Measuring the Value of Information in NuVal Shelf Nutrition Label

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Abstract

The objective of this study is to estimate the value of information provided by the NuVal shelf nutrition label—a prominent example of a new interpretive approach to front-of-package nutrition labeling that provides a multiple-level nutrition symbol. The rollout of NuVal at a supermarket in a Midwest town allowed us to estimate a mixed logit demand model for yogurt using household and barcode-level scanner data. We found the NuVal label promoted purchases of healthier yogurts. The average value of NuVal information in the yogurt category is estimated to be about 3% of total expenditures on yogurt. There is evidence suggesting that households who made less use of conventional nutrition labels prior to NuVal rollout may stand to benefit more from NuVal labels. Overall, our results indicate that there is a significant willingness to pay, on the part of consumers, for a universal adoption of an interpretive multiple-level shelf or front-of-package nutrition symbol.

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The diet for the majority of the U.S. population does not meet the Dietary Guidelines for Americans (DGA) (USDA and DHHS, 2010). Per capita caloric intake from solid fats and added sugars exceeds the recommended limit by 180%, the highest percentage of foods and food components consumed excessively by Americans, followed by refined grains (100%) and sodium (49%) (USDA and DHHS, 2010). Processed and packaged foods and beverages account for over 50% of total calories consumed by an average American (Eicher-Miller, Fulgoni and Keast, 2012). To increase taste, improve mouth feel, reduce production cost, and/or increase shelf life, many processed products are high in saturated fat, added sugar, and sodium.

Alarmed by the low nutritional quality of some processed foods, a number of policy interventions have been proposed to reduce consumption of some of the least nutritious food products. A prominent example is proposals of large excise taxes on sugar-sweetened beverages (SSBs) that appear to be gaining momentum in recent years. As of February 2017, seven U.S. cities, led by Berkeley, CA, have passed excise taxes of at least one penny per ounce on SSBs (County Health Rankings and Roadmaps, 2017). An evaluation of the Berkeley tax estimates that the policy reduced SSB consumption by 25% relative to comparison cities (Falbe et al., 2016). Although, by the law of demand, large taxes targeted at less nutritious foods reduce consumption of the taxed foods, this policy can be costly to consumers in lost consumer surplus at least in the short run.[1]

An alternative, and perhaps less controversial, policy is to provide nutrition information so that consumers can make their own informed decisions. The benefit of this information provision approach is that any reduction in consumption of less nutritious foods would be due to preference changes toward healthier diets. Consequently, there is no loss in consumer surplus.

[1] In the long run, it is possible for the benefit of improved health to outweigh the cost if such taxes result in healthier total diet.

Traditionally, information disclosure has been central to U.S. nutrition policymaking. The Nutrition Labeling and Education Act (NLEA) of 1990 mandating standardized Nutrition Facts labels on most packaged foods by 1994 and the required disclosure of trans fat content on Nutrition Facts labels by 2006 are representative of this policy. These regulations had some success in improving population diet quality. For example, although still above DGA recommended levels, intake of saturated fats has declined across demographic subgroups largely due to mandatory fat content disclosure under the NLEA (Mathios, 2000) together with voluntary health claims (Ippolito and Mathios, 1995) and diffusion of fat-heart-disease information (Chern, Loehman, and Yen, 1995). The nutrition facts label would be most effective if consumers correctly process the disclosed information, which is often in lengthy format on the back or side of the package, and act on it by choosing healthier products. However, this may not be an easy and natural process for some, especially those who are time-constrained and less health-conscious. The literature documents that food label use varies significantly across sociodemographic subgroups (Ollberding, Wolf and Contento, 2010) and that diet and health knowledge is one of the strongest predictors of label use (Drichoutis, Lazaridis and Nayga, 2006). Over the decade following NLEA's full implementation, consumer use of most nutrition labels had declined (Todd and Variyam, 2008). These and the continuing post-NLEA increases in prevalence of obesity (Flegal et al., 2002) and obesity-related medical costs (Finkelstein et al., 2009) further warrant the quest for new labeling strategies that potentially supplement the Nutrition Facts label.

One strategy is to present simplified nutrient information on the front of package (FOP). Research concludes that consumers prefer short FOP labels to lengthy Nutrition Facts labels hidden on the back or side of the package (Drichoutis et al., 2006). The food industry has

developed a number of FOP nutrition labeling systems (Hersey et al., 2013). In a recent example, the trade associations Grocery Manufacturers Association (GMA) and Food Marketing Institute (FMI), in 2011, unveiled a nutrient-based FOP nutrition labeling system, called Facts Up Front, with both absolute amounts and percentage daily values (%DV) of calories, saturated fat, sodium, and sugars per serving of the product. Participant companies have the option to include amounts and %DVs of two of eight nutrients (potassium, fiber, protein, vitamin A, vitamin C, vitamin D, calcium, and iron) to encourage (GMA and FMI). It is worth nothing that nutrient-specific FOP labels such as Facts Up Front do not provide additional information not already on the required Nutrition Facts labels. Instead, these labels make select nutrition facts more prominent and, thus, have the potential to reduce consumer search cost. There is mixed evidence on whether nutrient-specific FOP labels actually lead to healthier purchases. One observational study found Facts Up Front to reduce calories and nutrients that DGA recommends to limit in purchases of 22 breakfast cereal brands (Zhu, Lopez, and Liu, 2016). However, a randomized controlled trial found no effect of nutrient-specific labels on food purchases (Ducrot et al., 2016).

There is concern, as was the case in the United Kingdom (Hersey et al., 2013), that a proliferation of different FOP label systems could confuse consumers and mitigate their potential effectiveness. In response, in 2009, the U.S. Food and Drug Administration (FDA) launched the Front-of-Package Labeling Initiative, the goal of which is to determine whether a single standardized FOP nutrition symbol should be used across all packaged foods (FDA, 2009). In the same year, at the request of Congress, the Centers for Disease Control and Prevention (CDC) and FDA, the Institute of Medicine's (IOM's) Committee on Examination of Front-of-Package Nutrition Rating Systems and Symbols was commissioned to review current approaches and propose guidance on a standardized FOP label. In its report released in 2011, the committee

recommended the development of a summary multiple-level nutrition symbol that goes on the fronts of packages and provides a clear ranking of the healthfulness of the labeled product (IOM, 2012). The IOM report encourages the FDA to shift from the current approach of providing more nutrition facts to an interpretive one that provides simple, direct, and science-based guidance to consumers on the nutritional quality of the product.

Interpretive shelf nutrition labels are a tool that provides summary multiple-level rating of the overall nutrition quality of a food product. It is interpretive because the rating reflects the interpretation of nutrition facts by nutrition and health experts based on scientific evidence on diet-health links. These labels distinguish from conventional FOP labels/symbols in two respects. First, compared to nutrient-specific labels such as Facts Up Front that simply feature select nutrition facts label information more prominently, interpretive shelf labels have the potential to provide new nutrition cues to consumers at the point of purchase. Second, although FOP symbols such as Walmart's Great For You and American Heart Association's Heart-Check are also interpretive in that products bearing these symbols meet some pre-specified criteria, they are not multiple-level—the type recommended by IOM (RTI, 2012). Also, these symbols are absent from products that either do not meet the selection criteria or do not participate in the specific labeling program, which could cause confusion among consumers. In addition, there is evidence that consumers may not deduce the lower nutrition quality of unlabeled products by observing healthier labeled products (Mathios, 2000).

There are two major shelf nutrition label systems in U.S. grocery stores: Guiding Stars (introduced in 2006) and NuVal (introduced in 2008). Guiding Stars ranks food products between no star (least healthy) and 3 (healthiest) stars, although, in practice, products that earn no star are often not labeled at the point of sale. By contrast, NuVal (introduced in 2008) scores

and labels products on a 1-100 scale with 1 indicates being least healthy and 100 the healthiest. At the participating retailer, the NuVal score is integrated into the shelf price tag (see Figure 1 as an example). As of February 2017, 16 retail chains had NuVal shelf labels compared with 5 chains using Guiding Stars. Recent research has shown Guiding Stars and NuVal to encourage healthy purchases (e.g., Rahkovsky et al., 2013; Zhen and Zheng, 2017).

NuVal scores foods based on an algorithm known as ONQI that profiles the content of 21 nutrients and the quality of four nutrition factors (Katz et al., 2010). The ONQI algorithm was developed by an expert panel independent of food industry interest. It penalizes nutrients (e.g., saturated fat, sodium, and sugar) and nutrition factors generally considered to have unfavorable health effects and rewards those (e.g., fiber, potassium) that are beneficial to health. Therefore, the higher the NuVal score, the healthier the food. In a test of the utility of ONQI, Chiuve, Sampson and Willett (2011) used the algorithm to evaluate the diet quality of over 100,000 health professionals who were followed for over two decades in two longitudinal surveys. They found that baseline diets scored lower by ONQI are associated with higher risks of total chronic disease, cardiovascular disease, diabetes, and all-cause mortality (Chiuve et al., 2011).

In this paper, we quantify the value of information embedded in the NuVal label. A grocery retailer's adoption of NuVal shelf label in a Midwestern city allowed us to estimate the effect of shelf nutrition label on consumer preferences for yogurts using a mixed logit demand model. Based on the demand estimates, we calculate that the information value of NuVal label is about 3-4% of total yogurt expenditures at the store that adopted NuVal. This research fills three gaps in the literature. First, no previous study has estimated the value of information from multiple-level interpretive labels—the type of nutrition labels IOM recommended to the FDA. As policymakers contemplate regulatory options on FOP labeling, the value of information

provided by various types of labels can be a useful metric for comparing the benefits and costs of candidate policies.

Second, this is the first study to estimate value of food label information at the barcode level using household-level data from actual purchase transactions in a real shopping environment. Previous research on this topic has only estimated demand at food group level based on retail scanner data aggregated from the barcode level (e.g., Teisl, Bockstael, and Levy 2001; Teisl, Roe, and Hicks 2002). Because NuVal rating is multiple-level and specific to the product barcode, estimating demand at this level is more appropriate and likely to improve precision of the coefficient estimates compared to aggregating products to a higher level. By using micro-level purchase data, we are able to examine how value of information differ across demographic groups. We found that households headed by persons aged less than 65, without young children, or without college degree benefit more from NuVal labels.

Finally, we proposed a procedure for recovering the value of information estimate from parameters of a mixed logit demand model. This new procedure is specific to discrete-choice demand models and, together with the procedure developed by Teisl et al. (2001) for continuous demand systems, completes the tool set for estimating value of label information based on consumer demand models.

The remainder of this article is organized as follows. We first review the emerging literature on demand effects of multiple-level interpretive nutrition labels, which is followed by a discussion of our mixed logit demand specification and estimation. We then introduce the conceptual framework of Foster and Just (1989) for measuring the welfare effect of information disclosure and our procedure for calculating value of information based on discrete-choice

models. Next, the scanner data and variable constructions are described, followed by discussion of empirical results. The final section provides concluding remarks.

Interpretive Labels and Consumer Demand

A few papers have evaluated the impacts of multiple-level interpretive labels on actual food purchases. Of those examined the Guiding Stars program, all used scanner data from Hannaford Supermarkets. Sutherland, Kaley, and Fischer (2010) compared sales trend of zero-star vs. that of starred ready-to-eat (RTE) cereal products. They found that, two years into the Guiding Stars program, sales of products with 1-3 stars grew at a higher rate than those of zero-star products, while the opposite was true before implementation. Cawley et al. (2015) analyzed aggregate pre- and post-Guiding Stars sales of 102 categories of food. The authors found that sales of foods rated as zero star declined by 8% on average, while sales of foods rated one to three stars did not change significantly. Rahkovsky et al. (2013) estimated a store-level conditional Rotterdam demand with four categories of RTE cereals classified by the star rating. They concluded that Guiding Stars increased sales of starred cereals at the expense of unstarred cereals with the largest gains accrued to one- and two-star products. The authors also found the Guiding Stars label made cereal demand less price elastic.

Two demand studies focused on NuVal. Nikolova and Inman (2015) analyzed purchase data collected through a retail chain's loyalty card program and from a control group of households from non-NuVal retailers. They found share of healthier product purchases increased following rollout of NuVal at this chain. Lastly, Zhen and Zheng (2017) estimated a difference-in-differences model of yogurt demand using store-level data from one NuVal store and five

non-NuVal stores in a city in the Midwest. They found that a one-point increase in NuVal score increases yogurt demand by 0.3%.

In sum, previous studies of interpretive shelf nutrition labels estimated reduced-form demand functions that are not conducive to welfare analysis. Note that even the Rotterdam demand system used in Rahkovsky et al. (2013) is not utility-theoretic in that the functional form is not consistent with utility maximization without imposing extreme restrictions on its parameters (Phlips, 1974). Therefore, one cannot simply use existing demand estimates to back out an estimate of the value of information.

Demand Model

To quantify the informational value of the NuVal label, we estimate a structural discrete choice demand model for yogurt, using the method proposed by McFadden (1974) and Train (2003). In a discrete choice framework, consumers face a choice set of J differentiated products. On each shopping trip, the consumer is assumed to purchase one unit of the product that yields her the highest utility. We allow the possibility that the consumer doesn't purchase any of the yogurt products in our sample on the shopping trip; that is, the choice set includes a *numéraire* or outside good. Unlike a conditional demand model that only contains the yogurt products in our sample, the *numéraire* is a composite good representing other excluded yogurt products and all other goods. This setup is required to obtain correct measure of welfare changes (LaFrance and Hanemann, 1989).

Formally, the utility consumer i obtains from purchasing the jth yogurt product on shopping trip t is specified as

(1) $$U_{ijt} = \gamma_{it}(y_i - p_{ijt}) + X_{jt}\beta_{it} + \sum_{s=1}^{5} d_s\alpha_s + w\alpha_w + w^2\alpha_{w2} + \varepsilon_{ijt},$$

where $j = 1, \ldots, J_t$ and J_t is the number of yogurt products in our sample available to household i on shopping trip t; y_i is the income of household i;[2] p_{ijt} is the price per pint (16 liquid ounces) of product j on household i's trip t; X_{jt} is a $1 \times K$ vector of observable attributes of product j that include the NuVal treatment variables; d_s are store dummies; w is linear weekly trend; ε_{ijt} is an independent and identically distributed error term; and γ_{it}, β_{it}, α_s, α_w, α_{w2} are parameters.

The observed product attributes include package size, and dummies for manufacturer, whether the product is a regular yogurt or yogurt drink, whether the product is NuVal-labeled, whether the product is on display or featured, and whether the price reduction is larger than five percent of the regular price. Our variable of interest is the dummy variable for whether the product is NuVal-labeled, one of the variables in X_{jt}. This variable, $Adopt_{jt}$, is equal to 1 if product j is labeled with a NuVal score at the store of trip t, and 0 otherwise. It captures the treatment effect of NuVal label on consumer demand for yogurt. We also include amounts of calories, total fat, saturated fat, cholesterol, sodium, carbohydrates, fiber, sugars, protein and calcium as additional attributes. Including a rich set of product characteristics, especially Nutrition Facts label information that is available to consumers at all times, is essential for controlling for omitted variables and avoiding spuriously attributing baseline taste differences as NuVal label effect.[3]

Finally, to complete the model and for identification purpose, the utility consumer i obtains from purchasing the *numéraire* good is specified as

[2] Note the term $\gamma_{it} y_i$ will be differenced away in estimation. See the definition of V_{ijt} in (4) below.

[3] An alternative way to lessen the omitted variable bias problem is to include a full set of product fixed effects. However, that approach is infeasible in our context because we have 199 yogurt products in our sample and including a full set of product dummies would lead to overfitting, poor identification of the parameters, and numerical issues for the nonlinear discrete-choice model. In a specification in which we did not include calorie and nutrient variables in the intercept, we obtained an implausibly large value of information estimate for NuVal equivalent to over 30% of total yogurt expenditures.

(2) $$U_{i0t} = \gamma_{it} y_i + \varepsilon_{i0t},$$

where subscript 0 denotes the outside good.[4]

The $K \times 1$ parameter vector β_{it} describes household i's taste for observable product attributes and NuVal labels, and γ_{it} represents household i's marginal utility of income on trip t. We assume these parameters are random. As marginal utility of income has to be positive, we assume γ_{it} follows a log normal distribution with log mean $\bar{\gamma}$ and log variance $(\sigma^{\gamma})^2$. For vector β_{it}, we assume its kth element β_{it}^k follows a normal distribution with mean $\bar{\beta}^k + Z_i\theta^k$ and variance $(\sigma^k)^2$. Z_i is a $1 \times D$ vector of observed household demographic variables, which include household size, income, the age and education level of the household head, and indicator for presence of children. θ^k is a $D \times 1$ vector of corresponding parameters. As a result, (1) can be rewritten as

(3) $$U_{ijt} = exp\left(\bar{\gamma} + \sigma^{\gamma} u_{it}^{\gamma}\right)\left(y_i - p_{ijt}\right) + \sum_{k=1}^{K}\left(x_{jt}^k \bar{\beta}^k + x_{jt}^k Z_i \theta^k + \sigma^k x_{jt}^k u_{it}^k\right) + \sum_{s=1}^{5} d_s \alpha_s + w\alpha_w + w^2 \alpha_{w2} + \varepsilon_{ijt},$$

where u_{it}^{γ}, u_{it}^k, $k = 1, \dots, K$, are i.i.d. standard normal random variables, and x_{jt}^k, $k = 1, \dots, K$, is the kth product attribute. This specification allows household tastes for product attributes to depend on both observed as well as unobserved household attributes, which is more general and realistic than other discrete choice models that do not allow random coefficients. In fact, as shown in McFadden and Train (2000), this mixed logit model is general in the sense that it can approximate arbitrarily close any discrete choice model.

Since we have 18 observed product attributes variables and 6 observed household demographic variables, potentially there could be 108 interaction variables $x_{jt}^k Z_i$ in (3). Again,

[4] Again, note the term $\gamma_{it} y_i$ will be differenced away in estimation. See the definition of V_{ijt} in (4) below.

this could lead to overfitting, poor identification and numerical issues in estimation. Therefore, we only include a selected few of them, guided by economic intuition. First, we interact our key variable of interest, $Adopt_{jt}$, with $Score_j$ and its square, and household demographic variables. $Score_j$ is product j's NuVal score. The interaction terms $Adopt_{jt} * Score_j$ and $Adopt_{jt} * Score_j^2$ give the model a triple-difference specification that accounts for the differential impact of NuVal label on yogurts with varying nutrition profile. The square term $Score_j^2$ allows for the possibility of a nonlinear effect. The interactions between $Adopt_{jt}$ and household demographics are intended to capture heterogeneity in the labeling effect across household types. Second, we interact the package size variable with the household size variable as households with more family members are likely to purchase products packaged in larger containers. Finally, we interact the dummy variable for whether the price reduction is larger than 5% of the regular price with the household income variable as households with higher income are less likely to respond to price reductions.

Demand Estimation

Assuming the error term ε_{ijt} is distributed i.i.d. with a Type I extreme value distribution, the probability for household i to purchase product j on trip t can be written as (McFadden, 1974)

(4) $$s_{ijt} = \int \frac{exp(V_{ijt})}{1+\sum_{k=1}^{J_t} exp(V_{ikt})} f(u_{it}) du_{it},$$

where $V_{ijt} = -exp(\bar{\gamma} + \sigma^{\gamma} u_{it}^{\gamma}) p_{ijt} + \sum_{k=1}^{K} (x_j^k \bar{\beta}^k + x_j^k Z_i \theta^k + \sigma^k x_j^k u_{it}^k) + \sum_{s=1}^{5} d_s \alpha_s + w\alpha_w + w^2 \alpha_{w2}$ and $f(\cdot)$ is the joint density for u_{it}^{γ} and u_{it}^k, $k = 1, \dots, K$. As a result, we can write the log likelihood function for our estimation problem as

(5) $$LL = \sum_{i=1}^{N} \sum_{t=1}^{T_i} \sum_{j=1}^{J_t} d_{ijt} ln\, s_{ijt},$$

where $d_{ijt} = 1$ if household i purchases yogurt product j on trip t and 0 otherwise, T_i is the number of trips taken by household i, and N is the number of households in our sample. The log likelihood function (5) is not directly estimable because the household characteristics, u_{it}^{γ} and u_{it}^{k}, are unobserved. We get around of this problem by estimating the simulated version of (5); that is,

(6) $$SLL = \sum_{i=1}^{N} \sum_{t=1}^{T_i} \sum_{j=1}^{J_t} d_{ijt} ln\ \widetilde{s_{ijt}},$$

where $\widetilde{s_{ijt}} = \frac{1}{R} \sum_{r=1}^{R} s_{ijt}(u_{it}^{r})$ and R is the number of simulations, which we set to be 100. The variables u_{it}^{r}, $r = 1, \ldots, 100$ are random numbers drawn from standard normal distributions.[5] This method is called the simulated maximum likelihood estimation (SMLE) method. The parameter estimates are obtained by searching for the maximum of (6) using the Broyden-Fletcher-Goldfarb-Shanno (BFGS) Quasi-Newton method. The software used was Matlab.

One potential concern with our specification and estimation procedure is whether the price variable as well as other advertising related variables such as whether the products are on display or featured or have a price reduction larger than 5% of the regular price are endogenous in the demand model. This is the classical example for endogeneity if aggregate level demand function is estimated as stores and firms may base their pricing and advertising decisions on market demand conditions. This is less of a concern when the demand function is estimated at the household level as firms and stores are not likely to change their decisions in respond to demand by a particular household. Therefore, when micro or household level data are used for demand estimation, the price and advertising related variables are often treated as exogenous.

[5] To take a sequence of draws that provide a better approximation to the relevant integral and reduce the variance caused by simulation than a purely random sequence, we draw numbers from the Halton Sequences and then convert those numbers into random numbers from the standard normal distributions (Spanier and Maiz, 1991).

Dube, Hitsch and Rossi (2010), Hendel and Nevo (2013) and Choi, Wohlgenant and Zheng (2013) are recent examples.

Value of Information Calculation

In a seminal paper, Foster and Just (1989) resolved a paradox in measuring the value of information disclosure surrounding a food safety incident. In standard welfare analysis, demand and consumer surplus will decline due to food scare if the incident is reported. But does this justify withholding information from the public for the sake of avoiding consumer welfare loss? Intuition suggests depriving the public of knowledge of the incident cannot be justified. However, for economists, the question is how to properly estimate the value of information, or equivalently the cost of ignoring/withholding information, in this type of situation. Foster and Just's solution is to introduce the concept of compensating surplus (CS), which measures the welfare loss of the uninformed consumer. It is written as

(7) $$CS = e(p_0, U_0, \theta_0) - \bar{e}(p_0, U_0, \theta_1 | q_0),$$

where p_0, q_0, U_0, and θ_0 are baseline price, purchase quantity, utility, and perceived product quality level, respectively; $e(\cdot)$ represents the expenditure function; θ_1 is the new level of perceived quality following the information release; and $\bar{e}(p_0, U_0, \theta_1 | q_0)$ is the level of expenditure necessary to maintain utility at U_0 given quality θ_1 and constraining purchase quantity at q_0. When perceived quality decreases from θ_0 to θ_1, CS is negative.

The welfare loss represented by CS comes from two sources. First, even if the consumer is fully informed of the incident, there is a welfare loss due to the decrease of quality from θ_0 to θ_1. This part of the welfare loss is represented by the compensating variation (CV), which is defined as $CV = e(p_0, U_0, \theta_0) - e(p_0, U_0, \theta_1)$ and is also negative for quality deterioration.

Second, consumer welfare decreases because the consumer is unaware of the quality change and hence cannot make optimal choices. Foster and Just (1989) call this part of the welfare loss the cost of ignorance (COI). It is the difference between CS and CV:

(8) $$COI = CS - CV = e(p_0, U_0, \theta_1) - \bar{e}(p_0, U_0, \theta_1 | q_0).$$

By the LeChatelier Principle, COI is always negative no matter there is a decline or improvement in quality.

Teisl, Bockstael, and Levy (2001) is the first to recognize that Foster and Just's insight, although originally developed to aid welfare analysis of contamination incidents, can be used to evaluate the welfare impact of food labeling policies. To the extent that food labels change consumers' perception of product quality, the value of information provided by the food labels is equal to the cost of ignorance (in absolute value) that would result if the labeling information was withheld from consumers. Using store-level sales data on six food categories collected from a field experiment in the late 1980s, the authors calculated the value of low-fat/sodium/cholesterol/calorie shelf labels, which are interpretive but not multiple-level and only appear on healthier products, to a representative consumer in an almost ideal demand model. They estimated the present value of these labels to range between $1.4 billion (mayonnaise) and $6.3 billion (milk) for U.S. consumers.

In our context, the introduction of the NuVal label didn't affect the underlying product quality, which could only change through reformulation.[6] However, the label could affect perceived quality by providing a useful rating on the product's nutrition profile. This change in

[6] This is a reasonable assumption for the short run. In the long run, manufacturers could potentially reformulate their lower-scoring products if sales of these less healthy foods are sufficiently depressed by NuVal or other nutrition profiling systems (RTI, 2011).

quality perception from θ_0 to θ_1 could lead to a shift in consumer demand, which can be identified by our structural demand model.

Specifically, we can compute value of information for every trip to the store that adopted the NuVal label during the sample period in which the NuVal label was adopted using the following procedure:

1. Set $Adopt_{jt} = 0$ for all j, compare level of utility across j and find the optimal choice d_{it}^0, that is, $\mathrm{d}_{it}^0 = argmax_j\left[U_{ijt} = \gamma_{it}\left(y_i - p_{ijt}\right) + X_{jt}\beta_{it} + \sum_{s=1}^{5} d_s\alpha_s + w\alpha_w + w^2\alpha_{w2} + \varepsilon_{ijt}\right]$. Recall that $Adopt_{jt}$ is a binary variable included in the product attribute vector X_{jt}. Setting $Adopt_{jt}$ to zero means removal of NuVal labels. Product d_{it}^0 therefore would be household i's optimal choice for trip t if NuVal labels were not adopted. U_{it}^0 is baseline utility associated with choice of d_{it}^0.

2. Set $Adopt_{jt}$ equal to its observed value for all j during trip t. Then, the expenditure for household i to achieve baseline utility U_{it}^0 with the restriction that he must choose d_{it}^0 even with NuVal information posted is defined implicitly as

(9) $$U_{it}^0 = \gamma_{it}\left(e(U_{it}^0, \theta_1 | \mathrm{d}_{it}^0) - p_{i\mathrm{d}_{it}^0 t}\right) + X_{\mathrm{d}_{it}^0 t}\beta_{it} + \sum_{s=1}^{5} d_s\alpha_s + w\alpha_w + w^2\alpha_{w2} + \varepsilon_{i\mathrm{d}_{it}^0 t},$$

where $e(U_{it}^0, \theta_1 | \mathrm{d}_{it}^0)$ is the restricted expenditure corresponding to $\bar{e}(p_0, U_0, \theta_1 | q_0)$ in (8) of the conceptual model with a single good.

3. Set $Adopt_{jt}$ equal to its observed $Adopt_{jt}$ for all j and find the optimal choice, that is, $\mathrm{d}_{it}^1 = argmax_j\left[U_{ijt} = \gamma_{it}\left(y_i - p_{ijt}\right) + X_{jt}\beta_{it} + \sum_{s=1}^{5} d_s\alpha_s + w\alpha_w + w^2\alpha_{w2} + \varepsilon_{ijt}\right]$. Product d_{it}^1 therefore represents consumer i's optimal choice when the NuVal label is posted. Then, the expenditure for the consumer to achieve the baseline utility U_{it}^0 without the restriction that he must choose d_{it}^0 is defined implicitly as

(10) $U_{it}^{0} = \gamma_{it}\left(e(U_{it}^{0},\theta_1) - p_{i\mathrm{d}_{it}^{1}t}\right) + X_{\mathrm{d}_{it}^{1}t}\beta_{it} + \sum_{s=1}^{5} d_s\alpha_s + w\alpha_w + w^2\alpha_{w2} + \varepsilon_{i\mathrm{d}_{it}^{1}t}$

where $e(U_{it}^{0},\theta_1)$ corresponds to $e(p_0, U_0, \theta_1)$ in (8).

4. After equating (9) and (10) and rearranging terms, the value of NuVal information is

(11) $e(U_{it}^{0},\theta_1|\mathrm{d}_{it}^{0}) - e(U_{it}^{0},\theta_1) = \frac{\left[-\gamma_{it}p_{i\mathrm{d}_{it}^{1}t} + X_{\mathrm{d}_{it}^{1}t}\beta_{it} + \varepsilon_{i\mathrm{d}_{it}^{1}t}\right] - \left[-\gamma_{it}p_{i\mathrm{d}_{it}^{0}t} + X_{\mathrm{d}_{it}^{0}t}\beta_{it} + \varepsilon_{i\mathrm{d}_{it}^{0}t}\right]}{\gamma_{it}}$.

By definition of d_{it}^{1}, $\left[-\gamma_{it}p_{i\mathrm{d}_{it}^{1}t} + X_{\mathrm{d}_{it}^{1}t}\beta_{it} + \varepsilon_{i\mathrm{d}_{it}^{1}t}\right] > \left[-\gamma_{it}p_{i\mathrm{d}_{it}^{0}t} + X_{\mathrm{d}_{it}^{0}t}\beta_{it} + \varepsilon_{i\mathrm{d}_{it}^{0}t}\right]$. So the value of information is positive by construction regardless whether NuVal 1) increases or decreases the perceived nutritional quality of each labeled product, and 2) induces the consumer to choose healthier or less healthy.

To calculate the value of information using (11), we need product price and observed product attributes, which we have. We also need to know the value of the parameters, which are obtained by estimating the mixed logit model using sample data. Finally, we also need to know the errors in the random coefficients, that is, u_{it}^{γ} and u_{it}^{k}, $k = 1, \ldots, K$, and the error term ε_{ijt}, $j = 1, \ldots, J_t$, which are neither observed nor estimated. To overcome this problem, we again use simulations. For each observed shopping trip, we simulate $R = 100$ sets of error terms. For each set, we compute the value of information for that trip using the procedure above. We then average the R values of information computed as the value of information for that trip.

Data

We analyze yogurt purchases by IRI BehaviorScan (Bronnenberg et al., 2008) panel households from a small town in the Midwest. We chose yogurt as the case study for three reasons. First, most consumers are familiar with yogurt and at least some consumers perhaps have an understanding of the nutrition of different yogurt products even before NuVal is available. This

allows us to examine how the advent of NuVal labels changes the taste and nutrition perceptions. Second, there is a large variation in the nutrition ranking of individual products as reflected by the NuVal score. This variation is important for identifying the effect of NuVal score on demand. Third, yogurt is relatively homogenous in the types of ingredients used. This likely makes yogurt products to be more or less substitutable with each other, which is important for model specification purposes because discrete-choice models restrict products to be substitutes.

The IRI BehaviorScan not only tracked household purchases but also weekly retail sales from the universe of grocery stores in this small town. Through a special agreement, IRI made the identities of the grocery stores available to us. By observing store sales, we know what products were available at what prices when a household visited the store even if the household did not purchase those products.[7] The benefit of possessing this extra piece of information is to reduce measurement error in the estimation of cross-price effects. We focus on trips to six grocery stores in the IRI data.[8] Of the six, one is owned by a regional grocery chain, which adopted the NuVal label in August 2010. Among the remaining five, two are each owned by a local independent grocer, two by a local food co-op, and one by another regional grocery chain. None of these five stores adopted the NuVal or other shelf nutrition labels during our sample period. Below, we call the store that adopted the NuVal label the NuVal store and other stores non-NuVal stores.

Because the NuVal store adopted NuVal labels in August 2010 and estimation with many products and/or observations is computationally intensive, we focus the analysis on the two months before the adoption event (i.e., June and July 2010) and the two months after the event

[7] Of course, if the entire store did not sell a single unit of a product, we would not know whether the product was available and its price. However, the bias created by this scenario is likely to be economically insignificant due to the zero market shares of such products.
[8] We dropped two other IRI stores in this town because they sold very few yogurt products.

(i.e., September and October 2010). A total of 1,666 households made 63,120 trips to the six stores during this sample period. On 27,218 of these trips, yogurt was purchased. As NuVal scores are specific to the Universal Product Code (UPC), we model yogurt demand at the barcode level.[9] From the household scanner data, we observe, on each shopping trip, the UPC of the yogurt purchased (if any) and price paid. We have household demographic data including household income, household size, presence of and age group of children, and the age and education level of the household head.

The store retail scanner data in BehaviorScan gives us the household's choice set for each trip and the prices for products the household did not purchase on each trip. For each UPC in the retail scanner data, we have information on weekly dollar and unit sales, whether the price mark-down is larger than 5%, and advertising and promotion activities in the store. The IRI data also provide product-specific information on the following time-invariant product characteristics for each UPC: the manufacturer, the package size and whether the product is regular yogurt, yogurt drink or smoothie.

The IRI scanner data, however, do not indicate whether a UPC was labeled with NuVal score at the treatment store. To construct the treatment variable $Adopt_{jt}$, we leverage a variable in the NuVal score dataset provided by NuVal's licensing company, NuVal LLC, that records the date on which a product was first scored by the company. In our conversion with staff at NuVal LLC, we learned that the company sends NuVal scores of newly rated UPCs to its retail partners on a monthly basis. In light of this, we assume a 30-day lag between when NuVal first scored the

[9] Throughout the empirical discussion, we use the terms "product" and "UPC" interchangeably.

product and when the label appears on store shelves.[10] Therefore, some UPCs may not be labeled in our demand model until sometime after September 1st, 2010 when our treatment period starts.

Our sample stores offered over 500 yogurt UPCs. Estimating barcode-level demand for all yogurt products is computationally burdensome, if not impossible even with a discrete-choice model. We use the following procedure to select a subset from the universe of UPCs into our demand model. For UPC j to be included in trip t of the demand model, it has to satisfy all of the following three criteria. First, UPC j had to be available for purchase at the store to which trip t was made as determined by the retail scanner data. Second, the UPC had been scored by NuVal LLC by December 1st, 2010. This is to ensure that we have its nutrition facts data to use as control variables. Third, the UPC had a dollar share of at least 0.001 in yogurt category in this town in 2010. Applying this selection procedure yields 199 yogurt UPCs accounting for 68% of the 2010 yogurt market in dollar sales in this town. The outside choice (i.e., the *numéraire*) encompasses both no purchase of yogurt and purchase of a yogurt product that is not one of the 199 UPCs whose demand we explicitly estimate in the mixed logit model.

Table 1 reports the summary statistics of the time-invariant product characteristics variables including nutrient information for the 199 UPCs. Product nutrient information is from the Nutrition Facts label and provided to us by NuVal LLC. Note all variables have been scaled such that mean of the scaled variable ranges between 0 and 1. This was done to avoid numerical issues in nonlinear estimation caused by variables measured on different scales. 31% of the products are produced by Danone, while 48% of the products by General Mills. 96% of the products are regular or soy-based yogurt, while the rest are yogurt drinks or smoothies. The

[10] We recognize that this is not an impeccable assumption. However, to the extent that it introduces measurement error in the NuVal variable, our estimate of the NuVal effect will be biased toward zero. Therefore, our value of information estimates may be interpreted as lower bounds of the true values.

average package size is 0.77 pint, or 12.32 ounces. Finally, we can see that the NuVal scores of the 199 UPCs range from 23 to 100, with an average score of 52. This wide variation in product healthfulness will help identifying the NuVal effect. Table 2 reports the results from a regression of the NuVal score on the nutrient variables. As expected, the R squared is 0.85, indicating that the variation in NuVal scores is largely determined by the differences in nutrients. Also, yogurt products with higher cholesterol, sodium and calcium but less sugar receive higher scores.

Table 3 reports the summary statistics of household characteristics variables for the 1,666 households in our estimation sample. 61% of the households have a head aged between 35 and 64 and 37% of the households have a head aged 65 or above, while the rest are headed by a person younger than 35. 17% of the household heads have a college or higher degree. The average income for the households is about $50,000 and the average household size is 2.3.

Table 4 reports the summary statistics for all variables used in estimation. These are calculated based on 10,960,538 product-trip observations (the unit of observation is one UPC on one trip) from 63,120 trips. On average, there are about 174 UPCs in a consumer's choice set on each trip. The average price over all products in the consumer's choice set per trip was $2.06 per pint (16 ounces). There were not much advertising and promotion activities in the stores. Only about 4% and 8% of the product-trip observations are associated with display or feature ad, respectively. By contrast, about 26% of the product-trip observations are those where the price reduction was 5% or greater of the regular price.

Empirical Results

Table 5 presents the parameter estimates from our mixed logit demand model. Several results are noteworthy. First, because the marginal utility of income parameter γ_{it} is assumed to follow

a lognormal distribution with log mean $\bar{\gamma}$ and log standard deviation σ^{γ}, the mean and median of γ_{it} take the form $exp\left[\bar{\gamma} + \frac{(\sigma^{\gamma})^2}{2}\right]$ and $exp(\bar{\gamma})$, respectively. Applying the estimates of $\bar{\gamma}$ and σ^{γ} to these formulas, the sample average marginal utility of income is 2.06 and the median is 1.84.

Second, most of the estimated coefficients on product characteristics ($\bar{\beta}^k$s) and their interactions with household characteristics (θ^ks) have the expected signs. Consumers have higher demand for products produced by the two leading firms of the industry, Danone and General Mills, and when the products are displayed, featured or promoted with a price reduction larger than 5% of the regular price. In addition, consumers have lower demand for larger packs on average; however, larger households have higher demand for large packs.

Finally, the posting of NuVal score is found to have a statistically significant effect on consumer demand. This effect first increases with the NuVal score up to a point but then decreases. The exact NuVal score associated with the maximum demand effect varies across household demographics. For example, for a household with a head younger than 35, without college degree and without children, this effect reaches its maximum at the score of 77. This may suggest that consumers associate yogurts rated as ultra-healthy (e.g., plain and nonfat) with lower palatability. The NuVal effect is lower for households headed by older adults (aged 65 and older) and for households with children. The former result would be plausible if older adults are more likely to use nutrition facts and other food labels even before rollout of NuVal labels so that the additional information in NuVal score has less of an effect on this demographic group. The literature, however, offers mixed evidence on whether older adults are more or less likely to use food labels (Drichoutis et al., 2006). Our result on households with children is consistent with expectations. Because these households are already more knowledgeable about the diet-health

link and use food labels more often (Drichoutis et al., 2006), NuVal is expected to have a smaller effect.

Elasticities Estimates

Once the structural parameters are obtained, we can use them to compute the elasticities. From (4), we can derive the own-price elasticity for product *j* by household *i* on trip *t* as follows,

$$(12) \quad e_{it,jj} = \frac{p_{ijt}\partial q_{ijt}}{q_{ijt}\partial p_{ijt}}$$

$$= \frac{p_{ijt}}{q_{ijt}} \int \left\{ \exp(\bar{\gamma} + \sigma^{\gamma} u_{it}^{\gamma}) \frac{\exp(V_{ijt})}{1+\sum_{k=1}^{J} \exp(V_{ikt})} \left[\frac{\exp(V_{ijt})}{1+\sum_{k=1}^{J} \exp(V_{ikt})} - \mathbf{1} \right] \right\} f(u_{it}) du_{it},$$

where $q_{ijt} = s_{ijt}$ by definition of the discrete choice demand model. Similarly, the cross-price elasticity for product *j* with respect to a change in the price of product *m* for household *i* on trip *t* is,

$$(13) \quad e_{it,jm} = \frac{p_{imt}\partial q_{ijt}}{q_{ijt}\partial p_{imt}}$$

$$= \frac{p_{imt}}{q_{ijt}} \int \left\{ \frac{\exp(\bar{\gamma}+\sigma^{\gamma} u_{it}^{\gamma}) \exp(V_{imt}) \exp(V_{ijt})}{\left[1+\sum_{k=1}^{J} \exp(V_{ikt})\right]^2} \right\} f(u_{it}) du_{it}.$$

For each of the 63,120 trips in our sample, we computed the own- and cross-price elasticities for all sample products sold in the store when the household made the trip using (12) and (13), respectively. From these, we obtained the product-specific median own- and cross-price elasticities for all 199 sample products. Table 6 summarizes the 199 median own-price elasticities. The median own-price elasticities range from -1.43 to -4.93 with an average of -3.01. This finding of very elastic product-level demand is consistent with expectations because of the large number of substitutes at the barcode level.

To save space, we report the median cross-price elasticities for seven UPCs in Table 7. These products are leading regular yogurts (i.e., not yogurt drinks or smoothies) in 6-ounce

packages, whose NuVal scores range from 26 to 99. As apparent in Table 7, the cross-price elasticities are small in magnitude, ranging from less than 0.001 to 0.021. This is expected for a demand system of 199 UPCs because the cross-price effect of one product's price change is dispersed across its 198 substitutes.

Value of Information in the NuVal Label

We now use the estimated structural parameters to quantify the informational value of NuVal labels. On 3,447 of the trips consumers made to the NuVal store after the NuVal label was adopted, one of the 199 sample products was purchased. We computed the informational value NuVal labels brought to the consumers who made these trips using the 4-step procedure detailed above. The standard errors of the estimated value of information are obtained by bootstrapping with 200 iterations. Table 8 reports the results. On average, the value of NuVal information is equivalent to 1.4 cents per trip and it is statistically significant. This is equivalent to about 3.1% of the expenditure on yogurt.

We also examined how value of NuVal labels varies across household types. In Table 9, we report the mean of the value of information by demographic group. Our results show that households with a head aged less than 65 benefit more from NuVal than households headed by older adults. This is in line with our earlier results that the demand effect of NuVal is lower for older adults: those who consider NuVal information to be less useful are less likely to respond to these labels. We also find that households without children aged 12 or younger and headed by a person without college degree benefit more from the NuVal labels than those households with a young kid or headed by a person with a college degree. This is consistent with the idea that people with more education and with young kids may already know a lot about the nutritional

value of the yogurt products they purchase and hence the NuVal labels bring them less additional information.

Spillover Effects

Our empirical model and analyses so far have assumed that the NuVal effect is limited to households shopping at the NuVal store, that is, the effect does not spillover to other stores that do not have NuVal labels. In reality, this assumption may not hold given that our data comes from a small town. Consumers may have the habit of visiting multiple stores for their grocery needs and, therefore, the new information they acquired from NuVal labels at the NuVal store may affect their food choices at other non-NuVal stores. Another potential source of spillover effect is that consumers who shop at the NuVal store may pass the information to their neighbors and friends, who shop at other stores. In these cases, consumer behavior in other stores will also be affected by NuVal.

To take the spillover effect into account, we re-estimated our empirical model with spillover variables. Specifically, $Spillover_{jt}$ is added to the observed product attributes vector X_{jt}. It is a dummy variable that equals one if trip t was to one of the five non-NuVal stores and if product j was sold and labeled with a NuVal score at the NuVal store in the same week trip t occurred, and zero otherwise. Similar to the adoption variable $Adopt_{jt}$ for identifying the NuVal effect at the NuVal store, we specify the coefficient for the spillover variable to be random and depend on the NuVal score and other consumer demographic variables. The summary statistics for $Spillover_{jt}$ and its interactions with other variables are reported in Table 10.

Results for the estimation with the spillover effects are reported in Table 11. The estimated coefficients are very similar to those reported in Table 5, both in terms of magnitudes

and statistical significance, indicating the robustness of our main estimation results above. As expected, the estimated spillover effect is smaller than the main effect at the NuVal store. For example, for a household with a head younger than 35, without college degree and without children, the average treatment effect for a product with NuVal score of 50 is an increase in consumer utility by 0.76 util while the spillover effect is only an increase of 0.39 util.

We then computed the value of information for all trips to the NuVal store and the control stores after the NuVal store adopted the label using the 4-step procedure described above. The average value of information for all trips and then by consumer demographics are reported in Tables 12 and 13, respectively. We found that on average, the informational value of NuVal to shoppers at the NuVal store is equivalent to about 4.2% of the expenditure on yogurt, while the value to consumers at other stores (i.e., value of the spillover effect) is equivalent to about 2.4% of yogurt expenditure. The average value of information by consumer demographics follows the same pattern with the size of the main effect being roughly twice that of the spillover effect. Also, the results show that households with a head aged less than 65 benefit more from NuVal than their older counterparts, and those without children aged 12 or younger and headed by a person without college degree benefit more from NuVal labels than those with young children or headed by a person with a college degree. These are again the same as the those reported in Table 9. In summary, our main results are robust to inclusion of a spillover effect.

Conclusions

In this paper, we used a supermarket's voluntary adoption of NuVal shelf labels to measure the value of NuVal information to shoppers. To this end, we first estimated changes to purchase behavior due to presence of NuVal labels under a mixed logit demand framework. This follows the simple logic that information has value if it induces changes in consumer behavior. Using

yogurt purchase as a case study, we found that NuVal has a nonlinear effect on yogurt purchases: the effect first increases with the NuVal score but peaks at a threshold NuVal score. The exact value of the threshold score depends on household demographics. Consistent with expectations, we found consumers who may have been less likely to use Nutrition Facts labels before NuVal became available tend to respond more to NuVal information. They include households without young children or headed by persons without college degrees. Consequently, these consumers benefit more from NuVal. On average, we estimate the value of NuVal information to be 3-4% of total yogurt expenditures at the NuVal store. As of 2006, low- and higher-income households spent about $19 and $27 per year on yogurts, respectively (Zhen et al. 2014, table 1). Assuming universal adoption of NuVal labels, our model implies annual increases of $0.57 and $0.81 per household in consumer welfare in the yogurt category alone for low- and higher-income households, respectively.

In lieu of proposed regulations on interpretive nutrition symbols, policymakers continue to modify the Nutrition Facts label with the intention to make it more effective in communicating nutrition facts to consumers. In May 2016, FDA published its final rule on the revision of the Nutrition Facts label (FDA 2016). Prominent changes include requiring increased type size and placing in bold type the number of calories, and mandatory declaration of added sugars. By making calorie information more prominent, users of the Nutrition Facts label who did not pay attention to calories before may be more likely to notice this information in the revised label and react. The rationale for mandating provision of added sugar information is to benefit consumers who are already aware of the adverse link between health and overconsumption of added sugars. However, it may be reasonable to expect these changes to have limited incremental effect on

healthy eating at the population level because the consumer segments standing to benefit most from these revisions may be relatively small.

Under Executive Orders 12866 and 13563, FDA is directed to calculate the costs and benefits of all regulatory options for all economically significant regulatory actions. In its regulatory impact analysis (RIA) of the 2016 final rule, FDA economists predicted the benefit to range from $0.2 billion to $5.2 billion (in 2014 dollars) per year assuming a discount rate of 3 percent (FDA 2016, table 14). The significance of this RIA is that FDA used a revealed preference approach to quantify the value of revised Nutrition Facts information[12], while it used the cost of illness approach to estimate the benefits associated with the original NLEA of 1990 (RTI 1991).[13] In this respect, our approach for calculating labeling benefits is closer to the current FDA approach than to its previous one.

Under the (bold) assumption that our 3% value of information estimate extends to all retail food-at-home categories regulated by FDA, a back of the envelope calculation suggests that NuVal may provide as much as $10.3 billion (in 2014 dollars) per year in value of information to U.S. consumers.[14] As such, a mandated adoption of NuVal or other similar multiple-level interpretive shelf or FOP nutrition symbol has the potential to create larger benefits to consumers than revisions to the Nutrition Facts label. Of course, the value of

[12] FDA's numbers are obtained by scaling willingness-to-pay (WTP) for the original Nutrition Facts label estimated by Abaluck (2011) in a working paper where the author estimated the WTP by revealed preference. FDA assumed the revision to have a smaller impact on food purchases than the original NLEA (FDA 2016).

[13] The cost of illness approach to benefit calculation counts medical costs and lost wages averted due to the policy being evaluated. It does not generally equal the willingness-to-pay estimate more accepted by economists. Note that the revealed preference approach implicitly accounts for cost of illness although the degree to which it is accounted for is affected by myopia, the discount factor, time inconsistency, and lack of knowledge on diet-health links.

[14] This is calculated by multiplying 3% by $342 billion, which was 2014 U.S. aggregate food-at-home expenditure reported by the Consumer Expenditure Survey excluding meats, and fresh fruits and vegetables that are either regulated by USDA or not required to have a Nutrition Facts label.

interpretive nutrition labels likely varies across product categories. Yogurt is a relatively homogenous group in terms of ingredients. Even without NuVal, consumers may be able to determine the healthfulness of a particular yogurt product using simple heuristics by looking for keywords such as fat-free and plain on the package. This suggests that value of NuVal-type labels may be higher in categories such as frozen meals that are more heterogeneous in recipe and more difficult for some consumers to select healthier options in the absence of a summary nutrition symbol. We leave empirical investigation of these possibilities to future research.

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Table 1: Summary Statistics of Time-Invariant Product Characteristics Variables

Variable	Mean	Std. Dev.	Min	Max
Danone	0.31	0.46	0	1
Mills	0.47	0.50	0	1
Type	0.96	0.18	0	1
Vol	0.77	0.72	0.25	4
Score	0.52	0.27	0.23	1
Calories	0.65	0.22	0.38	1.25
Fat	0.14	0.27	0	1.72
Sfat	0.09	0.18	0	1.35
Chol	0.11	0.17	0	1.30
Sodium	0.89	0.18	0.22	1.58
Carbo	0.76	0.26	0.17	1.25
Fiber	0.10	0.28	0	1.50
Sugars	0.60	0.25	0.17	1.10
Protein	0.63	0.25	0.20	1.80
Calcium	0.51	0.14	0	1.10

Notes: Number of products included: 199. Variable definitions: Danone: =1 if the product is produced by Groupe Danone and 0 otherwise; Mills: =1 if the product is produced by General Mills Inc. and 0 otherwise; Type: =1 if the product is "yogurt" or "soy yogurt" and 0 otherwise (e.g. "cultured dairy drink", "yogurt drink" or "yogurt smoothie"); Vol: package size of the product in pts (1 pt=16 ounces); Score: the original NuVal score/100; Calories: total calories in kcal per 0.85 grams of serving; Fat: total fat in grams per 17 grams of serving; Sfat: saturated fat in grams per 17 grams of serving; Chol: cholesterol in milligrams per 3.4 grams of serving; Sodium: sodium in milligrams per 1.7 grams of serving; Carbo: carbohydrate in grams per 5.67 grams of serving; Fiber: fiber in grams per 34 grams of serving; Sugars: sugars in grams per 5.67 grams of serving; Protein: protein in grams per 17 grams of serving; Calcium: calcium in daily percentage points per 4.25 grams of serving. Deciles of the original NuVal scores: 10th: 24; 20th: 27; 30th: 28; 40th: 32; 50th: 40; 60th: 59; 70th: 61; 80th: 81 and 90th: 94.

Table 2 Regression Results of NuVal Score on Nutrient Variables

Variable	Coef.	Std. Err.
Constant	0.72***	0.06
Calories	0.43	0.32
Fat	-0.28	0.26
Sfat	-0.34	0.28
Chol	0.19*	0.11
Sodium	0.21***	0.05
Carbo	0.35	0.25
Fiber	0.03	0.04
Sugars	-1.52***	0.14
Protein	-0.08	0.08
Calcium	0.15**	0.07
R^2: 0.8547		

Notes: Number of observations: 199. * denotes statistical significance at 10% level. ** denotes statistical significance at 5% level. *** denotes statistical significance at 1% level.

Table 3: Summary Statistics of Household Demographic Variables

Variable	Mean	Std. Dev.	Min	Max
Midage	0.61	0.49	0	1
Older	0.37	0.48	0	1
Educ	0.17	0.38	0	1
Kid	0.07	0.25	0	1
Income	0.50	0.33	0.05	1.22
Family	0.23	0.12	0.1	0.8

Notes: Number of households: 1,666. Variable definitions: Midage: =1 if the age of the household head is between 35 and 64 and 0 otherwise; Older: =1 if the age of the household head is greater than or equal to 65 and 0 otherwise; Educ: =1 if the household head has at least a college degree and 0 otherwise; Kid: =1 if the household has a child less than 12 years old and 0 otherwise; Income: annual household income in $100,000s; Family: number of people in the household (in 10 persons).

Table 4: Summary Statistics of Variables Used in Estimation

Variable	Mean	Std. Dev.	Min	Max
Price	0.65	0.84	0	5.23
Danone	0.06	0.23	0	1
Mills	0.29	0.45	0	1
Type	0.43	0.50	0	1
Vol	0.18	0.27	0	4
Calories	0.25	0.31	0	1.25
Fat	0.02	0.10	0	1.72
Sfat	0.02	0.07	0	1.35
Chol	0.02	0.08	0	1.3
Sodium	0.38	0.44	0	1.58
Carbo	0.31	0.38	0	1.25
Fiber	0.05	0.16	0	1.50
Sugars	0.23	0.31	0	1.10
Protein	0.24	0.29	0	1.8
Calcium	0.20	0.24	0	1.10
Adopt	0.04	0.20	0	1
Adopt*Score	0.03	0.13	0	1
Adopt* $Score^2$	0.02	0.09	0	1
D	0.10	0.30	0	1
F	0.15	0.35	0	1
Pr	0.28	0.45	0	1
Adopt*Midage	0.03	0.17	0	1
Adopt*Older	0.01	0.12	0	1
Adopt*Educ	0.01	0.09	0	1
Adopt*Kid	0.00	0.05	0	1
Vol*Family	0.04	0.08	0	2
Pr*Income	0.15	0.30	0	1.22

Notes: The summary statistics are based on 10,960,538 product-trip observations (the unit of observation is one product on one trip) from 63,120 trips as on average, a consumer faced about 174 UPCs on each trip. Variable definitions: for Danone, Mills, Type, Vol, Calories, Fat, Sfat, Chol, Sodium, Carbo, Fiber, Sugars, Protein, Calcium and Score, see the notes in Table 1; for Midage, Elder, Educ, Kid, Family and Income, see the notes in Table 2; Price: price of the product per pint (16 ounces); Adopt: =1 if the product was sold in the NuVal store after August 2010 and the product had already been scored at least one month earlier; D: =1 if the product was on display and 0 otherwise; F: =1 if the product was featured and 0 otherwise; Pr: =1 if the temporary price reduction for the product is 5% or greater of the regular price and 0 otherwise.

Table 5: Mixed Logit Estimation Results

Variable	Parameter	Estimate (Std. Err.)	Variable	Parameter	Estimate (Std. Err.)
Income-Price	$\bar{\gamma}$	0.61(0.02)***	Calories	$\bar{\beta}_{Calories}$	4.99(0.54)***
	σ_{γ}	0.47(0.02)***		$\sigma_{Calories}$	2.70(0.11)***
Danone	$\bar{\beta}_{Danone}$	0.19(0.04)***	Fat	$\bar{\beta}_{Fat}$	-2.19(0.56)***
	σ_{Danone}	0.11(0.22)		σ_{Fat}	-0.07(0.11)
Mill	$\bar{\beta}_{Mill}$	1.20(0.03)***	Sfat	$\bar{\beta}_{Sfat}$	5.45(0.56)***
	σ_{Mill}	0.00(0.08)		σ_{Sfat}	0.10(0.14)
Type	$\bar{\beta}_{Type}$	-0.60(0.09)***	Chol	$\bar{\beta}_{Chol}$	-5.75(0.20)***
	σ_{Type}	-0.02(0.09)		σ_{Chol}	-0.57(0.47)
Vol	$\bar{\beta}_{Vol}$	-2.09(0.08)***	Sodium	$\bar{\beta}_{Sodium}$	-0.60(0.07)***
	σ_{Vol}	-0.47(0.06)***		σ_{Sodium}	-0.01(0.08)
Vol*Family	θ_{Vol_Family}	1.39(0.14)***	Carbo	$\bar{\beta}_{Carbo}$	-6.66(0.34)***
Adopt	$\bar{\beta}_{Adopt}$	-0.40(0.31)		σ_{Carbo}	-0.03(0.10)
	σ_{Adopt}	-0.08(0.19)	Fiber	$\bar{\beta}_{Fiber}$	0.85(0.07)***
Adopt*Score	θ_{Adopt_Score}	3.12(0.65)***		σ_{Fiber}	-0.01(0.07)
Adopt*Score^2	$\theta_{Adopt\_\mathrm{Score}^2}$	-2.02(0.54)***	Sugar	$\bar{\beta}_{Sugar}$	1.99(0.26)***
Adopt*Midage	θ_{Adopt_Midage}	-0.14(0.25)		σ_{Sugar}	0.02(0.14)
Adopt*Older	θ_{Adopt_Elder}	-0.42(0.25)*	Protein	$\bar{\beta}_{Protein}$	-0.66(0.14)***
Adopt*Educ	θ_{Adopt_Educ}	-0.11(0.08)		$\sigma_{Protein}$	-0.04(0.11)
Adopt*Kid	θ_{Adopt_Kid}	-0.27(0.14)*	Calcium	$\bar{\beta}_{Calcium}$	-1.52(0.12)***
D	$\bar{\beta}_{d}$	0.54(0.04)***		$\sigma_{Calcium}$	-0.09(0.13)
	σ_{d}	0.95(0.08)***	Store 1	α_1	-1.91(0.12)***
F	$\bar{\beta}_{f}$	0.49(0.03)***	Store 2	α_2	0.52(0.04)***
	σ_{f}	0.06(0.09)	Store 3	α_3	0.10(0.05)**
Pr	$\bar{\beta}_{pr}$	0.07(0.03)**	Store 4	α_4	0.04(0.06)
	σ_{pr}	0.04(0.06)	Store 5	α_5	0.89(0.04)***
Pr*Income	θ_{Pr_Income}	0.36(0.04)***			
W	α_{w}	2.36(0.21)***			
W^2	α_{w2}	-2.37(0.19)***			
Log-Likelihood		-160,202.8			

Notes: Number of trips used in estimation: 63,120. W denotes weekly trend variable. Store 1-5 denotes dummies for stores 1-5. See Tables 1—3 for the definitions of other variables. * denotes statistical significance at 10% level. ** denotes statistical significance at 5% level. *** denotes statistical significance at 1% level.

Table 6: Summary Statistics of Median Own-price Elasticities

	Mean	Std. Dev.	Min	Max
Own-price Elasticity	-3.01	0.61	-4.93	-1.43

Notes: summary statistics for the 199 median own-price elasticities.

Table 7: Median Cross-price Elasticities for Seven Representative UPCs

Elasticity	**51(26)**	**39(35)**	**196(40)**	**70(59)**	**28(65)**	**76(81)**	**132(99)**
51(26)	-2.943	0.002	0.001	0.020	0.006	0.021	0.011
39(35)	0.010	-3.786	0.001	0.018	0.006	0.018	0.010
196(40)	0.008	0.001	-4.194	0.015	0.005	0.015	0.010
70(59)	0.009	0.002	0.001	-2.734	0.006	0.019	0.010
28(65)	0.007	0.002	0.001	0.016	-2.550	0.017	0.010
76(81)	0.009	0.002	0.001	0.018	0.006	-2.706	0.010
132(99)	0.007	0.001	0.001	0.016	0.006	0.017	-2.195

Notes: The seven representative UPCs are all popular regular yogurt products in 6-ounce packages. NuVal scores of the UPCs are in parentheses. The values in the table represent the cross-price elasticities for the product in the row to a change in the price of the product in the column. For example, the value in third row and first column (0.008) indicates the demand for UPC 196 will increase by 0.08% when there is a 10% increase in the price of UPC 51. The values in diagonal are own-price elasticities.

Table 8: Informational Value of the NuVal Labels

Mean of Value of Information	$0.014 (0.003)***
Mean of (Value of Information / Expenditure)	0.031 (0.007)***

Notes: The informational value of the NuVal labels was computed for each of the 3,477 trips consumers made to the NuVal store after the NuVal label was adopted and also where one of the 199 yogurt products was purchased. Standard errors are in parentheses. * denotes statistical significance at 10% level. ** denotes statistical significance at 5% level. *** denotes statistical significance at 1% level.

Table 9: Informational Value of the NuVal Labels by Demographic Groups

Demographic Group	# of Trips	Mean of Value of Information	Mean of (Value of Information / Expenditure)
Young	75	$0.018 ($0.017)	0.027 (0.026)
Midage	2299	$0.018 ($0.004)***	0.032 (0.007)***
Older	1103	$0.007 ($0.003)**	0.014 (0.007)**
Educ=0	2786	$0.015 ($0.003)***	0.027 (0.006)***
Educ=1	691	$0.010 ($0.004)***	0.017 (0.006)***
Kid=0	3240	$0.014 ($0.003)***	0.026 (0.006)***
Kid=1	237	$0.007 ($0.005)	0.012 (0.008)

Notes: The informational value of the NuVal labels was computed for each of the 3,477 trips consumers made to the NuVal store after the NuVal label was adopted and also where one of the 199 yogurt products was purchased. The means of these values of information by consumer demographic group are reported here. Standard errors are in parentheses. * denotes statistical significance at 10% level. ** denotes statistical significance at 5% level. *** denotes statistical significance at 1% level.

Table 10: Summary Statistics of Spillover Variables

Variable	Mean	Std. Dev.	Min	Max
Spillover	0.13	0.34	0	1
Spillover*Score	0.07	0.20	0	1
Spillover*Score2	0.04	0.13	0	1
Spillover*Midage	0.10	0.30	0	1
Spillover*Older	0.03	0.18	0	1
Spillover*Educ	0.02	0.14	0	1
Spillover*Kid	0.01	0.09	0	1

Notes: Number of products included: 199. Variable definitions: Spillover: =1 for UPCs in control stores if $Adopt_{jt}$ for the corresponding UPCs equal 1 in the treatment store during the same week, and 0 otherwise.

Table 11: Mixed Logit Estimation Results with Spillover Variables

Variable	Parameters	Estimate (Std. Err.)	Variable	Parameters	Estimate (Std. Err.)
Income-Price	$\bar{\gamma}$	0.59(0.02)***	Calories	$\bar{\beta}_{Calories}$	4.91(0.54)***
	σ_{γ}	0.45(0.02)***		$\sigma_{Calories}$	2.68(0.11)***
Danone	$\bar{\beta}_{Danone}$	0.14(0.04)***	Fat	$\bar{\beta}_{Fat}$	-2.53(0.55)***
	σ_{Danone}	0.10(0.19)		σ_{Fat}	-0.07(0.11)
Mill	$\bar{\beta}_{Mill}$	1.07(0.03)***	Sfat	$\bar{\beta}_{Sfat}$	5.67(0.55)***
	σ_{Mill}	-0.01(0.08)		σ_{Sfat}	0.09(0.14)
Type	$\bar{\beta}_{Type}$	-0.55(0.09)***	Chol	$\bar{\beta}_{Chol}$	-5.22(0.20)***
	σ_{Type}	-0.02(0.09)		σ_{Chol}	-0.48(0.41)
Vol	$\bar{\beta}_{Vol}$	-2.05(0.08)***	Sodium	$\bar{\beta}_{Sodium}$	-0.60(0.07)***
	σ_{Vol}	-0.47(0.06)***		σ_{Sodium}	-0.01(0.08)
Vol*Family	θ_{Vol_Family}	1.30(0.14)***	Carbo	$\bar{\beta}_{Carbo}$	-6.39(0.34)***
Adopt	$\bar{\beta}_{Adopt}$	-0.53(0.32)*		σ_{Carbo}	-0.03(0.10)
	σ_{Adopt}	-0.10(0.21)	Fiber	$\bar{\beta}_{Fiber}$	0.84(0.07)***
Adopt*Score	θ_{Adopt_Score}	3.95(0.66)***		σ_{Fiber}	-0.02(0.07)
Adopt*Score^2	$\theta_{Adopt\_\mathrm{Score}^2}$	-2.76(0.55)***	Sugar	$\bar{\beta}_{Sugar}$	1.75(0.27)***
Adopt*Midage	θ_{Adopt_Midage}	-0.15(0.25)		σ_{Sugar}	0.01(0.15)
Adopt*Older	θ_{Adopt_Elder}	-0.43(0.25)*	Protein	$\bar{\beta}_{Protein}$	-0.67(0.14)***
Adopt*Educ	θ_{Adopt_Educ}	-0.12(0.08)		$\sigma_{Protein}$	-0.04(0.12)
Adopt*Kid	θ_{Adopt_Kid}	-0.27(0.14)*	Calcium	$\bar{\beta}_{Calcium}$	-1.47(0.12)***
Spillover	$\bar{\beta}_{Spillover}$	-0.39(0.17)**		$\sigma_{Calcium}$	-0.09(0.13)
	$\sigma_{Spillover}$	0.16(0.07)**	D	$\bar{\beta}_{d}$	0.58(0.04)***
Spillover*Score	$\theta_{Spillover\_Score}$	3.08(0.36)***		σ_{d}	0.91(0.09)***
Spillover*Score^2	$\theta_{Spillover\_\mathrm{Score}^2}$	-3.04(0.32)***	F	$\bar{\beta}_{f}$	0.41(0.03)***
Spillover*Midage	$\theta_{Spillover\_Midage}$	0.23(0.14)*		σ_{f}	0.07(0.09)
Spillover*Older	$\theta_{Spillover\_Elder}$	-0.36(0.14)***	Pr	$\bar{\beta}_{pr}$	0.11(0.03)***
Spillover*Educ	$\theta_{Spillover\_Educ}$	-0.21(0.05)***		σ_{pr}	0.04(0.06)
Spillover*Kid	$\theta_{Spillover\_Kid}$	-0.25(0.07)***	Pr*Income	θ_{Pr_Income}	0.32(0.04)***
Store 1	α_1	-1.88(0.12)***	W	α_{w}	2.20(0.21)***
Store 2	α_2	0.47(0.04)***	W^2	α_{w2}	-2.38(0.19)***
Store 3	α_3	0.04(0.05)			
Store 4	α_4	-0.01(0.06)			
Store 5	α_5	0.82(0.04)***			
Log-Likelihood		159,973.1			

Notes: Number of trips used in estimation: 63,120. W denotes weekly trend. Store 1-5 denotes dummies for store 1-5. See Tables 1–3 for definitions of other variables. * denotes statistical significance at 10% level. ** denotes statistical significance at 5% level. *** denotes statistical significance at 1% level.

Table 12: Informational Value of the NuVal Labels with Spillover Effects

	Adoption	Spillover
Mean of Value of Information	$0.019(0.005)***	$0.011(0.002)***
Mean of (Value of Information/Expenditure)	0.042(0.011)***	0.024(0.004)***

Notes: The informational value of the NuVal labels was computed for each of the 3,477 trips consumers made to the NuVal store after the NuVal label was adopted, and for each of the 11,557 trips consumers made to other stores after the NuVal label was adopted in the NuVal store (spillover effect), and also where one of the 199 yogurt products was purchased. Standard errors are in parentheses. * denotes statistical significance at 10% level. ** denotes statistical significance at 5% level. *** denotes statistical significance at 1% level.

Table 13: Informational Value of the NuVal Labels with Spillover Effects by Demographic Groups

Demographic Group	Adoption			Spillover		
	# of Trips	Mean of VOI	Mean of (VOI /Expenditure)	# of Trips	Mean of VOI	Mean of (VOI /Expenditure)
Young	75	$0.023(0.018)	0.035(0.028)	177	$0.005(0.002)***	0.009(0.004)**
Midage	2299	$0.024(0.006)***	0.042(0.010)***	8315	$0.013(0.002)***	0.026(0.003)***
Older	1103	$0.009(0.005)*	0.020(0.010)**	3065	$0.004(0.002)**	0.007(0.003)**
Educ=0	2786	$0.020(0.005)***	0.037(0.010)***	9811	$0.011(0.002)***	0.021(0.003)***
Educ=1	691	$0.014(0.006)**	0.023(0.010)**	1746	$0.006(0.002)***	0.012(0.003)***
Kid=0	3240	$0.019(0.005)***	0.035(0.010)***	10778	$0.010(0.002)***	0.020(0.003)***
Kid=1	237	$0.010(0.010)	0.018(0.012)	779	$0.005(0.002)***	0.009(0.003)***

Notes: The informational value of the NuVal labels was computed from each of the 3,477 trips consumers made to the NuVal store after the NuVal label was adopted, and from each of the 11.557 trips consumers made to other store after adoption (spillover effect), and also where one of the 199 yogurt products was purchased. The means of these values of information by consumer demographic groups are reported here. Standard errors are in parentheses. * denotes statistical significance at 10% level. ** denotes statistical significance at 5% level. *** denotes statistical significance at 1% level.

Figure 1: Examples of Price Tags with NuVal Scores

Note: rating from 1 (the least healthy) to 100 (the healthiest).