Measuring the Informational Value of Interpretive Shelf Nutrition Labels to Shoppers

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Abstract

We use the voluntary adoption of the NuVal shelf nutrition labels by a grocery retailer to estimate the value of these labels to shoppers in the yogurt category. Using an incomplete quadratic almost ideal demand system to represent consumer demand, we found a statistically significant positive effect of these shelf labels on demand for yogurt with above-average NuVal scores. The coefficients on the NuVal treatment variable in the demand equations for yogurt with below-average NuVal scores and unlabeled yogurt are not statistically significant. The value of nutrition information brought by NuVal labels is estimated to be 3.1% of consumer expenditures on yogurt at the store that uses the labels.

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Confronted with the continuing obesity epidemic, US policy makers are demanding policy proposals that improve diet quality and reduce obesity prevalence. Processed and packaged foods and beverages account for over 50% of total calories consumed by an average American (Eicher-Miller et al., 2012). 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.

Traditionally, information disclosure policies have played a major role in federal nutrition policy making. Prominent examples include 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. These labeling regulations would be most effective if people choose healthier products because they see, read, and understand the often lengthy and hidden (on the back or side of the package) nutrition information. However, for an average person who makes over 200 daily food decisions (Wansink & Sobal, 2007), reviewing and processing all of this labeling information may be challenging. Indeed, the literature has documented that food label use varies significantly across sociodemographic subgroups (Ollberding et al., 2010) and that diet and health knowledge is one of the strongest predictors of label use (Drichoutis et al., 2006). In addition, over the decade following NLEA's full implementation, consumer use of most nutrition labels had declined (Todd & Variyam, 2008). The obesity epidemic that has escalated post-NLEA and other health concerns associated with food choices motivated the search for more effective labeling strategies that supplement the Nutrition Facts label.

In response, the food and beverage industry, through its Grocery Manufacturers Association and Food Marketing Institute, introduced the Front-of-Package (FOP) labels.[1] Food and beverage manufacturers voluntarily decide whether or not to adopt FOP labels. A basic FOP label lists calories per serving and information about saturated fat, sodium and sugar – nutrients the Dietary Guidelines for Americans recommend limiting, on the front of the food package. In addition, manufacturers may also include information on two nutrients to encourage. These nutrients – potassium, fiber, protein, vitamin A, vitamin C, vitamin D, calcium and iron – are under-consumed and are needed to build a "nutrient-dense" diet, according to the Dietary Guidelines for Americans. It is worth noting that the FOP labels do not provide consumers with

[1] More information is available at http://www.factsupfront.org/.

new information that is already in the NFP. Instead, they simply highlight information on a few key nutrients. Hersey et al. (2013) reviewed the literature on front-of-package and shelf nutrition labels. Studies have found that labels similar to FOP reduce consumer's time to process nutrition information, but results regarding whether this type of labels can help consumers choose the healthier products are mixed.

Around the same time, private enterprises heeded the business opportunities with providing interpretive shelf nutrition labels. Interpretive shelf nutrition labels, now an important aspect of healthy food retail, are a tool that provides summary information on the overall nutrition quality of a food product. They provide nutrition cues to shoppers and may be effective in promoting healthy food choices at the point of purchase. These summary labels offer one of a small handful of practical policy tools to influence consumer nutrition behavior associated with obesity and diet-related noncommunicable diseases.

In 2012, the Institute of Medicine reviewed various nutrition labels currently in use including FOP and interpretative shelf nutrition labels. It concluded with a recommendation to develop a government-sponsored summary multiple-level nutrition symbol that goes on the front of the package and provides a clear ranking of the healthfulness of the products (IOM, 2012). Such a label is essentially an interpretive shelf nutrition label. The IOM report encourages government regulators to shift from the current cognitive approach of providing more written information on nutrition facts to an interpretive one that provides simple, direct, and science-based guidance to consumers on the nutritional quality of the products.

If FDA were to propose mandatory interpretive summary nutrition labels on food and beverage products whether using existing systems such as NuVal and Guiding Stars that are currently available on the market or designing a new scoring system, the agency would need to conduct a formal Regulatory Impact Analysis, as required by Executive Orders 13563 and 12866, to compare the benefits against the costs of the proposed regulation. Besides the R&D costs of developing a new nutrition rating system or adapting an existing one, the costs of incorporating these labels into the product design can be significant given the breadth of such a regulation if becomes a law. In this case, it would be important to estimates the value of information provided by these labels to consumers, which may end up accounting for a significant portion of total benefits.

The objective of this study is to quantify the informational value of NuVal—one of two major shelf nutrition label systems (the other being Guiding Stars) in the United States—to shoppers in the yogurt category. NuVal scores foods on a scale from 1 to 100 based on an algorithm that profiles the content of 21 nutrients and the quality of four nutrition factors (Katz et al., 2010). The algorithm 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. Our sample contains four years (2008–2011) of retail scanner data from six food stores in a city in the Midwest. We leverage the voluntary adoption of NuVal labels by one of the six stores in August 2010 to identify the effect of these labels on yogurt sales. To estimate the value of information contained in NuVal labels, we follow the methodology developed by Foster and Just (1989) for calculating value of food contamination information disclosure and later extended by Teisl et al. (2001) to calculate the value of nutrition information. Our empirical results put the value of information provided by NuVal labels at 3.1% of total yogurt expenditures at the treatment store.

Several studies have examined the effect of the Guiding Stars shelf labeling program and found the program to increase purchases of healthier products relative to less healthy ones (Sutherland et al., 2010; Rahkovsky et al., 2013; Cawley et al., 2014). However, previous research has not estimated the value of interpretive shelf nutrition labels to consumers. The study that most closely relates to ours is Teisl et al. (2001), where the authors estimated the value of low-fat, sodium, cholesterol, and calorie shelf labels to consumers using scanner data collected from a field experiment conducted during 1986–1988. Our study differs from theirs in several aspects. First, we quantify the value of information provided by an interpretative nutrition label, while they quantified the value of information provided by FOP labels. Second, we focus on a labeling intervention that posts nutrition scores on both healthier and less healthy products, whereas the intervention examined in Teisl et al. (2001) only shelf-tagged descriptive labels on healthier products. There is evidence that consumers may not deduce the lower nutritional quality of unlabeled products by observing labeled healthier products (Mathios, 2000). Finally, consumer preferences, nutrition knowledge and attitude, and the retail food market have experienced significant changes in the 20 years since data used in Teisl et al. were collected.

Value of Nutrition Information

Foster and Just (1989) set out to resolve a paradox in measuring the value of information disclosure surrounding a food contamination incident. Obviously, if the incident is announced, market demand for the implicated product will fall, which means reduced consumer surplus in a standard welfare analytical framework. Does this suggest correct information should be withheld from the public to avoid the reduction in consumer welfare? The answer is absolutely not. But for the economists, the question becomes how to properly estimate the value of information or the cost of ignoring/withholding correct information in this situation. To address this, Foster and Just (1989) introduced the concept of compensating surplus (CS), which measures the welfare loss of the uninformed consumer. It is written as

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

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

The welfare loss represented by CS comes from two sources. First, even when the consumer is informed of the quality change, 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 if there is a decrease in quality. Second, consumer welfare decreases because the consumer is unaware of the quality change and hence cannot make optimal decisions. Foster and Just (1989) call this part of the welfare loss the cost of ignorance (COI). It is the difference between CS and CV:

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

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

Because the non-optimal expenditure $\bar{e}$ is unobservable, we cannot use (2) in empirical analysis. Foster and Just (1989) showed that (2) can be written as a function of the observables

(3) $$\text{COI} = e(p_0, U_0, \theta_1) - (p_0 - p_1)q_0 - e(p_1, U_0, \theta_1),$$

where p_1 is the price level that causes demand to stay at q_0 given U_0 and θ_1. This equality holds because $e(p_1, U_0, \theta_1)$ is associated with the same consumption bundle as $\bar{e}(p_0, U_0, \theta_1 | q_0)$, but the former must be corrected for the fact that the price of the product of interest is really p_0 rather than p_1. Teisl et al. (2001) extended (3) to the case where quality for more than one good is affected:

(4) $$\text{COI} = e(\mathbf{p}_0, U_0, \boldsymbol{\theta}_1) - \mathbf{q}_0'(\mathbf{p_0} - \mathbf{p}_1) - e(\mathbf{p}_1, U_0, \boldsymbol{\theta}_1).$$

where $\mathbf{p}$, $\mathbf{q}$, and $\boldsymbol{\theta}$ are column vectors of price, quantity, and perceived quality, respectively. In the context of the present study, the value of information in the NuVal label is the negative of the COI measure.

Demand Model

To obtain a utility-theoretic expenditure function, we use the quadratic almost ideal demand (QUAID) (Banks et al., 1997) to represent consumer demand for yogurt and a *numéraire*. Unlike a conditional demand model that contains just yogurt products, the *numéraire* is a composite good representing all services and goods other than yogurt. This setup is required to obtain correct measure of welfare changes (LaFrance and Hanemann, 1989). QUAID has more flexible Engel curves than the almost ideal demand (AID) model (Deaton and Muellbauer, 1980) but retains the exact aggregation property of AID such that the researcher can use aggregate data to infer household-level behavior. The budget share equation is

(5) $$w_{ilt} = \alpha_{ilt} + \sum_{j=1}^{n} \gamma_{ij} \ln p_{jlt} + \beta_{ilt} \ln\left[\frac{x_{lt}}{a(\mathbf{p}_{lt})}\right] + \frac{\lambda_{ilt}}{b(\mathbf{p}_{lt})}\left\{\ln\left[\frac{x_{lt}}{a(\mathbf{p}_{lt})}\right]\right\}^2$$

where w_{ilt} is the share of per capita yogurt category i expenditure in total income; the subscripts l and t denote store and time, respectively; p_{jlt} is the price index for yogurt category j normalized by price of the *numéraire* good; n is the number of yogurt groups; x_{lt} is average weekly household income of households that shopped in store l during week t, and α, γ, β, and λ are parameters. The $a(\mathbf{p}_{lt})$ and $b(\mathbf{p}_{lt})$ terms are defined as

$\ln a(\mathbf{p}_{lt}) = \alpha_0 + \sum_{i=1}^{n} \alpha_{ilt} \ln p_{ilt} + 0.5 \sum_{i=1}^{n} \sum_{j=1}^{n} \gamma_{ij} \ln p_{ilt} \ln p_{jlt}$ and $b(\mathbf{p}_{lt}) = \prod_{i=1}^{n} p_{ilt}^{\beta_{ilt}}$, respectively. The underlying indirect utility function for the budget share equation (5) is

$$\ln(U)=\left\{\left[\frac{\ln x-\ln a(\mathbf{p})}{b(\mathbf{p})}\right]^{-1}+\lambda(\mathbf{p})\right\}^{-1} \tag{6}$$

where the store and time subscripts are drop for brevity and $\lambda(\mathbf{p})=\sum_{i=1}^{n}\lambda_i \ln p_i$.

We assume the intercept α_{ilt} and the income coefficients β_{ilt} and λ_{ilt} to be linear functions of a number of demand shifters. Specifically,

$$\begin{aligned}\alpha_{ilt} &= a_i+\sum_{k=2}^{L}a_{ik}st_k+\sum_{k=1}^{L}a_{ikt}st_kT_t+\sum_{y=09}^{11}a_{iy}yr_y+\sum_{m=2}^{12}a_{im}mn_m+a_{gi}age_{lt}+a_{si}size_{lt}+a_{ci}col_{lt} \\ &+a_{itreat1}D_t+a_{itreat2}D_t\left(\%NV_t-\%NV_0\right)\end{aligned}, \tag{7}$$

$$\beta_{ilt}=b_i+\sum_{y=09}^{11}b_{iy}yr_y+b_{gi}age_{lt}+b_{si}size_{lt}+b_{ci}col_{lt}\text{, and} \tag{8}$$

$$\lambda_{ilt}=h_i+\sum_{y=09}^{11}h_{iy}yr_y+h_{gi}age_{lt}+h_{si}size_{lt}+h_{ci}col_{lt} \tag{9}$$

where st_k is a dummy for store k , T_t is a linear time trend, yr_y is a dummy for year y , mn_m is a dummy for the m th month of the year, age_{lt} is the proportion of households with heads under 35 that shopped at store l in week t , $size_{lt}$ is the average household size, col_{lt} is the proportion of households with at least some college education, and a , b , and h are parameters. The year fixed effects control for any demand effects from the 2008–2009 recession and the subsequent recovery. We use the store fixed effects and store-specific trends to account for unobserved store heterogeneity and possible secular trends in yogurt demand that predated the introduction of NuVal at the treatment store.

We measure the demand effects of posting NuVal labels using two variables that enter (7). D_t is a dummy variable equal to one at the treatment store after NuVal adoption, and zero before the adoption or at control stores. The variable $\%NV_t$ is calculated using the number of NuVal-labeled yogurt UPCs divided by the total number of yogurt UPCs in week t at the treatment store. The constant term $\%NV_0$ takes the value of $\%NV_t$ when t is the first week of NuVal adoption at the treatment store. Therefore, the difference $\%NV_t-\%NV_0$ tracks changes in NuVal label coverage at the treatment store over time. The coefficient a_{treat1} reveals the binary effect of instituting the labeling program, while a_{treat2} measures the marginal effect of increasing label coverage on demand. This specification allows for nonlinearity treatment effects from the labels. The total effect of the labeling program on yogurt demand is

$$d\log(q_{ilt}) = \frac{a_{itreat1} + a_{itreat2}(\%NV_t - \%NV_0)}{w_{ilt}} \tag{10}$$

where q_{ilt} is the purchase quantity of yogurt group 1.

The NuVal Label

NuVal, licensed through NuVal LLC, is essentially a new price tag with the NuVal score for the product on it. See Figure 1 for examples of the NuVal labels. It scores food products on a scale from 1 to 100 based on the Overall Nutritional Quality Index (ONQI) algorithm (Katz et al., 2010). The ONQI algorithm was developed by a multidisciplinary team of public health and nutrition scientists independent of food industry interests from 2005 to 2007 and was also recently validated by independent researchers.[2] The NuVal nutritional scoring system takes the health effects of more than 30 nutrients and nutrition factors into account and aims to rank foods by their relative healthfulness (Katz et al., 2007). Nutrients with generally favorable effects on health such as fiber, vitamins and omega-3 fatty acids are placed in the numerator, where higher values increase the NuVal score. Nutrients with generally unfavorable effects on health such as saturated fat, trans fat, sodium, sugar and cholesterol are placed in the denominator, where higher values decrease the NuVal score. In addition to nutrients, the ONQI algorithm also takes into account other key nutrition factors that measure the quality and density of nutrients, as well as the strength of their association with specific health conditions.

Using the developed scoring system, NuVal LLC started scoring food products in the middle of 2008. In the same year, it formed a partnership with Topco Associates LLC, which is a private business consulting company jointly owned by many grocery retail chains, to market the NuVal labels to grocery stores. In January 2009, Price Chopper and Hy-Vee became the first two retail chains that adopted the NuVal labels. Due to the large number of food products on the market, NuVal scored food products over time. By November 2010, it had scored 75,000 food products.

[2] Chiuve et al. (2011) used ONQI to score the diet quality of over 100,000 men and women who started as healthy individuals in two longitudinal surveys spanning more than 20 years. The authors found that baseline diets that were scored lower by the ONQI algorithm are significantly associated with higher risks of chronic disease later in the surveys.

By November 2014, it had been adopted by thirty-three retail chains and several public school systems throughout the U.S.[3]

Data and Empirical Specification

We acquired NuVal scores for yogurt products at the Universal Product Code (UPC) level from NuVal LLC—NuVal's licensing company. In addition to nutrition scores, the NuVal data also record the date on which the product was scored by NuVal. The first yogurt UPC was provided with a NuVal score in January 2009. The number of yogurt UPCs assigned a score rose to 1,778 by December 2011.

Yogurt sales data come from the IRI Academic Data Set (Bronnenberg et al., 2008). We use store-level data from six food stores in a Midwestern city with a population of 66,000 in the 208-week period starting on December 31st, 2007 and ending on December 25th, 2011. This gives us a panel data with 1,248 store-level observations. The treatment store implemented NuVal in August 2010. For estimation purpose, we assume the first treatment week to be the week starting on August 16th, 2010.[4] At the time of this writing, the chain to which this treatment store belongs still uses NuVal. We verified that no other stores in this city had NuVal or Guiding Stars labels. To create the $\%NV_t$ variable, we assume there is a one-month lag between the date on which the UPC was scored by NuVal's licensing company and when the UPC was labeled at the treatment store. Based on our discussion with staff at NuVal about how, in general, product scores are provided to and used by its retail partners, this seems to be a reasonable assumption.

To construct household demographic variables for each store-week, we use the IRI BehaviorScan that had between 2471 and 2129 sample households in the Midwestern city during our sample period. Using shopping trips data reported by these households and their household demographics, we are able to create the age_{lt}, $size_{lt}$, col_{lt}, and x_{lt} variables that varied across stores and over time.

One would ideally estimate a QUAID demand at the UPC level because NuVal scores and labels yogurt at this level. However, the dimension of the parameter space when there are several hundred unique UPCs renders this approach infeasible. As a result, we reduce the number

[3] Most information in this paragraph was taken from NuVal's online newsroom, http://www.nuval.com/News.
[4] This turns out to be an innocuous assumption. The empirical results remain unchanged if the treatment is assumed to start on August 2nd or September 6th, 2010.

of parameters by aggregating all yogurt UPCs into three yogurt groups, i.e., $n = 3$. The first yogurt group contains UPCs that were assigned an above-median score by the end of 2011 and ever sold at the treatment store. The median NuVal score for the yogurt category was 48. The second yogurt group collects UPCs sold at the treatment store but received a below-median score. We put all other UPCs into the third yogurt group.

For each yogurt group j, we create the panel price index p_{jlt} based on the panel rolling-window CCD (RWCCD) price index documented in Zhen et al. (2015). The RWCCD index is a panel extension of the multilateral CCD index of Cave, Christensen and Diewert (1982). The index value at each store-week observation is the geometric mean of bilateral comparisons of UPC-level prices between the target store-week and all other store-weeks in the rolling window (e.g., the past one year). The elementary bilateral index used to calculate RWCCD is the superlative Törnqvist index. The multilateral CCD price index is transitive in that the relative price between any two locations does not depend on prices at another location (Deaton and Dupriez, 2011). We use the rolling window to continuously update the UPC basket to account for product entry and exit. Although a conventional chained price index can also update the product mix over time, it has been widely documented that chained price indexes are susceptible to chain drift in high frequency data (de Haan and van der Grient, 2011). Chain drift is a phenomenon where the time series price index does not return to its base even when UPC-level prices go back to their base levels (Forsyth and Fowler, 1981). Ivancic, Diewert, and Fox (2011) found that using a multilateral price index to create the time series price index eliminates chain drifts. We set the size of the rolling window to one year based on our prior experience with calculating price indexes using high frequency scanner data.

Table 1 reports summary statistics on expenditure, volume, and unit value by yogurt group. Note that per capita expenditure and volume are for all shoppers not just those that purchased yogurt. Compared with the control stores, the treatment store sold more yogurt on a per capita basis. Average unit value for yogurt group 2 and 3 was higher in the treatment store relative to the control store, but about the same for group 1 between the treatment and control stores.

Empirical Results

We estimate the QUAID model (5) using nonlinear seemingly unrelated regressions (SUR) with three yogurt budget share equations. The budget share equation for the *numéraire* good is not estimated due to the adding-up condition. Table 2 presents the regression results. 48 of the 141 coefficient estimates are statistically significant at the 10% level or better. Importantly, all price coefficients are statistically significant with p-values less than 0.0001. The adjusted R^2 are 0.47, 0.4 and 0.35 for the budget share equations of yogurt group 1, 2, and 3, respectively.

Table 3 reports unconditional Marshallian demand and income elasticities. Consistent with a priori expectations, all yogurt own-price (cross-price) elasticities are negative (positive). The income elasticities are positive and less than one but not statistically significant. This should not be surprising because much of the household-level income variation has been smoothed out by averaging in aggregate data.

Back to table 2, the effect of labels on demand is measured by coefficients $a_{itreat1}$ and $a_{itreat2}$. Of the six treatment coefficients across the budget share equations, only $a_{itreat2}$ in the equation for yogurt group 1 is statistically significant (p-vale=0.06). Evaluating this effect at the median of the treatment sample indicates that a one percentage point increase in $\%NV_t$ increases demand for yogurt with above-average scores by 0.57%. The statistically insignificant coefficients on D_t suggest that the effect of the labeling program on demand may have been gradual.

To estimate value of NuVal information, we follow a four-step procedure for every observation of the treatment store in the treatment period. First, we calculate baseline utility level U_0 by equation (6) and purchase quantities $\mathbf{q}_0$ by equation (5) conditional on observed prices $\mathbf{p}_0$ and income, and setting D_t and $\%NV_t - \%NV_0$ to zero, which is the counterfactual no labeling scenario. Second, we use equation (6) to solve for the level of income x_{lt} (i.e., total expenditures) required to reach U_0 conditional on baseline prices and observed values of D_t and $\%NV_t - \%NV_0$ (i.e., with labels). Third, we use equation (5) to calculate purchase quantities $\mathbf{q}_1$ under labeling and income level obtained in step two. Fourth, we use Hicksian price elasticities (evaluated at U_0, $\mathbf{p}_0$, and with labels) and percent change in purchase quantities (from $\mathbf{q}_1$ to $\mathbf{q}_0$) to solve for percent change in prices required to bring purchases to $\mathbf{q}_0$ conditional on U_0 and with labels. The percent price changes give $\mathbf{p}_1$. Now, we have obtained all the inputs into equation (4) for obtaining a cost of ignorance estimate, which is the negative of value of information.

As the percentage of yogurt UPCs that were labeled increased over time, the informational value of the labeling program also increased. By the end of 2011, we estimate the value of NuVal information to shoppers in the yogurt category to be \$0.01 per capita per week, or 3.1% of total yogurt dollar sales, at the treatment store where 86% of yogurt products had been labeled.

Conclusion

In this paper, we use a supermarket's voluntary adoption of NuVal shelf nutrition labels to estimate the value of this nutrition information to shoppers brought by this interpretive nutrition label. Our results based on a QUAID model estimated using retail scanner data indicate that these labels increased sales of labeled yogurt products that received above-average nutrition scores. We estimate that the value of NuVal labels on yogurt products represented 3.1% of total yogurt expenditures at the treatment store. This is not a trivial estimate considering that, the yogurt category generated \$5.03 billion in sales in US supermarkets in 2014[5] and as of November 2015, 24 US supermarket chains had posted NuVal labels across all food and beverage categories. It is important to recognize that our estimated value of NuVal labels refers to changes in short-run consumer welfare. The value of these labels in the long run could be much larger if the demand effect is sustained over time and health outcomes improve as a result.

Although beyond the scope of the current study, we envision at least three potentially fruitful avenues for future research. First, because shelf labeling occurs at the UPC level, it will be useful to estimate a utility-theoretic demand model where each UPC is a unique product. We expect this to produce more precise estimates for the demand effect and value of nutrition information. Second, to understand the effect of NuVal labels on the entire food basket, it is essential to examine food sales across all grocery aisles. Although the IRI Academic Data Set has only a limited number of food categories, both Nielsen and IRI collect retail and household scanner data that can be used for this purpose. Third, from a public health perspective, it is critical to identify the segments of consumers (e.g., low vs. higher-income, obese vs. non-obese)

[5] http://www.statista.com/statistics/348910/us-supermarkets-yogurt-dollar-sales/.

who benefit from interpretive shelf nutrition labels most. This has to be addressed using micro data on household food purchases.

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Table 1. Summary Statistics			
	Yogurt group 1: UPCs with above-median scores	Yogurt group 2: UPCs with below-median scores	Yogurt group 3: unscored UPCs
Average per capita expenditures ($/week)			
Treatment store	0.172	0.193	0.075
Control stores	0.107	0.120	0.063
Average per capita volume purchase (ounce/week)			
Treatment store	0.102	0.093	0.041
Control stores	0.065	0.065	0.039
Unit value ($/ounce)			
Treatment store	0.110	0.131	0.115
Control stores	0.110	0.120	0.105

Table 2: QUAID Parameter Estimates			
	Equations		
Regressors	Yogurt group 1: UPCs with above-median scores	Yogurt group 2: UPCs with below-median scores	Yogurt group 3: unscored UPCs
Constant	0.0374	0.0736	0.0819
	(0.1661)	(0.1679)	(0.0821)
D_t	0.0126	-0.0519	0.0113
	(0.0419)	(0.0423)	(0.0207)
$D_t \times (\%NV_t - NV_0)$	0.2291	0.1845	0.0685
	(0.1225)	(0.1236)	(0.0606)
lnp_1	-0.4907	0.1833	0.0564
	(0.0224)	(0.0196)	(0.0114)
lnp_2		-0.4707	0.0764
		(0.0283)	(0.0148)
lnp_3			-0.1304
			(0.0191)
age	0.0238	0.1597	-0.0165
	(0.5115)	(0.5172)	(0.2529)
age × income	22.4997	26.1676	6.7950
	(6.6750)	(6.7481)	(3.3006)
age × income^2	1.7862	-11.5541	25.5337
	(50.4292)	(50.9751)	(24.9288)
size	0.0959	0.0699	0.0370
	(0.0734)	(0.0742)	(0.0363)
size × income	-0.7652	-1.8479	-0.8740
	(0.7075)	(0.7153)	(0.3501)
size × income^2	-0.3996	7.8214	2.7333
	(4.3184)	(4.3667)	(2.1363)
college	0.0369	0.2251	-0.0236
	(0.2050)	(0.2072)	(0.1013)
college × income	-4.0239	-5.0716	-1.9614
	(1.8430)	(1.8633)	(0.9118)
college × income2	1.2403	17.3949	14.7030
	(9.6692)	(9.7762)	(4.7820)
adj R^2	0.4498	0.4349	0.3244

Notes : Parameter estimates and their standard errors (in parentheses) are multiplied by 1,000 to enhance readability. Coefficient estimates for store, year, and trend fixed effects are omitted from this table for brevity.

Table 3. Unconditional Marshallian Price and Income Elasticities				
	With respect to price of			
Demand for	Yogurt group 1	Yogurt group 2	Yogurt group 3	Income elasticity
Yogurt group 1: UPCs with above-median scores	-2.900	0.711	0.219	0.459
	(0.080)	(0.066)	(0.041)	(0.934)
Yogurt group 2: UPCs with below-median scores	0.615	-2.577	0.256	0.352
	(0.057)	(0.097)	(0.052)	(0.876)
Yogurt group 3: unscored UPCs	0.384	0.521	-1.888	0.605
	(0.071)	(0.106)	(0.119)	(0.815)
Notes: Standard errors in parentheses. All values are medians over the entire sample.				