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Abstract

Consumers often rely on product quality disclosures to make their purchase decisions. Voluntary nutrition labeling (VNL), a means of nutrition quality disclosure, was introduced in the last decade by leading food manufacturers and selected food retailers. To the extent that consumers make inferences based on VNL disclosures as they consider buying non-VNL food products, information spillovers occur. However, previous studies on the effectiveness of VNL programs have not considered information spillover effects. In this study, we examine consumer responses to VNL by incorporating both product participation and information spillover effects. Empirical results from the U.S. ready-to-eat cereal market confirm a positive participation effect of VNL and a strong negative spillover effect on non-VNL products (non-participating food products), especially those that are relatively unhealthy (high in sugar, saturated fat and/or sodium). These findings indicate that ignoring the effects of VNL information spillovers in models of consumer choices may lead to underestimation of the impact of VNL on consumer valuation of participating products and overestimation of consumer valuation of non-participating products, suggesting that an incentive in a firm's voluntary participation in self-regulated labeling programs may be to avoid negative treatment externalities. Overall, this article shows the importance of including spillover effects in the evaluation of VNL programs and that VNL could play a positive role in improving the healthiness of consumer choices.

Keywords: voluntary nutrition labeling; information spillovers; food labeling.

JEL codes: D12, L66, I19, M30

1. Introduction

Over the last decade, the U.S. food industry has introduced and expanded the use of various voluntary nutrition labeling (VNL), including both front-of-package (FOP) and retail-shelf nutrition labeling systems. Compared to the mandatory Nutrition Facts Panels (NFPs) introduced in the 1990s, VNL is determined by the manufacturers and/or retailers in the food industry, not by a regulator.[1] Thus, VNL constitutes a form of voluntary quality disclosure.

In contrast to NFPs, nutritional information presented in VNLs is characterized as simpler and more accessible to consumers.[2] Plausible explanations for firms' participation in VNL include adopting self-regulated programs to avoid stricter mandatory policies, generating public goodwill, raising rivals' costs, and meeting consumers' increasing demand for healthier diets.

Despite a growing body of empirical work on the effectiveness of nutritional labels, previous work has not included information spillovers of VNL programs.[3] However, in the literature on firms' voluntary participation in environmental programs, Lyon and Maxwell (2007) and Zhou, Segerson and Bi (2016) point out that traditional evaluation methods may be inappropriate for voluntary programs in the presence of information

[1] Note that VNL systems were introduced in addition to the mandatory NFP; they do not provide new nutritional information not included in the NFP. The issue of information diffusion is obviated in NFPs since participation is mandatory. For a classification of the types of FOP labeling options, see Kees, Royne and Cho (2014).

[2] NFP use by consumers has been on the decline, in part due to the complexity of the information (Todd and Variyam, 2008). It has also been found to have negative effect on nutritional quality (Moorman, Ferraro, and Huber, 2012). Likewise, Wansink, Sonka and Hasler (2004), Berning, Chouinard and McCluskey (2008), and Kiesel and Villas-Boas (2010) find that simplified labeling may be more effective for the majority of consumers.

[3] Recent work on VNLs includes Zhu, Lopez and Liu (2016) and Hersey et al. (2013). For a review of consumer responses to labeling, see Grunert and Wills (2007) and for a review of nutritional labeling and consumer choices, see Kiesel, McCluske and Villas-Boas (2011).

spillovers from participating to non-participating firms. This is particularly relevant to evaluating VNL programs that seek to communicate nutritional information in a simpler format. If the nutritional information of participating VNL products spills over to consumers considering buying non-participating products and these information spillovers are ignored, then the evaluation of VNL impacts will be mismeasured. As with voluntary participation in environmental programs, distinguishing between the effect of participation and the effect of information spillovers is crucial in evaluating the overall effectiveness of VNL programs.

In this study, we examine consumer responses to VNLs by incorporating both participation and information spillovers. In 2007, FOP panels[4] summarizing four key nutrients were introduced in U.S. food markets as a simple and easy-to-use VNL. The number of participating firms has increased from a few leading food companies in 2007 to over 80 major food manufacturers and retailers in 2017. This provides a distinctive opportunity to test whether FOP creates an information spillover from participating products to non-participating products during post-adoption process. Our identification strategy for separating the participation and spillover effects is to exploit variations in FOP implementation in a particular food market. With this strategy, a key issue will be to identify the time that each participating product implemented the new FOP. By using a unique panel of packaging and nutrition information, we are able to collect the exact date that a particular product adopted FOP nutritional information.

The U.S. ready-to-eat cereal (RTEC) market provides a good case study of

[4] The FOP system was first introduced as “Nutrition at a Glance” by Kellogg’s and “Nutrition Highlights” by General Mills, but renamed by the U.S. food industry as “Facts Up Front" in early 2011.

spillovers of nutritional information disclosures. First, the RTEC industry has been a leader in experimenting with different nutritional information disclosure formats on a voluntary basis since the early 2000s. Second, none of the national brands has a truly dominant hold on the market, which imposes a considerable information burden on consumers. Third, the RTEC category is economically and nutritionally important as it is the largest among breakfast foods in the United States, with approximately $10.6 billion in sales in 2015 (Plunkett, 2016).

Empirical results from the U.S. RTEC market confirm a positive effect of participation in VNL on consumer choices. We also find a strong negative impact of FOP on consumer choices of non-participating products, especially those that are unhealthy (high in sugar, saturated fat, and sodium). These findings imply that ignoring the information diffusion effect cannot capture the spillovers to non-FOP brands, resulting in underestimation of the effectiveness of VNL on the likelihood that a consumer will purchase a FOP product, and possible over-estimation of the impact of VNL on non-participating products. The findings also highlight that an incentive for a firm's participation in self-regulated nutritional labeling programs is to avoid the negative treatment externalities of VNL.

The remainder of this paper is structured as follows. Section 2 briefly describes the evolution of VNL in the U.S. with particular reference to the RTEC market. Section 3 details our empirical strategy for identifying spillover effects. Section 4 summarizes the data collection and measurement of spillover effects as well as product healthiness. Section 5 presents and discusses estimation results, and Section 6 presents our conclusions.

2. Evolution of VNLs in the U.S. RTEC Market

Three common types of VNL have been used in the food industries (Pereira, 2010; Norton, Rucker and Lamberton, 2015). The two most relevant to the present study are those that correspond to FOP display of nutritional information. In Figure 1 we illustrate the evolution of VNLs with a particular focus on the U.S. RTEC market. The first type is the criteria-based system, in which qualified products can print certain FOP symbols based on the firms' own criteria or guidelines. Examples include Smart Choice labels and Walmart's *Great For You* labels. A second type is the fact-based system, in which FOP labels normally restate some of the facts listed on the Nutrition Facts Panel in a more concise manner in order to help consumers quickly find the key nutritional information they need. A third type is an evaluative system that provides consumers with an overall assessment of a product's healthfulness, such as the NuVal nutrition scoring system, which rates foods with a numeric score from 1 to 100.[5]

[FIGURE 1 AROUND HERE]

Figure 1 provides a timeline of the introduction of major VNL label types relevant to the U.S. RTEC market. In October 2007, Kellogg's launched one of the first fact-based FOP nutritional labeling systems, called Nutrition at a Glance, based on the European Guideline Daily Amounts (GDA) system. At the same time, General Mills introduced the Nutrition Highlights system with an almost identical format. This fact-based FOP system was later renamed Facts Up Front by the Grocery Manufacturers

[5] Zhen and Zheng (2015), using NuVal to evaluate product healthiness, show that higher NuVal scores lead to an increase in the product's sales.

Association (GMA) and the Food Marketing Institute, and it became a joint voluntary nutritional labeling initiative for the whole food and beverage industry in the United States.

The fact-based FOP system, which uses a carrot and stick approach, is set up to provide busy consumers, especially parents, with consistent and reliable nutritional information when they shop. Using easy-to-read symbols, the system places contents of four key “nutrients to limit” (calories, sugar, sodium, and saturated fat) on the fronts of food packages of participating products. Manufacturers have the option to include up to two additional “nutrients to encourage,” such as fiber, protein, potassium, calcium, and vitamins, for health-conscious consumers to consider in deciding whether to purchase their products. It is worth noting that fact-based FOP labeling mainly reiterates the key nutritional information already presented in the mandatory NFP, but in a simpler way.

Under the federal guidelines, all participating companies need to present fact-based FOP symbols in a standardized format on all their eligible products rather than on selective products only. Since implementation, the number of products carrying fact-based FOP labels has continued to grow in the U.S. food market. So far, there are more than 80 participating companies, including leading manufacturers such as Nestlé, Coca-Cola, Pepsi Co., General Mills, etc.

The RTEC industry, along with other food industries, also launched a consumer education campaign to further increase consumer awareness of FOP labels and nutritional information. The gradual implementation of the fact-based FOP labeling provides a distinctive opportunity to test whether there exists any information spillover effect from participating products to non-participating products following the adoption of FOP by participating RTEC producers.

3. Estimation Strategy

3.1 Model of Consumer Choices

We model consumer demand for differentiated products following the Berry, Levisohn and Pakes (BPL) model (1995), which is essentially a random coefficient logit model of consumer choices in the context of product and consumer characteristics. Assuming there is a total number of *G* manufacturers (e.g. Kellogg's, General Mills, PepsiCo., Ralcorp, etc.) that produce RTEC products under a variety of brand names, let *j = 1, …,* with *j* denoting a RTEC product brand. Let ϕ_{jt} be a binary variable that indicates whether or not brand *j* disclosed voluntary nutritional information at occasion *t* (ϕ_{jt}=1 if it did) and ψ_t denote the degree of information spillovers in market *t*.

The conditional indirect utility of consumer *i* from purchasing RTEC product *j* belonging to manufacturer *g* in market *t* is represented by:

$$
\begin{aligned}
u_{ijt} &= \alpha_i p_{jt} + \beta_i X_{jt} + \gamma_i \phi_{jt} + \lambda_i (1 - \phi_{jt}) \psi_t + \xi_{jt} + \epsilon_{ijt} \\
&= \delta_{jt} + \mu_{ijt} + \epsilon_{ijt} \quad , \qquad (1)
\end{aligned}
$$

where p_{jt} is the price of RTEC brand *j* in market *t*. X_{jt} is a vector of other observable product attributes and marketing variables such as nutritional quality and advertising. The specification shows that the information spillover effect applies only to non-disclosing brands. The parameters γ_i and λ_i capture the VNL participation effect and information spillover effect, respectively.

As shown in (1), the indirect utility can be decomposed into three parts: a mean utility term δ_{jt}, which is common to all consumers; a consumer-specific deviation from that mean, μ_{ijt}; and idiosyncratic taste, where ϵ_{ijt} is a mean zero stochastic term distributed independently and identically as a type I extreme value distribution. Let $Z_{jt} = [p_{jt},\ X_{jt},\ \phi_{jt},\ (1-\phi_{jt})\psi_t]$ and $\theta = [\alpha, \beta, \gamma, \lambda]$; then the mean utility $\delta_{jt} = Z'_{jt}\theta + \xi_{jt}$. The utility deviations are stated as $\mu_{ijt} = Z'_{jt}(\Omega D_{it} + \Theta V_i)$, where D_{it} is a vector of individual specific variables, and Ω is a matrix of coefficients measuring how taste characteristics vary across individuals; V_i is a vector of unobserved consumer characteristics that have a standard multivariate normal distribution, and Θ is a scaling matrix.

We complete the consumer choice model by defining an outside good that offers the possibility not to buy any of the products included in the choice set. Thus, the probability that consumer *i* purchases a unit of brand *j* in market *t* is

$$Prob_{ijt} = \frac{\exp\left[\alpha_i p_{jt} + \beta_i X_{jt} + \gamma_i \phi_{jt} + \lambda_i \left(1-\phi_{jt}\right)\psi_t + \xi_{jt}\right]}{1 + \sum_{r=1}^{J} \exp[\alpha_i p_{rt} + \beta_i X_{rt} + \gamma_i \phi_{rt} + \lambda_i (1-\phi_{rt})\psi_t + \xi_{rt}]}$$

$$= \frac{\exp(\delta_{jt} + \mu_{ijt})}{1 + \sum_{r=1}^{J} \exp(\delta_{rt} + \mu_{irt})}. \qquad (2)$$

Aggregating over consumers to the market level in a given period, the market share of brand *j* is given by

$$s_{jt} = \int I\left\{\left(D_{it}, v_i, \epsilon_{ijt}\right): u_{ijt} \geq u_{ikt} \forall k = 0, \dots, J\right\} dH(D)G(v)dF(\epsilon), \qquad (3)$$

where $H(D)$, $G(v)$, and $F(\epsilon)$ are cumulative density functions of the corresponding variables defined in scalar form. In market equilibrium, (3) corresponds to the aggregate probability that individuals in market *t* collectively choose product *j*.

3.2 Identification

Given the potential endogeneity of RTEC prices, we use instrumental variables in the estimation of the consumer choice model. Following Nevo (2001) and Berry, Levinsohn and Pakes (1999), we use cost shifters for RTEC products (prices of corn and rice and firms' advertising expenditure) as instruments. Additionally, we use own prices for RTEC product brands in different cities (Hausman and Taylor 1981) as exogenous instruments for RTEC prices in a given market. Notice that all the non-price product characteristic variables in X are also valid instruments since they are assumed to be independent of ξ.

Finally, we also use a set of optimal instruments to help identify random coefficients and increase efficiency. Chamberlain (1987) shows that under conditional moment restrictions, the efficient instruments are the expected values of the derivatives of the conditional moment condition with respect to the parameters. Berry, Levinsohn and Pakes (1999) propose using approximations of the optimal instruments for the BLP model. Reynaert and Verboven (2014) compare the performance of the approximation and the exact implementation of the optimal instruments, and demonstrate that both of them can overcome several estimation problems of the BLP model and substantially increase estimation efficiency and stability. We test for the validity of instruments with first-stage F-tests and Hansen J tests.

3.3 GMM estimator

The specified demand model can be estimated using a nonlinear Generalized Methods of Moments (GMM) estimator. We follow a mathematical program with equilibrium constraints (MPEC) approach to BLP, as modified by Dubé, Fox and Su (2012), to estimate parameters of the demand model.

The predicted market shares are restricted to match the observed shares, where δ can be solved from:

$$s_{jt} - S_{obs} = 0 \quad (4)$$

Let IV denote a set of instrumental variables. The moment function is then given by:

$$g(\delta) = E[IV'\xi] = E[IV'(\delta - Z'\theta)] = 0 \quad (5)$$

Let A be the GMM weighting matrix; the estimated parameters are solved from the following constrained minimization problem:

$$\min_{\theta,\xi,g} \; g'Ag \;\; s.t. \quad s_{jt} = S_{obs}\,, \quad (6)$$

where $g = IV'\xi$.

As noted by Nevo (2012), the set of instrumental variables during estimation plays a dual role: control for price endogeneity and to generate moment conditions to identify random coefficients.

4. Data

4.1 Data Sources and Management

The data used to operationalize the model are from three main sources: (1) RTEC household purchases data from Nielsen Homescan, (2) RTEC product-level weekly TV advertising exposure from Nielsen Media Research, and (3) RTEC packaging information, including labeling and nutrition information, from Mintel Global New Products Database. All datasets were obtained from the Zwick Center for Food and

Resource Policy at the University of Connecticut.

The Nielsen Homescan database tracks purchases of RTECs across Designated Market Areas (DMAs) in the United States, including New York, Boston, Detroit, Washington DC, Atlanta, San Francisco, and Seattle. Purchases for at-home consumption include buying at big box retailers, grocery stores, convenience stores, automatic vending machines and on-line retailers. This dataset is the main resource for the explanatory variables used in the analysis.

The Nielsen Media Research database provides brand-level TV advertising exposure on a weekly basis for each DMA, measured in gross rating points (GRPs). A higher GRP means more consumers were exposed to a brand's TV advertising aired in a given area and week. As the most heavily advertised food product category in the United States, RTEC advertising is a key non-price variable affecting choices in the relevant markets.

Mintel's Global New Products Database provides detailed product listings for 245 categories of food, drink, and other grocery store items since 1996. These listings are based on new product packaging, new product introductions, new product varieties, and product reformulations. This dataset is used to identify the precise date that a particular brand started using fact-based FOP labeling on its products.

Merging the three data sources and aggregating brand/DMA/biweekly level generates 14,550 observations used in the BLP model. The market is defined as a combination of a DMA and a biweekly period. The potential market size is defined as the combined per capita consumption (in ounces) of RTECs plus the outside good (e.g., cold and hot cereals) times population. The total potential consumption is calculated as the per capita consumption of all cereals times the population of the market *t*.

4.2 Measurement of product healthiness

We adopt the Nutrition Profile Index (NPI)[6] to measure RTEC product healthfulness at the brand level. NPI scores reflect nutrition quality assessments of food products and are calculated based on a model developed for the Food Standards Agency of the United Kingdom (Castetbon, Harris and Schwartz, 2011). Rather than relying on a single nutrient measurement, the NPI scores take into account both positive (e.g., protein, fiber, vitamins) and negative (e.g., sugar, sodium, saturated fat) nutrients in the entire nutrient composition, providing a comprehensive evaluation of the nutritional quality of food products. Table 1 reports product characteristics of leading national RTEC brands.

[TABLE 1 AROUND HERE]

4.3 Measurement of spillover effects

We operationalize the key variable of the market information spillover level ψ_t by utilizing the exact introduction dates of VNL for participating brands. Specifically, we define ψ_t as the cumulative number of RTEC products that had disclosed VNL labels at *t*:

$$\psi_t = \sum_{m=0}^{N} \phi_{mt}. \qquad (7)$$

Figure 2 illustrates the trend of the total number of RTEC products (in the sample

[6] As a robustness check, we also use the NuVal score as an alternative measure of product healthfulness.

used in this study) with FOP labels since their introduction in 2007. By the 17^{th} week of 2008, there were nine RTEC products with fact-based FOP labels in the RTEC choice set. As illustrated in the diagram, the total number of RTEC products has continued to increase during our sample period. A greater presence of FOP-labeled products implies a reinforcement of the potential information spillover effects on consumer valuation of non-participating products.

[FIGURE 2 AROUND HERE]

Once all the empirical variables were operational, the BLP-based demand model for RTEC products including information spillover effects from FOP-labeled products was estimated. The results are presented in the following section.

5. Results and Discussion

5.1 Consumer demand results

Table 3 presents the estimation results for the BLP models. All of the first stage F statistics exceed 10, indicating that the use of price instruments is appropriate in all specifications. The Hansen J statistics and p-values suggest there is no evidence that the price instruments are correlated with unobserved demand shocks. Firm/quarter/DMA fixed effects are included in all specifications. Price has a negative effect, while advertising has a positive effect on consumer RTEC choices, as expected.

[TABLE 3 AROUND HERE]

We first estimate the effect of VNL in a conventional way, without considering any spillover effect, and report the results in column (1) of Table 3. *FOP* is a dichotomous variable that indicates either disclosing (*FOP=1*) or not (*FOP=0*), and it is designed to capture the VNL participation impact. From column (1), the mean estimate of the participation effect is 0.248, which is marginally significant at the 10% level. With regard to consumer preference for product healthfulness, the mean parameter of *NPI* is positive and highly significant.

We then include the information spillover effect in specification (2), in which *Spillover* is defined by ψ_t, as described in section 4.3. The mean parameter of *Spillover* is negative and significant, and its deviation coefficient is also significant, implying that there is a negative spillover effect, on average, but the influence is heterogeneous across consumers. One interesting finding to emerge is that the estimated mean participation effect becomes triple and more significant once we control for the diffusion effect in model (2). These results indicate the existence of a negative program spillover effect of VNLs from participating RTEC products to non-participants, and suggest that overlooking information spillovers tends to underestimate overall program effectiveness.

Specification (3) adds interaction terms of product healthfulness (measured by NPI), with both participation and spillover effects, to get a better understanding of variation by nutritional information levels. The mean estimate of *FOP*NPI* is 2.595, which is significant at the 10% level, meaning that among FOP-disclosed RTEC products, consumers prefer those that are relatively healthier (i.e. have a higher NPI). This finding is consistent with previous studies (Zhu, Lopez, and Liu 2016). An interesting finding is that the mean parameter of *Spillover*NPI* is also positive and marginally significant, suggesting that the negative information spillovers on non-disclosing products can be alleviated when the product is relatively healthier. From parameter estimates in model

(3), it seems that the voluntary initiative can encourage consumers to purchase relatively healthier RTEC alternatives from both participating and non-participating manufacturers.

5.2 Marginal effect of healthfulness

The marginal effect of healthfulness (MEH=$\partial Prob_{ijt}/\partial NPI_i$) measures how the choice probabilities vary across products with different healthfulness levels. Based on demand estimates from specification (3), we then calculate the impact of *FOP* on MEH ($\frac{\Delta\partial Prob_{ijt}/\partial NPI_i}{\Delta FOP}$) and the impact of information spillovers on MEH ($\frac{\Delta\partial Prob_{ijt}/\partial NPI_i}{\Delta Spillover}$) for each observation. The distribution of the impacts is shown in Figure 3. The positive sign for all observations in panel (a) indicates that *FOP* has a generally positive impact on the marginal effect of healthfulness. From panel (b), although the calculated average impact of information spillovers on MEH is -0.0006, the overall effect is positive for relatively healthier RTEC products.

5.3 Simulation results

Another major advantage of using the structural demand model discussed in previous sections is that it allows researchers to handle counterfactual predictions and outcomes. Demand estimates confirm a negative information spillover effect from participants to non-participants in fact-based FOP labeling. In this section, we conduct additional counterfactual experiments based on demand estimates from specification (3).

Notice that in the current practice (Scenario 0), only Kellogg's and General Mills are adopting FOP labels; Post and Quaker are not. Thus, in Scenario 1 we first simulate consumers' response when Post decides to disclose fact-based FOP labels. Then, in

Scenario 2, we simulate the case when Quaker employs the FOP labels. Finally, we consider the situation when both Post and Quaker adopt FOP labels in Scenario 3.

Table 3, column 2, reports the effects when Post starts to disclose fact-based FOP nutritional information on its RTEC brands. Doing so leads to a general increase in the market shares of all Post products. Similarly, when Quaker participates in the voluntary initiative, all of its products have a general increase in simulated shares, as shown in column 3. In all scenarios, the outside shares of alternative choices (e.g. other RTEC products, hot cereals) go down from 65.62% to 65.19% (S1), 64.99% (S2), and 64.47% (S3), respectively, implying that consumers have a tendency to switch to RTEC products sold with fact-based FOP labels. In fact, based on the GNPD records, RTEC products of Post and Quaker were observed to adopt FOP labels beginning in 2013. Thus, from a competition standpoint, the subsequent VNL participation of Post and Quaker after our data period is consistent with the simulation results. Overall, simulation results presented in this section support the hypothesis that firms have an incentive to join the voluntary labeling program because they expect it will enable them to avoid the adverse spillover effects from participating rival products, especially those that are relatively healthier.

5.4 Labeling policy implications

While there has been significant research on the economics of nutrition labeling, particularly the lack of effectiveness of the Nutrition Facts Panel resulting from the 1990 Nutrition Labeling and Education Act in the U.S., empirical work on the effectiveness of voluntary nutrition labeling is lacking. The results of this study support the notion that the private provision of information can push consumer choices towards healthier food products both by enhancing the effectiveness of participating products and by discouraging the purchase of non-participating products. What is clearly beyond the scope of this paper is the emerging policy and legal issue of false or exaggerated health claims in an unregulated VNL environment.[7] Recent legal cases and complaints to government agencies both suggest that this may be an area where the government can play a role in improving VNL or at least in ensuring and standardizing the format of information presented to consumers.

6. Conclusions

This paper investigates the effects of information spillovers from voluntary nutrition labeling (VNL) on consumer choices of participating and non-participating food products, using the U.S. ready-to-eat cereal industry as a case study. Empirical results support the hypothesis that information spillovers do affect consumer choices at the product-brand level, enhancing the probability that participating products get chosen and decreasing the probability that non-participating products are bought. This finding highlights the incentive for firms to participate in voluntary labeling programs in order to avoid the negative effects of the information externalities. In addition, the empirical findings underscore that unhealthy products (those high in sugar, sodium, and saturated fats) are particularly negatively impacted by voluntary labeling. Ignoring labeling

[7] In this regard, the U.S. Food and Drug Administration established a Front-of-Package Labeling Initiative in 2009, issuing warning letters to selected manufacturers whose claims were not consistent with provisions of the Federal Food, Drug and Cosmetic Act, which requires labels to be truthful and not misleading. Likewise, the Gerber Products Co. faced a class action lawsuit, which started in 2012, regarding mislabeling of their baby foods in terms of sugar and nutrition contents (Davis, 2014).

information spillovers in empirical analyses leads to an under-estimation of consumer valuation of VNL on participating products and over-valuation of non-VNL products. Given the potential for VNL to lead to healthier food choices by providing a private solution to a public health issue, the implications for the role government policy point to ensuring the accuracy of VNL claims rather than further mandatory labeling.

The results presented in this study contribute to the ongoing policy debate regarding the effectiveness of voluntary nutritional labeling programs in the U.S. and abroad. Some of the limitations of our analysis suggest fruitful avenues for further research. First, although our empirical framework allows for consumer heterogeneity, we do not explicitly distinguish the effects across different demographic groups, such as different ethnic groups or consumers with different educational attainments. Second, this article relies only on the demand side without considering a potential supply side response by manufacturers, which, via pricing, promotion, or advertising strategies, could further affect consumer choices and the effectiveness of voluntary nutrition labeling. Finally, whether the results of this study hold in industries other than the U.S. ready-to-eat cereal industry is a question that awaits further empirical analysis.

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Table 1. Summary Statistics of Top National RTECs

Firm/Brand	Cal. (/oz)	Sugar (g/oz)	Sat. Fat (g/oz)	Sodium (mg/oz)	Fiber (g/oz)	Shares (%)	NPI Score	VNL Date
Kellogg's								
Frosted Flakes	103	11	0	129	1	2.96	42	8/13/2008
Frosted Mini-Wheats	99	6	0	3	3	3.42	74	3/11/2008
Raisin Bran	90	8	0	162	3	1.94	54	3/13/2008
Froot Loops	110	13	1	132	1	1.24	39	4/22/2008
Rice Krispies	108	3	0	254	0	1.17	41	3/13/2008
Special K	107	4	0	204	1	0.71	44	2/13/2008
Special K Red Berries	103	9	0	199	1	1.23	48	3/5/2008
Apple Jacks	109	12	0	124	0	0.96	40	8/22/2008
Corn Pops	106	13	0	108	0	0.82	33	12/7/2007
Cocoa Krispies	108	11	1	117	1	0.53	42	No VNL
Honey Smacks	99	16	0	41	1	0.34	48	No VNL
Eggo	110	11	1	110	2	0.27	46	No VNL
General Mills								
Cheerios	103	1	0	186	3	3.41	58	3/12/2008
Cinnamon Toast Crunch	121	9	0	196	1	1.82	37	3/19/2008
Lucky Charms	114	11	0	190	1	1.41	36	6/19/2008
Kix	96	7	0	131	3	1.18	56	No VNL
Cocoa Puffs	112	13	0	149	1	0.87	39	7/17/2008
Reese's Puffs	121	11	0	187	1	0.67	34	7/21/2008
Trix	105	9	0	158	1	0.51	42	No VNL
Cheerios Fruity	104	8	0	130	2	0.48	48	No VNL
Fiber One	56	0	0	103	13	0.42	78	No VNL
Post								
Honey Bunches of Oats	112	6	0	140	2	3.37	54	No VNL
Grape-Nuts	101	2	0	140	3	0.78	70	No VNL
Fruity Pebbles	112	12	1	164	3	0.67	26	No VNL
Cocoa Pebbles	111	12	1	151	3	0.56	26	No VNL
Shredded Wheat	97	0	0	0	3	0.21	82	No VNL
Quaker								
Cap'n Crunch								
Life Cinnamon	113	12	1	209	1	0.65	28	No VNL
Cap'n Crunch Crunchberries	104	7	0	134	2	0.74	53	No VNL
Cap'n Crunch Peanut Butter Crunch	113	13	1	196	1	0.64	28	No VNL

Notes: Based on the Nutrition Profiling Index (NPI) scores, RTEC products with less than 40 points are classified as having poor nutritional quality. K/GM/P/Q represent Kellogg’s/General Mills/Post/Quaker.	116	9	1	208	1	0.40	32	No VNL

Table 2. Demand Estimation Results

	(1)		(2)		(3)	
Variable	Mean Parameter	Deviation	Mean Parameter	Deviation	Mean Parameter	Deviation
Constant	-7.294***	0.132	-8.927***	0.208	-4.777***	-0.105
	(0.378)	(2.306)	(0.852)	(3.719)	(1.079)	(6.326)
Price	-5.283***	1.576*	-7.667***	1.592	-1.566**	-0.431*
	(1.239)	(0.879)	(2.742)	(4.007)	(0.709)	(0.230)
GRP	1.081**	-0.082	1.368**	-0.046	0.850***	0.110
	(0.500)	(2.490)	(0.696)	(5.507)	(0.287)	(3.146)
FOP	0.248*	0.471	0.908**	0.493	0.510**	0.231
	(0.139)	(1.225)	(0.479)	(2.192)	(0.239)	(1.223)
Spillover			-3.134**	2.971**	-3.639**	1.848**
			(1.487)	(1.160)	(1.724)	(0.803)
FOP*NPI					2.595*	0.664
					(1.405)	(4.972)
Spillover*NPI					1.928*	-0.192
					(1.012)	(13.411)
NPI	2.715***	1.043*	2.689***	0.943		
	(0.683)	(0.572)	(0.805)	(0.737)		
General Mills	-0.583	-0.196	-0.219	-0.324	-0.428	0.560
	(0.629)	(3.119)	(0.501)	(2.660)	(1.036)	(1.975)
Post	-0.941	0.289	-0.813	-1.257	-0.434*	0.489
	(1.018)	(2.324)	(1.205)	(1.130)	(0.237)	(4.281)
Quaker	-1.503*	-1.077*	-1.680*	-1.983**	-1.493*	1.173
	(0.834)	(0.563)	(1.002)	(0.765)	(0.818)	(6.905)
Year Fixed Effects	Yes		Yes		Yes	
Quarter Fixed Effects	Yes		Yes		Yes	
DMA Fixed Effects	Yes		Yes		Yes	
Observations	14,550		14,550		14,550	
First stage F statistics	19.204		23.194		21.483	
p-value	0.000		0.000		0.000	
Hansen J statistics	16.821		18.509		15.394	
p-value	0.183		0.295		0.127	

Table 3. Simulated Market Shares (%) under Alternative VNL Scenarios

Firm/Brand	(1) S0: Current Practice	(2) S1: Post Discloses	(3) S2: Quaker Discloses	(4) S3: Both Post and Quaker Disclose
Kellogg's	**15.60**	**15.69**	**15.75**	**15.87**
Frosted Flakes	2.96	2.90	2.98	3.03
Frosted Mini-Wheats	3.42	3.65	3.66	3.44
Raisin Bran	1.94	1.68	1.86	2.18
Froot Loops	1.24	1.27	1.24	1.29
Rice Krispies	1.17	0.82	0.93	0.85
Special K	0.71	0.80	0.77	0.75
Special K Red Berries	1.23	1.36	1.25	1.25
Apple Jacks	0.96	1.15	1.02	0.93
Corn Pops	0.82	0.81	0.87	0.96
Cocoa Krispies	0.53	0.54	0.56	0.50
Honey Smacks	0.34	0.37	0.36	0.37
Eggo	0.27	0.35	0.25	0.31
General Mills	**10.77**	**10.83**	**10.78**	**10.80**
Cheerios	3.41	3.47	3.45	3.53
Cinnamon Toast Crunch	1.82	1.96	1.72	1.81
Lucky Charms	1.41	1.35	1.49	1.47
Kix	1.18	1.07	1.15	0.98
Cocoa Puffs	0.87	0.90	0.89	0.74
Reese's Puffs	0.67	0.64	0.64	0.66
Trix	0.51	0.42	0.45	0.54
Cheerios Fruity	0.48	0.53	0.48	0.58
Fiber One	0.42	0.49	0.51	0.49
Post	**5.58**	**6.11**	**5.29**	**5.82**
Honey Bunches of Oats	3.37	3.64	3.29	3.75
Grape-Nuts	0.78	0.90	0.71	0.55
Fruity Pebbles	0.67	0.66	0.63	0.65
Cocoa Pebbles	0.56	0.61	0.45	0.59
Shredded Wheat	0.21	0.30	0.21	0.28
Quaker	**2.43**	**2.18**	**3.20**	**3.04**
Cap'n Crunch	0.65	0.63	0.86	0.67
Life Cinnamon	0.74	0.64	1.15	1.16
Cap'n Crunch Crunchberries	0.64	0.55	0.68	0.81
Cap'n Crunch Peanut Butter Crunch	0.40	0.36	0.51	0.40
Total	34.38	34.81	35.01	35.53
Outside Shares	65.62	65.19	64.99	64.47

Figure 1. Timeline of Major Voluntary Nutritional Labeling Systems in Use in the RTEC Market, 2004-2014

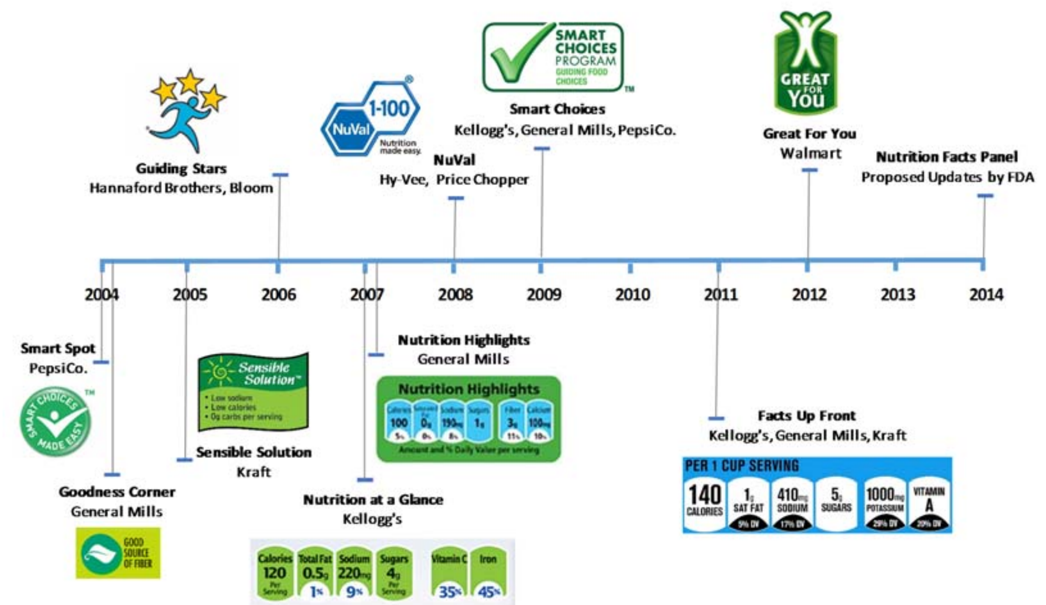

Figure 2. Number of Products in the Sample with FOP Labels

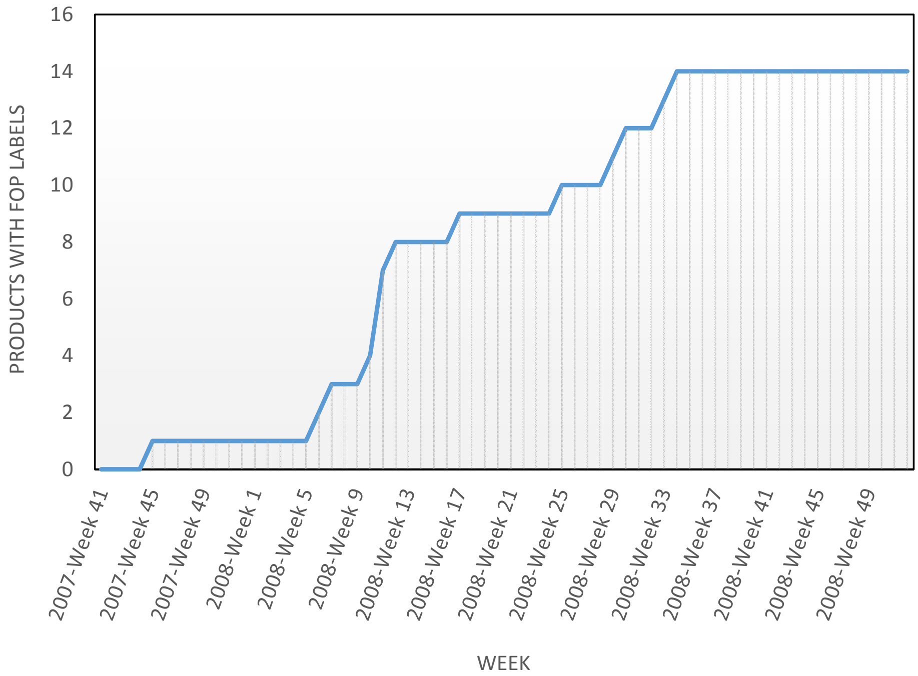

Figure 3. Density Distribution for the Impacts on Marginal Effect of Healthfulness

(a) Impact of FOP on MEH (b) Impact of information spillovers on MEH