the DDD models (Equations 2–4) with the corresponding continuous moderating variables. We confirm that the results are robust to the models with the continuous moderators (see Table W5 in the Web Appendix).

Comprehensive model with all moderating effects. To determine whether the moderating analyses results are robust to having all the interaction effects in a single model, we reestimate a comprehensive DDD model (combining Equations 2–4). We do so with both the discrete and continuous measures of the moderating variables. We confirm that the results are robust to the comprehensive model formulation (see Table W6 in the Web Appendix).

Addressing brand mortality bias. A DD modeling approach requires the survival of the units of analysis over time to observe the change in their outcomes or behavior of interest before and after a treatment. Because the treatment occurs at the category level, and we are interested in how the introduction of FOP affects the overall nutritional quality of all products at the category level, and all the categories are present before and after FOP adoption, we believe that estimating the DD

[15] Based on a 2,000 calorie diet, DVs for fat, saturated fat, cholesterol, sodium, sugar, fiber, and protein are 65 g, 20 g, 300 mg, 2,400 mg, 50 g, 25 g, and 50 g, respectively. There is no recommended DV for sugar; however, the newly designed NFP includes the DV for added sugar (50 g). Because the data do not distinguish added sugar from sugar, we use the same recommended DV for sugar. More detailed information can be accessed at http://www.fda.gov/food/ingredientspackaginglabeling/labelingnutrition/ucm274593.htm (accessed December 12, 2018) and https://www.fda.gov/food/new-nutrition-facts-label/daily-value-new-nutrition-and-supplement-facts-labels (accessed April 5, 2020).

Table 4. Effect of FOP Nutrition Labeling on Content of Calories and Individual Nutrients.

	Dependent Variables						
	(1) ln(Calories)	**(2) ln(Saturated fat)**	**(3) ln(Sodium)**	**(4) ln(Sugar)**	**(5) ln(Fiber)**	**(6) ln(Protein)**	**(7) ln(Unsaturated fat)**
FOP	**−.0125***** **(.0045)**	**−.0135**** **(.0063)**	**−.0147**** **(.0060)**	**−.0108**** **(.0050)**	−.0351 (.0675)	−.0010 (.0030)	−.0061 (.0287)
Time trend	.0006** (.0002)	.0020 (.0013)	.0008* (.0005)	.0000 (.0003)	.0042 (.0044)	−.0001 (.0002)	−.0004 (.0022)
Brand fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Category fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Category-specific time trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21,067	21,092	20,781	21,074	21,089	21,054	14,732
R^2	.8694	.7753	.7305	.8509	.7472	.8534	.8188

*$p < .10$.
**$p < .05$.
***$p < .01$.
Notes: The focal variable of interest and its coefficient estimate (i.e., DD estimate) that is statistically significant is highlighted in bold. Robust standard errors that are clustered at the category level are in parentheses. Sample sizes vary across the DD models because of missing nutrient information for some products.

Table 5. Overview of Validation Analyses.

Analysis	**Description**	**Key Insights/Takeaways**
A: Robustness Checks		
Alternative measures of nutritional quality	For each product, the overall nutrition score is calculated by adding the Percent Daily Values (%DVs) of positive elements—fiber and protein—and (100 − %DVs) of negative elements—fat, saturated fat, cholesterol, sodium, and sugar—and dividing by the number of nutrients. The weighted overall nutrition scores are also computed by using the category-specific mean and variance of each nutrient's %DV as weights.	Our core result is robust to these alternative dependent variables.
Continuous moderating variables	We replace all the dichotomous moderating variables in the models with the corresponding continuous moderating variables.	Our moderating analyses results are robust to the continuous moderators.
Comprehensive model with all moderating effects	We estimate a comprehensive DDD model with all the interaction effects in a single model to check if the results related to the moderating analyses are robust.	Our results are robust to the comprehensive model formulation.
Addressing brand mortality bias	We estimate a DD model with a new sample that consists of existing brands only.	The issue of brand mortality does not bias the FOP effect.
New brands versus existing brands	We test whether the FOP effect differs across new brands and existing brands.	The FOP effect is stronger for new brands.
Addressing dominant category bias	We compute a jackknife pseudo-value to estimate the bias between the DD estimate calculated with the entire data and that calculated with the data without a specific category.	The FOP effect is not driven by a dominant category.
B: Self-Selection Challenges		
Correlation between FOP adoption and category healthiness	• We conduct a t-test to examine if there is a difference between the treatment and control categories in terms of category healthiness. • We conduct a correlation analysis between FOP adoption timing and category healthiness. • We pick the treatment categories in which FOP labeling was adopted no more than six months earlier than in the control categories and estimate a DD model.	There is no statistically significant correlation between FOP category adoption and category healthiness, and thus these can assuage concerns about potential unobserved factors affecting both category-specific timing of FOP adoption and nutritional quality of products.

(continued)

Table 5. (continued)

Analysis	Description	Key Insights/Takeaways
Firms present in both treatment and control categories	We estimate a DD model with only those firms that are present in both treatment and control categories.	The FOP effect is robust to the subset of the sample, and thus we can rule out a potential bias due to the possibility that the firms in the treatment and control categories are intrinsically different.
Alternative periods used for classification of treated group	We estimate DD models with different end points of the focal estimation time period that create different compositions of treatment and control groups.	The variation in FOP timing used for group composition does not drive the FOP effect.
C: Falsification Tests		
Test of the parallel trend assumption	We estimate a model of nutritional quality with interaction terms between the treatment group indicator and (1) year dummies, (2) quarter dummies, (3) linear time trend variable in the pre-FOP adoption period.	The parallel trend assumption holds true in our study.
Fake treatment (placebo test)	For the treatment categories, we work with only the pre-FOP period data and treat the first half of the actual pre-FOP period as the new pre-FOP period and the latter half of the actual pre-FOP period as the fake post-FOP period and estimate the proposed DD model.	The statistically insignificant DD estimate rules out placebo effects. We confirm that the potential presence of unobserved temporal factors that can blur the FOP effect is not a concern in our study.
Fake treatment group	We randomly classify half of our control categories as fake treatment categories and the other half as control categories as they are and estimate the proposed DD model.	The insignificant bootstrap DD estimates indicate that the FOP effect we find is not due to any spurious effects and confirm the validity of the construction of our treatment group.
Fake outcomes	We estimate DD models with the following three fake outcomes: unit pack size, total pack size, and package volume.	The FOP adoption does not affect the outcomes that are not supposed to be affected by FOP adoption.

models with the sample of brands that exist before and after the FOP category adoption and those that appear after the event is not a threat to validity of the results. For a similar research design, see Agrawal et al. (2018) and Bonfrer et al. (2020). Following FOP adoption, firms may launch new brands with better nutritional profiles or improve the nutritional profiles of products under existing brands. Nonetheless, to establish the robustness of the results, we estimate the main model (presented in Equation 1) with a sample that consists of only brands that exist in both pre- and post-FOP adoption periods. We confirm that the main result is robust, and thus, brand mortality does not change the main results (see Table W7 in the Web Appendix).

New brands versus existing brands. Given that the sample consists of new and existing brands, an interesting question is whether the FOP category introduction effect differs across the two types of brands. In line with Moorman, Ferraro, and Huber's (2012) argument, we expect that the FOP effect would be stronger for new brands, because improving nutrition by launching new brands is less likely to be risky than adjusting the nutritional profiles of products of existing brands. To check the potential differential effect of the introduction of FOP, we estimate a model with an interaction term between FOP and the indicator variable of new versus existing brands in the form of Equation 2. We find that the positive FOP effect is statistically stronger for new brands (see Table W8 in the Web Appendix).

Addressing dominant category bias. To check whether a few dominant treatment categories might be driving the reported results, following Moorman, Ferraro, and Huber (2012), we compute a jackknife pseudo-value to estimate the bias between the DD estimate calculated with the entire data and that calculated with the data without a specific category (Zhou, Obuchowski, and McClish 2002). We confirm that the DD estimate based on the full data falls within the 95% confidence interval around the mean of the jackknife pseudo-values which confirms that the main result is not driven by an influential or dominant category.

Self-Selection Challenges

Categories were assigned into the treatment and control groups based on the timing of FOP adoption at the category level. We argued that the timing of the adoption of FOP by the first adopter brand in a category is exogenous to nutritional quality of products of other brands in the category. Furthermore, we removed the first adopter brands from the treatment group categories to rule out unobserved factors that are specific to first adopter brands that may not hold for the other brands that adopt later in the category. Inclusion of year fixed effects help control for the omitted variables. In addition to year fixed effects, we included category fixed effects in the DD models to control for unobserved time-invariant factors that possibly led to differences between the treatment and control categories. The category fixed effects help absorb the category-specific factors that drive nutritional quality. Despite this set of cautious steps, one can make the argument that the firms in the treatment categories are inherently different from those in the control categories, or there may be some unobserved factors affecting both the timing of FOP adoption and the nutritional quality of a category which could contaminate the observed effect of FOP adoption. To further address concerns about potential selection biases, we conducted the following supplementary analyses.

Potential correlation between FOP category adoption and category healthiness level. To test whether the treatment and control categories differed in terms of their healthiness level, we conduct a t-test that compares the mean NPI scores between the treatment and control categories. The result indicates that the healthiness levels of the two groups are not statistically different ($t = -1.6590$, p-value $= .1402$). In addition, we test whether there is a correlation between the FOP adoption timing and category-specific nutritional quality. To do so, we sample data from the treatment categories only and identify the timing of FOP adoption (by the first time adopter brands) in each of the treated categories. A correlation test shows that there is no statistically significant correlation between FOP adoption timing and category healthiness ($r = .2484$, p-value $= .1382$). Finally, we pick the treatment categories in which FOP labeling was adopted no more than six months earlier than in the control categories and run the DD model. The narrow time window between these treated categories and the control categories helps us construct similar sets of treatment and control categories, and a comparison of products across these similar sets of categories further rules out any time-varying factors that could affect changes in nutritional quality. We confirm that the DD estimate is robust to the subset of data (see Table W9 in the Web Appendix).

Firms in both treatment and control categories. To empirically address the possibility that the firms in the treatment and control categories are intrinsically different, we work with only firms that are present in both treatment and control categories and estimate the main DD model. The result (see Table W10 in the Web Appendix) indicates that the FOP effect on nutritional quality is still positive and statistically significant. Thus, the possibility that the reported results are driven by inherent differences between the firms in the treatment and control categories is ruled out.

Testing with an alternative estimation period for classification of treatment and control categories. Recall that we classify a category as a treatment group if we observe the FOP adoption in the "focal time period" (January 2003 to December 2011). If we shift the end point and change the focal time period to January 2003 through September 2011, the categories that adopted FOP later between October 2011 and December 2011 (which were classified as treatment categories in the original analyses) would now be classified as "control" categories. If any unobserved category-specific confounding factors were to drive the results, we would expect the effect of FOP adoption to be weaker or absent in the sample based on the new focal time period. Thus, we estimate the DD models on multiple new focal time periods with different end points (by shifting the end points by 3 months up to 12 months with a 3-month interval). The results (see Table W11 in the Web Appendix) suggest that variation in FOP adoption across categories and classification of categories based on adoption timing do not threaten the validity of the main results.

Falsification Tests

The identifying assumption behind the DD modeling approach is the parallel trend assumption, which assumes that the treatment and control groups have similar trends in the outcome of interest (nutritional quality, in our context) before the intervention (FOP category adoption, in our context). To test the validity of the assumption, following previous studies (Angrist and Pischke 2009), we include a set of interaction terms between the group indicator variable and dummy variables for all the years before FOP adoption and estimate a model of nutritional quality. We find that the coefficients associated with the interaction terms—the "parallel-trend coefficients"—are not statistically significant (see Table W12 in the Web Appendix), which suggests the treatment and control categories were not different before FOP adoption. We also conduct a test of joint significance of the parallel-trend coefficients, and the result does not show any significant trends. We conduct these tests at the granular (quarterly) level. We find that the estimates of the parallel-trend coefficients are not statistically significant separately and jointly (see Table W13 in the Web Appendix). We also estimate a model with an interaction term between the group indicator variable and the linear time trend variable. The results show (see Table W14 in the Web Appendix) that the two groups of categories do not have different linear time trends in the pre-FOP period. These tests provide empirical support for the parallel trend assumption behind the DD approach.

Next, following economics (Gertler et al. 2011; Puri, Rocholl, and Steffen 2011) and marketing (Janakiraman, Lim, and Rishika 2018) literature, we conduct the following tests: the fake treatment test or the "placebo" test (see Table W15 in the Web Appendix), fake treatment group (see Table W16 in the Web Appendix), and fake outcome tests (see Table W17 in the Web Appendix). The key takeaway is that we find statistically significant results of FOP adoption in conditions when we expect to, and we do not find a statistically significant effect of FOP adoption when we do not expect to find one. The set of results, taken together, provides support for our DD identification strategy and rules out any spurious correlations in our core set of results. Nevertheless, we acknowledge that we work with observational data, and we remind readers that the causal interpretation of these results is valid subject to the identifying assumptions of the DD model.

Discussion and Conclusion

Food labels play a key role in the strategies designed to inform and induce healthy food choice behaviors among consumers. According to a recent World Health Organization report (Kelly and

Jewell 2018, p. vii), "Nutrition labelling is one of the policy tools that can support healthy diets, both in stimulating consumers to make informed healthier food choices and in driving manufacturers to reformulate products to avoid making unfavorable nutrient content disclosures." In this research, we conducted a systematic examination of the supply-side consequences of the voluntary adoption of a widely used FOP nutrition labeling program, the Facts Up Front–style FOP label. Next, we discuss the implications of the results for theory and practice.

Implications for Theory

There is increasing consensus among recent studies that focus on consumer response to the FOP labels that they help draw consumers' attention to nutrition information and form their perceptions of product healthiness (Ikonen et al. 2020). Studies based on purchase transaction data have established that FOP labels facilitate consumers' choice of healthier products (Zhu et al. 2016). Thus, although the benefits of FOP labels in informing consumers about the healthiness of the products is receiving a fair amount of attention in research, there is little research on the firm side of this issue. Ikonen et al. (2020) argue that "the implementation of different FOP labels can motivate manufacturers to refine their recipes, leading to healthier product assortments" (p. 375), and Dubois et al. (2020) suggest that more research is needed to examine "the impact of labeling systems on the decision of manufacturers to reformulate their products."

The present study helps fill this critical research gap in the literature by examining the issue of FOP labels from the firm side. Specifically, we theorize that adoption of FOP labels increases the salience of nutritional information and helps lower consumers' search costs for the nutritional information subsequently leading to a "nutritional information clearinghouse" effect whereby food manufacturers compete along the nutrition dimension. The results highlight the role of voluntary provision of nutrition information in improving the nutritional quality of products. Previous research in the area of mandatory provision of nutrition information (i.e., the NLEA) has suggested that although the NLEA clearly increased nutrition provision, the legislation has had an overall negative impact on brand nutrition possibly due to the perceived negative correlation between nutrition and taste (Moorman, Ferraro, and Huber 2012). Our results suggest that voluntary FOP labels may be more effective due to the nutritional information clearinghouse effect, thus offering a different theoretical perspective and lens through which nutrition labels can be examined.

For a deeper understanding of the effect of FOP, we examine the specific brand and category characteristics for which FOP effects are likely to be enhanced. Specifically, we investigate factors for which food manufacturers have a greater motivation and opportunity to innovate. Studies that examine effects of nutrition labels have identified the moderating role of category-, brand-, or firm-level factors (Moorman, Ferraro, and Huber 2012; Nikolova and Inman 2015). For brand-level moderating factors, the present results show that the effect of FOP is greater for premium brands and brands with a narrower product line breadth. These results highlight how product differentiation and a focused product line strategy that helps lower consumer nutrition search costs serve as motivating factors for firms to innovate more after FOP adoption. At the category level, we find that the FOP effect is greater for unhealthy categories and product categories with a greater degree of competitive intensity. These results suggest that manufacturers tend to innovate more following FOP adoption in categories where there is greater opportunity to do so, such as inherently unhealthy categories and categories with intense competition, where the need to differentiate and lower consumers' nutrition search costs is greater. The result related to the FOP effect in unhealthy categories also supports findings from previous research showing that after the NLEA was enacted, brands in unhealthy categories improved nutrition more than those in healthy categories (Moorman, Ferraro, and Huber 2012).

A key question motivating this study is, Why does FOP work in stimulating product innovation? We believe that the answer lies in understanding the underlying mechanism. We theorize and test for the role of nutritional information salience as the primary underlying driver of the FOP effects. We argue that FOP labels serve as a source of "nutritional information clearinghouse" in which they increase the salience of nutrition information and decrease consumers' cost of processing nutritional information at the point of purchase. The change in consumer behavior incentivizes manufacturers to compete on the attribute (i.e., nutrition) that aligns with consumer preferences and to develop nutritionally better products. To test this underlying mechanism, we conducted additional analyses that suggest FOP adoption in a product category lowers the calories and the amounts of saturated fat, sugar, and sodium in products. Calories, saturated fat, sugar, and sodium are the four basic elements displayed on a Facts Up Front–style FOP label. Sugar, sodium, and saturated fat are referred to by the FDA as the nutrients to limit, suggesting that consumers should try to limit their intake.[16] Because FOP labels clearly emphasize the calories and the three nutrients, and given the public emphasis on the negative health consequences of these nutrients over time (Wyatt, Winters, and Dubbert 2006), one would expect consumers to pay most attention to the calorie count and those nutrients that would induce firms to lower their content in products. Our results support this expectation, bolstering our argument for information salience as the underlying mechanism driving the FOP effect. Next, we discuss the implications of our findings for policy makers and for marketing.

Implications for Policy Makers

Unlike nutrition claims, which can selectively highlight only the nutrients that make a product look healthier, the FOP labels we examine are standardized and present the key nutrient

[16] See https://www.fda.gov/food/nutrition-education-resources-materials/how-understand-and-use-nutrition-facts-label (accessed August 27, 2019).

information from the NFP on the front of the package. However, there can still be skepticism about the implications of the effect of FOP labels in the marketplace. Our results demonstrate that FOP labels are beneficial for consumers, as the labels tend to spur overall nutritional quality improvement in a product category. Drawing on a set of packaged food products (see Table 3), we find that FOP adoption leads to a decrease in average calories (−13.23%), saturated fat (−15.39%), sugar (−25.72%), and sodium (−19.08%). In addition, food manufacturers improve products' nutritional quality by reducing the content of nutrients to limit that are actually displayed on FOP labels. This implies that policy makers, in partnership with food manufacturers and retailers, should encourage adoption of voluntary labeling programs that are standardized and transparent, such as Facts Up Front–style FOP labels, and consider options for broadening the information presented in FOP labels. We believe that policy makers should also invest in educational campaigns that inform consumers about the value of FOP labels, which would provide more incentives for food manufacturers to offer nutritionally better products.

Implications for Marketing

Our results have implications for food manufacturers and grocery retailers. For food manufacturers, the result that FOP adoption can stimulate improvement in the nutritional quality of food products in the category implies that manufacturers must devote significant resources to product innovation to stay competitive. Given the result that firms innovate and produce nutritionally better products following FOP adoption, firms that lag in innovation will fail to attract enough consumer demand to survive and compete in the category. Specifically, manufacturers in unhealthy and more competitive categories can be more strategic and invest in innovation such that they are ready to provide better products following FOP adoption. For food retailers, our results suggest that they should partner with manufacturers and give them incentives to adopt FOP, as this can lead to better-quality products for their consumers, which can ultimately help in building a positive brand image. Retailers can also promote products with FOP labels, especially in more competitive and unhealthy product categories, which can spur manufacturers toward more innovation and lead to an increase in the nutritional quality of the foods over time in the category. We encourage retailers to invest in measures that help monitor and track the sales of products with FOP labels and provide this feedback to their manufacturers regularly to speed up the competitive effect of FOP labels. It is worthwhile to note how the Smart Choices logo developed by the food industry, including grocery retailers, received a lot of criticism and was eventually suspended when it started showing up on products such as Kellogg's Froot Loops cereal (Stark and Khan 2009). Although retailers have invested in developing and promoting some FOP labeling systems, we suggest that retailers must invest in and promote a comprehensive, universal, and simple-to-use and understand FOP labeling system that consumers can trust unequivocally.

From the consumer perspective, although extant research has documented that consumers pay attention to FOP labels (Ikonen et al. 2020), we establish that FOP adoption results in nutritionally better products on retailers' shelves. Our results show that the FOP effect is greater for premium brands and brands with a narrower product line breadth. These results suggest that consumers who are looking for healthier alternatives should consider premium brands and more focused brands in terms of product line in their consideration sets. We also find that the brands that adopted FOP labeling have nutritionally better products than those that did not adopt the labeling. This suggests that the presence of a FOP label on a package is a good indicator that the product is a better choice overall than other products that do not carry FOP labels. In summary, our findings offer insights for policy makers, manufacturers, retailers, and consumers and help solidify FOP labeling in tackling the obesity epidemic.

Limitations and Directions for Future Research

Although this study is the first to conduct a systematic and empirical analysis of the impact of FOP adoption on nutritional quality of products, it is not without its limitations. When possible, a randomized controlled trial can help establish the causal effect of FOP adoption cleanly; however, it was not practical in this context. Thus, we relied on panel data and econometric techniques to shed light on the causal effect that is valid within the bounds of the DD modeling approach and its identifying assumptions. We focused on one widely used and standardized FOP label. We suggest that future research could examine other types of labels. Given the competitive response to FOP adoption, future research could examine the effect of FOP adoption on various market structure–related questions, such as entry and exit of brands following FOP adoption, change in brand- versus category-level sales, customer brand loyalty and underlying brand switching patterns, and marketing-mix effectiveness of brands that adopt FOP labels. We believe that this study sheds light on the importance of firms' voluntary participation in initiatives that signal stewardship of corporate social responsibility. We hope that this study encourages researchers to examine the consequences of firms' adoption of nutrition-related policy changes as public policy makers continue to find ways to encourage consumers to make healthier dietary choices.

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References

Agrawal, Ajay, Christian Catalini, Avi Goldfarb, and Hong Luo (2018), "Slack Time and Innovation," *Organization Science*, 29 (6), 1056−73.

André, Quentin, Pierre Chandon, and Kelly Haws (2019), "Healthy Through Presence or Absence, Nature or Science? A Framework for Understanding Front-of-Package Food Claims," *Journal of Public Policy & Marketing*, 38 (2), 172−91.

Angrist, Joshua D. and Jörn-Steffen Pischke (2009), *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton, NJ: Princeton University Press.

Balcombe, Kelvin, Iain Fraser, and Salvatore Di Falco (2010), "Traffic Lights and Food Choice: A Choice Experiment Examining the Relationship Between Nutritional Food Labels and Price," *Food Policy*, 35 (3), 211–20.

Bauer, Hans H., Daniel Heinrich, and Daniela B. Schäfer (2013), "The Effects of Organic Labels on Global, Local, and Private Brands: More Hype than Substance?" *Journal of Business Research*, 66 (8), 1035–43.

Bayus, Barry L. and William P. Putsis Jr. (1999), "Product Proliferation: An Empirical Analysis of Product Line Determinants and Market Outcomes," *Marketing Science*, 18 (2), 137–53.

Bonfrer, André, Pradeep K. Chintagunta, John H. Roberts, and David Corkindale (2020), "Assessing the Sales Impact of Plain Packaging Regulation for Cigarettes: Evidence from Australia," *Marketing Science*, 9 (1), 234–52.

Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer (2013), "Salience and Consumer Choice," *Journal of Political Economy*, 121 (5), 803–43.

Borenstein, Severin and Nancy L. Rose (1994), "Competition and Price Dispersion in the U.S. Airline Industry," *Journal of Political Economy*, 102 (4), 653−83.

Cadario, Romain and Pierre Chandon (2020), "Which Healthy Eating Nudges Work Best? A Meta-Analysis of Field Experiments," *Marketing Science*, 39 (3), 465–86.

Centers for Disease Control and Prevention (2018), "Obesity," (September 18), https://www.cdc.gov/healthyschools/obesity/facts.htm.

Chandra, Ambarish and Mariano Tappata (2011), "Consumer Search and Dynamic Price Dispersion: An Application to Gasoline Markets," *RAND Journal of Economics*, 42 (4), 681−704.

Drichoutis, Andreas C., Panagiotis Lazaridis, and Rodolfo M. Nayga Jr. (2005), "Nutrition Knowledge and Consumer Use of Nutritional Food Labels," *European Review of Agricultural Economics*, 32 (1), 93–118.

Drichoutis, Andreas C., Panagiotis Lazaridis, and Rodolfo M. Nayga Jr. (2009), "Would Consumers Value Food-Away-from-Home Products with Nutritional Labels?" *Agribusiness*, 25 (4), 550–75.

Dubois, Pierre, Paulo Albuquerque, Olivier Allais, Céline Bonnet, Patrice Bertail, Pierre Combris, et al. (2020), "Effects of Front-of-Pack Labels on the Nutritional Quality of Supermarket Food Purchases: Evidence from a Large-Scale Randomized Controlled Trial," *Journal of the Academy of Marketing Science* (published online April 24), DOI:10.1007/s11747-020-00723-5.

Emrich, Teri E., Joanna E. Cohen, Wendy Y. Lou, and Mary R. L'Abbé (2013), "Food Products Qualifying for and Carrying Front-of-Pack Symbols: A Cross-Sectional Study Examining a Manufacturer Led and a Non-Profit Organization Led Program," *BMC Public Health*, 13 (846), 1–9.

FoodNavigator-USA (2012), "FDA Offers Support in Industry Roll-Out of Facts Up Front Labeling," (February 24), http://www.foodnavigator-usa.com/Trends/Food-labeling-and-marketing/FDA-offers-support-in-industry-roll-out-of-Facts-Up-Front-labeling.

Gertler, Paul J., Sebastian Martinez, Patrick Premand, Laura B. Rawlings, and Christel M.J. Vermeersch (2011), *Impact Evaluation in Practice*, 1st ed. Washington, DC: World Bank.

Gielens, Katrijn (2012), "New Products: The Antidote to Private Label Growth?" *Journal of Marketing Research*, 49 (3), 408–23.

Goldfarb, Avi and Catherine E. Tucker (2011), "Privacy Regulation and Online Advertising," *Management Science*, 57 (1), 57–71.

Goldfarb, Avi and Catherine E. Tucker (2014), "Conducting Research with Quasi-Experiments: A Guide for Marketers," working paper (March 28), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2420920.

Griffith, Rachel, Martin O'Connell, Kate Smith, and Rebekah Stroud (2018), "Children's Exposure to TV Advertising of Food and Drink," IFS Briefing Note BN238, The Institute for Fiscal Studies.

Hamburg, Mary (2010), "Open Letter to Industry from Dr. Hamburg," FDA (March 3), http://www.food-label-compliance.com/Sites/5/Downloads/Hamburg-Open-Letter-to-Industry-Food-Labels-030310.pdf.

Hwang, Minha and Sungho Park (2016), "The Impact of Walmart Supercenter Conversion on Consumer Shopping Behavior," *Management Science*, 62 (3), 817−28.

Ikonen, Iina, Francesca Sotgiu, Aylin Aydinli, and Peeter W.J. Verlegh (2020), "Consumer Effects of Front-of-Package Nutrition Labeling: An Interdisciplinary Meta-Analysis," *Journal of the Academy of Marketing Science*, 48 (3), 360–83.

Jain, Yogendra Kumar and Santosh Kumar Bhandare (2014), "Min Max Normalization Based Data Perturbation Method for Privacy Protection," *International Journal of Computer & Communication Technology*, 3 (4), 45–50.

Janakiraman, Ramkumar, Joon Ho Lim, and Rishika Rishika (2018), "The Effect of a Data Breach Announcement on Customer Behavior: Evidence from a Multichannel Retailer," *Journal of Marketing*, 82 (2), 85−105.

Julia, Chantal, Léopold K. Fézeu, Pauline Ducrot, Caroline Méjean, Sandrine Péneau, Mathilde Touvier, et al. (2015), "The Nutrient Profile of Foods Consumed Using the British Food Standards Agency Nutrient Profiling System Is Associated with Metabolic Syndrome in the SU.VI.MAX Cohort," *Journal of Nutrition*, 145 (10), 2355–61.

Kelly, Bridget and Jo Jewell (2018), "What is the Evidence on the Policy Specifications, Development Processes and Effectiveness of Existing Front-of-Pack Food Labelling Policies in the WHO European Region?" *Health Evidence Network (HEN) Synthesis Report 61*, Copenhagen: WHO Regional Office for Europe.

Kiesel, Kristin, Jill J. McCluskey, and Sofia B. Villas-Boas (2011), "Nutritional Labeling and Consumer Choices," *Annual Review of Resource Economics*, 3 (1), 141−58.

Koopmans, Lambert H., Donald B. Owen, and Judah I. Rosenblatt (1964), "Confidence Intervals for the Coefficient of Variation for the Normal and Log Normal Distributions," *Biometrika*, 51 (1/2), 25–32.

Lamey, Lien, Barbara Deleersnyder, Jan-Benedict E.M. Steenkamp, and Marnik G. Dekimpe (2018), "New Product Success in the Consumer Packaged Goods Industry: A Shopper Marketing Approach," *International Journal of Research in Marketing*, 35 (3), 432−52.

Meyer, Bruce D. (1995), "Natural and Quasi-Experiments in Economics," *Journal of Business & Economic Statistics*, 13 (2), 151−61.

Moorman, Christine (1996), "A Quasi Experiment to Assess the Consumer and Informational Determinants of Nutrition Information Processing Activities: The Case of the Nutrition Labeling and Education Act," *Journal of Public Policy & Marketing*, 15 (1), 28−44.

Moorman, Christine (1998), "Market-Level Effects of Information: Competitive Responses and Consumer Dynamics," *Journal of Marketing Research*, 35 (1), 82−98.

Moorman, Christine, Rosellina Ferraro, and Joel Huber (2012), "Unintended Nutrition Consequences: Firm Responses to the Nutrition Labeling and Education Act," *Marketing Science*, 31 (5), 717−37.

Nikolova, Hristina Dzhogleva and J. Jeffrey Inman (2015), "Healthy Choice: The Effect of Simplified Point-of-Sale Nutritional Information on Consumer Food Choice Behavior," *Journal of Marketing Research*, 52 (6), 817−35.

Pires, Tiago (2018), "Measuring the Effects of Search Costs on Equilibrium Prices and Profits," *International Journal of Industrial Organization*, 60, 179−205.

Puri, Manju, Jörg Rocholl, and Sascha Steffen (2011), "Global Retail Lending in the Aftermath of the US Financial Crisis: Distinguishing between Supply and Demand Effects," *Journal of Financial Economics*, 100 (3), 556–78.

Rayner, Mike, Peter Scarborough, and Tim Lobstein (2009), "The UK Ofcom Nutrient Profiling Model: Defining 'Healthy' and 'Unhealthy' Foods and Drinks for TV Advertising to Children," (October), https://www.ndph.ox.ac.uk/cpnp/files/about/uk-ofcom-nutrient-profile-model.pdf.

Rishika, Rishika, Ashish Kumar, Ramkumar Janakiraman, and Ram Bezawada (2013), "The Impact of Customers' Social Media Participation on Customer Visit Frequency and Profitability: An Empirical Investigation," *Information Systems Research*, 24 (1), 108–27.

Roe, Brian, Alan S. Levy, and Brenda M. Derby (1999), "The Impact of Health Claims on Consumer Search and Product Evaluation Outcomes: Results from FDA Experimental Data," *Journal of Public Policy & Marketing*, 18 (1), 89−105.

Russo, J. Edward, Richard Staelin, Catherine A. Nolan, Gary J. Russell, and Barbara L. Metcalf (1986), "Nutrition Information in the Supermarket," *Journal of Consumer Research*, 13 (1), 48−70.

Salop, Steven (1976), "Information and Monopolistic Competition," *American Economic Review*, 66 (2), 240−45.

Salop, Steven and Joseph Stiglitz (1977), "Bargains and Ripoffs: A Model of Monopolistically Competitive Price Dispersion," *Review of Economic Studies*, 44 (3), 493−510.

Scarborough, Peter, Anna Boxer, Mike Rayner, and Lynn Stockley (2007), "Testing Nutrient Profile Models Using Data from a Survey of Nutrition Professionals," *Public Health Nutrition*, 10 (4), 337−45.

Sophos, Mary (2017), "Facts Up Front: Front-of-Pack Labeling Initiative," U.S. Chamber of Commerce Foundation (September 25),https://www.uschamberfoundation.org/facts-front-front-pack-nutrition-labeling-initiative.

Sorensen, Alan T. (2000), "Equilibrium Price Dispersion in Retail Markets for Prescription Drugs," *Journal of Political Economy*, 108 (4), 833–50.

Stark, Lisa and Huma Khan (2009), "The Breakfast Battle: Consumers May Not Be Making Smart Choices After All," ABC News (October 21),https://abcnews.go.com/Politics/Health/fda-scrutinizes-food-labels-cereals-smart-choices-program/story?id=8878025.

Stigler, George J. (1961), "The Economics of Information," *Journal of Political Economy*, 69 (3), 213–25.

Tucker, Catherine, Juanjuan Zhang, and Ting Zhu (2013), "Days on Market and Home Sales," *RAND Journal of Economics*, 44 (2), 337–60.

Wang, Emily, Christian Rojas, and Christoph Bauner (2015), "Evolution of Nutritional Quality in the US: Evidence from the Ready-to-Eat Cereal Industry," *Economics Letters*, 133, 105–08.

Wu, Fang, Joffre Swait, and Yuxin Chen (2019), "Feature-Based Attributes and the Roles of Consumers' Perception Bias and Inference in Choice," *International Journal of Research in Marketing*, 36 (2), 325–40.

Wyatt, Sharon B., Karen P. Winters, and Patricia M. Dubbert (2006), "Overweight and Obesity: Prevalence, Consequences, and Causes of a Growing Public Health Problem," *American Journal of the Medical Sciences*, 331 (4), 166–74.

Zhao, Ying (2006), "Price Dispersion in the Grocery Market," *Journal of Business*, 79 (3), 1175–92.

Zhou, Xiao-Hua, Nancy A. Obuchowski, and Donna K. McClish (2002), *Statistical Methods in Diagnostic Medicine*. New York: John Wiley & Sons.

Zhu, Chen, Rigoberto A. Lopez, and Xiaoou Liu (2016), "Information Cost and Consumer Choices of Healthy Foods," *American Journal of Agricultural Economics*, 98 (1), 41–53.