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# A comparative analysis of hedonic models of nutrition information and health claims on food products: An application to soup products

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**ABSTRACT**
Over time, the quality of data on food purchases and label information has improved such that hedonic analyses to determine the implicit prices of product attributes can be conducted using more detailed data than in the past. With the availability of more extensive data, it is important to understand the characteristics of the data and implications of using different data sources on results of analyses. The purpose of this study was twofold: (1) compare results between two sources of label information and (2) develop a better understanding of the effects of product claims and nutrition information on the value of products to consumers. Trans fat claims, organic claims, private label, package size, and several nutrients were found to influence implicit prices for soup products, and the results between the two data sources are comparable.

**KEYWORDS**
Health claims; food labeling; scanner data; hedonic model; implicit prices

Over time, the quality of data on food purchases and label information has improved such that hedonic analyses to determine the implicit prices of product attributes can be conducted using more detailed data than in the past. In particular, proprietary commercial data on household food purchases collected through in-home barcode scanning or collected directly from stores are now being used extensively in food research studies including hedonic modeling. These data often include both nutrition and product claims information at the individual Universal Product Code (UPC) level, which allows researchers to analyze consumer food purchase behavior in more depth compared with more limited data sources that must be obtained manually from product labels.

For example, Bonanno (2016) used weekly IRI store scanner data for eight U.S. cities/metropolitan areas to conduct a hedonic analysis of health and nonhealth attributes on yogurt prices. Bimbo, Bonanno, and Viscecchia (2016) used monthly IRI store scanner data for 17 regions in Italy to conduct

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a hedonic analysis of the effects of health claims on implicit prices for Italian yogurt. Vickner (2015) used Nielsen store scanner data for a hedonic analysis of the U.S. breakfast sausage market. Muth et al. (2013) used Nielsen store scanner data in a hedonic model finding that carb-conscious labeling statements had the most significant positive effect on product prices using data from a time period when low-carbohydrate diets were popular. Schulz, Schroeder, and White (2012) used InfoScan data from Freshlook Marketing Group on meat department random-weight sales from retail food stores nationwide to run a hedonic model on the beef steak market and found that brand names, organic claims, religious processing claims, and premium cuts garner higher prices. In addition, Huang and Lin (2007) used weekly Nielsen household scanner data to estimate a hedonic model to determine the effects of organic certification on fresh tomato prices.

With the availability of more extensive data on product attributes from labels in commercial scanner datasets, it is important to understand the characteristics of the data and implications of using different data sources on results of analyses. For this paper, we had access to household-based scanner data and label data from IRI in addition to label data obtained from an alternative supplier, Gladson. Of the commercial data providers in the U. S., only IRI currently collects label data that can be linked directly to UPC-level purchase data from retail or in-home scanning (Muth et al., 2016).[1] The purpose of this study was twofold: (1) compare the results of analyses between two sources of label information to determine whether the quality of the data is similar and (2) develop a better understanding of the effects of product claims and nutrition information on the value of products to consumers. Because the label data included not only product claims but also nutrition information, we were able to examine whether including nutrition variables in a hedonic model influenced the results of analyses.

The results of this research are useful for understanding food manufacturer incentives for including health labeling statements on products and the implications of differences in the IRI and Gladson nutrition datasets for conducting food product research using these data. We focused the analysis on the soup product category because it has a high degree of variation in the labeling statements on products, it is a frequently consumed product comprising a meal or a portion of a meal, and it has not been examined extensively in the literature. Furthermore, the soup market is expected to continue growing between 2013 and 2018 from $6.9 billion to $8 billion with ready-to-eat wet soups holding the highest share of soup sales at 31.2% (Kraushaar & Topper, 2015). According to research using the National Health and Nutrition Examination Survey between 2003 and 2006, 94% of

[1]In addition to IRI and Gladson, other commercial suppliers of label data in the U.S. include Label Insight and Mintel (for new product introductions). Nielsen also sells UPC-level purchase data but label data must be linked from one of the other suppliers.

respondents consumed soup over the past 12 months with 41% of participants consuming soup four or more times a month during the winter (Zhu & Hollis, 2013). Although this study focuses on soup products, the information on the types of claims and nutrition information now available from these data sources may be useful to other researchers interested in studying how this information affects consumer choices.

## Background on food labeling policy

Many people consider health and nutrient claims on food labels to be a public health tool that makes Americans more knowledgeable about the foods they purchase and consume (Labiner-Wolfe, Jordan Lin, & Verrill, 2010; Roe, Levy, & Derby, 1999). The information provided on food product labels in the U.S. is based on food labeling policies established by the U.S. government. Specifically, the Nutrition Labeling and Education Act (NLEA) of 1990 gave the U.S. Food and Drug Administration (FDA) the authority to require food manufacturers to list the amounts of fat, cholesterol, sodium, carbohydrates, and protein contained in their products and to place those amounts in the context of a typical daily diet on the basis of realistic serving sizes (FDA, 1994). The NLEA also required the FDA to develop standards for nutrient content claims, health claims such as "lite" and "low sodium," and other labeling statements (U.S. Food and Drug Administration, 1994). In May 2016, the FDA enacted changes to the Nutrition Facts Label (NFL) and serving sizes that were originally targeted to go into effect for most manufacturers on July 26, 2018, but have now been delayed to January 1, 2020 (U.S. Food and Drug Administration, 2016a). New requirements include declaring added sugars and an associated percent daily value (%DV); changing the definition of dietary fiber; updating Daily Reference Values and Reference Daily Intakes, including establishing values for young children; increasing the prominence of calories; and updating serving sizes for many foods (U.S. Food and Drug Administration, 2016a). With the exception of the additional requirement to list trans-fatty acids starting in 2006, these are the first significant revisions to the label since it was launched.

However, the new changes do not explicitly change the requirements for including labeling claims on foods. Three types of labeling claims—nutrient content, health, and structure/function—began appearing on food products after the NLEA was signed into law in 1990 with an effective date of May 8, 1994, for most products. Nutrient content claims are statements that directly or by implication characterize the level of a nutrient found in a food (e.g., "low fat," "high in oat bran," or "contains 100 calories") (21 CFR 101.13(b), 21 CFR 101.13(a)) (U.S. Food and Drug Administration, 2013). Recognized nutrient content claims include "good source," "high," "more," "low," "free," "less," and "fewer"; "light" or "lite"; claims regarding calories, sodium, fat, saturated fat, and cholesterol; and others as specified in the regulations. Health claims are food labeling statements that expressly or by implication characterize the relationship between a specific food or a component of a food *and* a disease or health-related condition (U.S. Food and Drug Administration, 2013). An example of an authorized health claim is "Three grams of soluble fiber from oatmeal daily in a diet low in saturated fat and cholesterol may reduce the risk of heart disease. This cereal has 2 grams per serving" (U.S. Food and Drug Administration, 2013). Finally, structure/function claims describe the effect that a substance has on the structure or function of the body and do not make reference to a disease. An example of a structure/function claim is "Calcium builds strong bones" (21 CFR 101.93).

In addition to the FDA's label regulations, other types of label information on food products include organic labeling statements regulated by the U.S. Department of Agriculture (USDA) and industry-led labeling initiatives. Organic labeling claims of "100% organic," "organic" (at least 95% organically produced ingredients with restrictions on the types of products for the remaining 5%), and "made with organic ingredients" (at least 70% organically produced ingredients) fall under the USDA's jurisdiction (USDA, 2012). Examples of industry-led labeling initiatives include the American Heart Association Heart-Check mark and the joint Grocery Manufacturers Association's and Food Marketing Institute's "Facts Up Front" initiative.

In this study, the data on labeling claims were generally obtained from the front of the package. For IRI, the data were coded by category of claim with different levels of the claim. These claims may be either nutrient-content claims, such as "no," "low," or "less" of a nutrient or component, or what IRI refers to as "functional" claims expressing a relationship between consumption of a nutrient and a health state. Gladson claims data were coded in a "Product Details" variable that included all information on the front of the package. Additional details of the coding process are included in the "Methods and data" section.

## Consumer purchasing behaviors related to labeling claims

Stanton, Wiley, and Hooker (2015) found that both private-label and national brand companies increased the use of labeling claims between 2009 and 2011. The question is, do consumers change their purchasing behavior because of them? The NLEA of 1990 motivated numerous studies investigating the effects of food labeling and nutrition information on consumer purchasing behaviors. Initially, most of the studies focused on the NFL, but later studies also focused on labeling claims. In examining consumers' reactions to specific types of labeling claims (i.e., nutrition claim, health claim, and reduction of disease risk claim) on different products using 2006 cross-sectional data, Verbeke, Scholderer, and Lähteenmäki (2009) found that health claims outperformed nutrition claims in credibility of the claim and product as well as the consumer's intention to buy the product; both of these claim types outperformed reduction of disease risk claims in terms of credibility and intention to buy. Kozup, Creyer, and Burton (2003) examined how nutrition information affected purchase behavior and found that when favorable nutrition information or health claims are presented consumers have more favorable attitudes toward the product and are more likely to purchase the product.

Several authors have used hedonic models to examine the impact of health claims on implicit prices. For example, Muth et al. (2013) used this method to study the impact of labeling statements on breakfast foods and cereals and found that some labeling statements for these foods are often associated with substantial increases in implicit prices for label attributes, but the authors did not consider nutrient information on the label. Szathvary and Trestini (2014) also used a hedonic model to examine fruit beverage products finding that nutrition and health claims significantly affect retail prices in Italy. Bimbo et al. (2016) found that all health claims they tested have a price premium in the Italian yogurt market with a cholesterol risk reduction claim having the highest implicit price.

However, other factors also influence the effect of label information on consumers. For instance, consumers with limited resources are more likely to be concerned about price instead of nutrition, and consumers who find the label difficult to understand are less likely to use the nutrition information (Cowburn & Stockley, 2005). Research has also shown that, in general, more consumers are interested in negative nutritional information such as calories, cholesterol, sodium, and sugar than positive nutritional information such as protein, calcium, and iron (Russo, Staelin, Nolan, Russell, & Metcalf, 1986). Furthermore, consumers may not understand which nutrients are important, focusing on fat or calorie information (Higginson, Kirk, Rayner, & Draper, 2002). Other research has found that consumers are less likely to choose a product with a package claim when the consumers have an established habit or history of buying a certain product (Aschemann-Witzel & Hamm, 2010). Although brand was a significant factor when consumers purchased beef steaks, Schulz et al. (2012) also found that organic claims and religious processing claims are significant in the beef steak market. These findings suggest that branding and brand loyalty may be more important to purchase decisions than nutrition-related labeling claims. Furthermore, Vickner (2015) found that convenience is a significant factor for consumers when he looked at the U.S. breakfast sausage market even when controlling for attributes such as package weight, product shape, fat, sodium, organic, kosher, meat type, and brand.

## Methods and data

We used hedonic price analysis based on Rosen's (1974) methodology to estimate the implicit values associated with individual food product attributes. This methodology is grounded on the hypothesis that consumer utility is generated by the qualities and characteristics of purchased products (Costanigro & McCluskey, 2011). Similar to the approach used by Muth et al. (2013), Szathvary and Trestini (2014), and Bonanno (2016), we estimated semi-log models using data on explicit product prices and the characteristics of the food product with a specific interest in the effects of health labeling claims.

### *Description of hedonic model*

Each individual product is composed of $n$ attributes $A_1,\ldots,A_n$. Together the attributes define the price of the product $P(A_1,\ldots,A_n)$, implying that the product price can be decomposed into implicit prices for each of the product attributes. Rosen (1974) refers to these implicit prices as hedonic prices. We can recover each of the implicit prices by specifying the hedonic price as a function of the attributes:

$$P(A_1, \ldots, A_n) = f(A_1, \ldots, A_n) \tag{1}$$

The derivation of hedonic prices is similar to that of traditional demand estimation in a competitive market where prices are the result of the interaction between demand and supply (Rosen, 1974). In this article, we do not attempt to estimate food product demand or supply curves; instead, we estimate the effect of labeling statements on the equilibrium prices of food products. We augment the Muth et al. (2013) model by including nutrition content variables to estimate a semi-log regression of food prices on labeling statements and other nutritional and non-nutritional characteristics of the food as follows:

$$\ln P = f(\mathbf{LS}, \mathbf{NI}, \mathbf{PC}) \tag{2}$$

where **LS** is a vector of binary variables indicating the labeling statements included on the product package, **NI** is a vector of product nutrition information included on the NFL, and **PC** is a vector of other product characteristics such as store brand and package size in ounces. The estimated coefficients on the **LS** variables measure the implicit value of each of the labeling statements, and the estimated coefficients on the **NI** variables measure the implicit value of the nutrient values on the label.

The semi-log specification is particularly useful for our research purpose because it allows the labeling statement indicator variables to be interpreted as the percentage changes in the price of the food product as a result of each of the product characteristics. As noted by Costanigro and McCluskey (2011), the semi-log model is by far the most common specification in applied hedonic models. Furthermore, Cropper, Deck, and McConnell (1988) found in a simulation analysis that simpler specifications of the price equation (including the semi-log specification) are better at measuring marginal "willingness to pay" when product attributes in the dataset are incomplete. We also conducted a Box–Cox test to ensure that the semi-log specification provided the best fit for both datasets used in the analysis.

In addition to estimating the hedonic model directly, we also calculated the percentage effects of the attribute for the indicator variables using Kennedy's (1981) adjustment:

$$g* = \exp\left(\hat{c} - \frac{1}{2}\hat{V}(\hat{c})\right) - 1 \quad (3)$$

where $\hat{c}$ is the estimate of a dummy variable coefficient $c$. The percentage effect is interpreted as relative percentage price differences compared to baseline (i.e., a non-private label soup product with no claims).

## Datasets used in the analysis

In this section, we describe each of the data sources used in the analysis. It is important to note that coding label information is an inexact science, thus leading to differences in the datasets. Data are at the UPC level, and each UPC is associated with variables that provide information on its package type and size, brand, flavor, manufacturer, and the manufacturer's parent company in addition to nutrition information and claims. For example, an UPC might represent a specific brand and flavor of condensed soup packaged in a can, and the information associated with the UPC includes a text description, package type (e.g., can), package size (e.g., number of ounces), brand name, flavor (e.g., chicken noodle), manufacturer name, and name of the manufacturer's parent company (typically the same as the manufacturer).

### Product characteristics data from IRI

The IRI datasets include two types of purchase data: the household-based scanner data (called Consumer Network) and retail point-of-sale scanner data (called InfoScan) (IRI, 2012). The UPC code links the product information and nutrition and label claims data for both of these datasets (Muth et al., 2016). The IRI product dictionary for nutrition attributes provides the full range of claims on the front of the package and nutrition values on the back of the package for food products. IRI derives the Consumer Network data from the National Consumer Panel, which is an operational joint venture equally owned by IRI and Nielsen. According to IRI, they code nutrition data only for edible food and beverage products with significant sales volume; therefore, the intention is to cover a large portion of sales rather than a large number of UPCs (Muth et al., 2016). For the IRI data for 2012 and earlier years, nutrition data are provided for over 635,000 active UPC codes. Approximately 48% of the UPCs in the Consumer Network data and 41% of the UPCs in the InfoScan data match the nutrition data.[2] In terms of total food sales, the percentage coverage of the IRI nutrition data is substantially higher, at 78% of sales in Consumer Network and 81% of sales in InfoScan (Muth et al., 2016).[3]

The IRI dataset also contains labeling statement information on up to 10 key nutrition claims and 22 other nutrition claims for each UPC. The key nutrition claims relate to calories, cholesterol, fat, fiber, organic, saturated fat, salt/sodium, sugar, trans fat, and whole grains. Most of the labeling statements available refer to the absence or limitation of negative nutrients (e.g., fat and salt) in contrast to the presence of positive nutrients (e.g., fiber and whole grains).

### *Product characteristics data from Gladson*

We used the 2012 version of the Gladson Nutrition Database, which includes hundreds of thousands of consumer packaged food products at the UPC level (Gladson, n.d.). Over 150 attributes are captured per product, including the full NFL, ingredients, labeling statements, and manufacturer at the UPC level (Gladson, n.d.).

In addition to product information on sales and non-nutritional attributes, the dataset also contains labeling statement information in its "ProductDetails" variable for each UPC. This variable includes all of the information available on the front of a product's package including labeling statements. As with the IRI data, most of the labeling statements on products refer to the absence or limited content of negative nutrients in contrast to the presence of positive nutrients.

### *Comparison of IRI and Gladson nutrition data*

For both the IRI and Gladson datasets for all products, nutrition values are expressed in amounts and %DV. Also, product claims data (generally on the front of the package) are coded by category of claim with different values of the claim. For food products as a whole, IRI provides better coverage than Gladson for private-label products (24.8% of total UPCs compared with 4.1%), and Gladson provides better coverage than IRI for branded products (23.1% of total UPCs compared with 19.5%) (Muth et al., 2016). Note that these differences are based only on UPC counts and not sales volumes represented by the UPCs; percentages of sales volumes with label data in both datasets are higher than the percentages of UPCs.

[2]To be considered a match, an UPC needs to have a non-null value for at least one variable in the nutrition data. However, more than 98% of the nutrition data records have values for 12 or more fields, and 78% of the records have values for 24 or more fields.

[3]The full details of the nutrition fields for IRI are in the ERS technical bulletin: Muth, M. K., Sweitzer, M., Brown, D., Capogrossi, K., Karns, S., Levin, D., … Zhen, C. (2016). *Understanding IRI household-based and store-based scanner data*. Technical Bulletin TB-1942. Washington, DC: U.S. Department of Agriculture, Economic Research Service.

### Price data from IRI

Because the Gladson data do not contain price information, we used the IRI Consumer Network data to generate an average price to apply to each UPC in both the IRI and Gladson datasets.[4] We calculated an average price per UPC by dividing the total dollars spent by total units sold per UPC, which is equivalent to calculating a sales-weighted average price. We then converted the average price per product to average price per ounce by dividing the average price (in cents) by the total ounces for the product as served.[5] Finally, we took the natural log of cents per ounce to use as the dependent variable in the hedonic regression models for each of the datasets of label information.

### Descriptive statistics

Descriptive statistics of the variables for soup products used in the models for both IRI and Gladson data are shown in Table 1. We only included those products that were in both datasets so that any differences in results are not simply a consequence of differences in the products included in the datasets.[6] For each of these datasets, we constructed the following UPC-level variables for the hedonic regression analysis:

Price: Continuous dependent variable in cents per ounce for each UPC in logarithmic form

Package size: Continuous variable measuring product weight (in ounces). For condensed soups, we multiplied the product weight by a factor of 2 to calculate total ounces; for dry soups, by a factor of 5.7; for ramen, by a factor of 5.3; and for instant noodles, by a factor of 3.8.[7]

Store brand: Indicator variable for store-brand products, also known as private-label or control brand (equals 1 if the brand is a store brand, 0 otherwise).

Labeling statements: Indicator variables for each possible labeling statement (equals to 1 if the UPC has the labeling statement, 0 otherwise). Missing values for labeling statements were recoded to 0 with the assumption that if the characteristic is not included in the dataset, it indicates it is not on the label and is, therefore, likely 0.

[4]Prices might not represent the exact value a household paid for an item; instead, IRI assigns prices based on the average price of the item at the retail outlet chain where the item was purchased in the market area the household resides. If the household shops at a store that is not represented in the IRI point-of-sale data, IRI uses the price that households input during the reporting (Muth et al., 2016).

[5]We calculated a price per ounce rather than a price per serving because the weight of a serving size varies across individual products. For condensed and dried soups, we converted the weight to an as-served weight before calculating the average price. Furthermore, the shelf label for the product indicates price per ounce, which allows consumers to compare the price of products.

[6]In the IRI data, 1,119 soup UPCs were dropped because they did not have associated nutrient or nutrition claims data. In the Gladson data, 823 soup UPCs were dropped that were not in the IRI data with nutrition information.

[7]We calculated the factor of 5.7 for dry soups by taking the average of the amount of water added to several dry-soup products based on the package instructions. We calculated the factor of 5.3 for ramen from the package instructions of ramen. We calculated the factor of 3.8 for instant noodle products, which had a mean weight of 2.11 ounces, by assuming these products require the addition of 8 ounces of water.

**Table 1.** Descriptive Statistics for Soup Products in IRI and Gladson.

| | IRI | | Gladson | |
|---|---|---|---|---|
| Variable | Mean | SD | Mean | SD |
| Price per ounce | 10.142 | 7.526 | 10.142 | 7.526 |
| Total ounces | 24.862 | 29.857 | 24.862 | 29.857 |
| Private label (1 = yes) | 0.224 | 0.417 | 0.199 | 0.399 |
| Organic claim (1 = yes) | 0.165 | 0.371 | 0.187 | 0.39 |
| Health claim variables | | | | |
| Calorie claim (1 = yes) | 0.161 | 0.368 | 0.189 | 0.391 |
| Cholesterol claim (1 = yes)* | 0.057 | 0.232 | 0.095 | 0.293 |
| Fat claim (1 = yes)* | 0.339 | 0.474 | 0.206 | 0.404 |
| Saturated fat claim (1 = yes)* | 0.033 | 0.179 | 0.153 | 0.36 |
| Trans fat claim (1 = yes) | 0.145 | 0.352 | 0.162 | 0.369 |
| Fiber claim (1 = yes) | 0.070 | 0.255 | 0.09 | 0.287 |
| Sodium claim (1 = yes) | 0.174 | 0.379 | 0.194 | 0.396 |
| Sugar claim (1 = yes)* | 0.005 | 0.067 | 0.022 | 0.146 |
| Whole grain claim (1 = yes)* | 0.018 | 0.134 | 0.007 | 0.083 |
| Nutrition variables | | | | |
| Calories | 123.729 | 63.996 | 123.609 | 64.249 |
| Cholesterol (mg) | 6.485 | 11.507 | 6.169 | 10.95 |
| Saturated fat (g) | 1.196 | 2.025 | 1.199 | 2.065 |
| Sodium (mg) | 653.244 | 260.181 | 656.487 | 256.21 |
| Carbohydrates (g) | 19.051 | 9.14 | 18.973 | 9.034 |
| Total fat (g) | 3.223 | 3.777 | 3.229 | 3.833 |
| %DV calcium[a] | 3.099 | 3.755 | 3.029 | 3.469 |
| %DV carbs | 6.347 | 3.139 | 6.307 | 3.06 |
| %DV cholesterol | 2.177 | 4.283 | 2.089 | 6.629 |
| %DV iron[a] | 6.522 | 6.421 | 6.498 | 6.234 |
| %DV sat fat | 6.033 | 10.051 | 6.07 | 10.237 |
| %DV sodium | 27.199 | 10.968 | 27.309 | 10.83 |
| %DV total fat | 4.982 | 5.778 | 4.995 | 5.859 |
| %DV vitamin A[a] | 17.054 | 26.693 | 16.85 | 25.646 |
| %DV vitamin C[a] | 6.329 | 15.613 | 6.376 | 15.854 |
| *N* | 875 | | 875 | |

*Note.* %DV = percent daily value.
[a]For calcium, iron, vitamin A, and vitamin C, only the %DV is included on food labels and not the levels of these nutrients.
**t*-test indicates statistically significant difference between IRI and Gladson datasets at $p < .05$.

Nutrition information: Either a continuous variable for the per-serving amounts of calories, carbohydrates, total fat, saturated fats, cholesterol, and sodium or for the %DV of carbohydrates, total fat, saturated fats, cholesterol, sodium, iron, vitamin A, and vitamin C.[8]

The IRI soup data have, on average, 1.2 labeling claims with some products having 0 claims and some having as many as 6 claims. Similarly, soup products in the Gladson data have, on average, 1.3 labeling claims with some products having 0 claims and some having as many as 6 claims. The characteristics of the soup products are relatively similar across many characteristics in the two datasets but are not identical. As indicated in Table 1, *t*-tests between the same variables in each of the datasets indicated that cholesterol claim, fat claim,

[8]We used per-serving nutrition information because the consumer sees this information on the Nutrition Facts Label.

saturated fat claim, sugar claim, and whole grain claim are statistically significantly different at the 5% level across the datasets. In contrast, none of the quantity or %DV variables is statistically different.

A number of factors could contribute to differences in the characteristics of soup products between the two datasets. First, the data may be captured at different points in time, thus resulting in differences in labeling statements and package size. Second, in some cases, product descriptions clearly indicate the product is condensed or dry and requires the addition of water to the product; however, it is not necessarily clear for all products. Third, products are coded differently in terms of whether they are branded or private label (22.4% private label for IRI versus 19.9% for Gladson).

## Hedonic model results

We estimated semi-log hedonic models with StataMP 14 using two methods of expressing nutrition values: one specification used quantities of nutrients as independent variables and the second used %DV of nutrients. We also estimated a model excluding the nutrition variables to determine whether it would have an effect on the estimated coefficients for the labeling claims. Tables 2 and 3 report the regression results using quantities of nutrients and %DV, respectively, including the parameter estimates, standard errors of the estimates, the $p$ values, and the percentage effect for each indicator variable on price. We interpreted the estimated coefficients on the binary labeling statement variables as percentage changes in price relative to the average per-ounce prices.

We also estimated models with interaction variables between private label and the following labeling claims: calorie, cholesterol, total fat, saturated fat, trans fat, fiber, sodium, sugar, whole grain, and organic. However, only the interaction between the fiber claim and private label was significant at the 5% level; therefore, the interactions were not included in the final specifications. The Breusch–Pagan test indicated no evidence of heteroskedasticity for the quantity or %DV models; for the labeling claims only model heteroskedasticity is likely present due to omitted variables. Tests for collinearity using the Variance Inflation Factor did not indicate that any variables were highly correlated in the %DV or labeling claims only models, but three variables were correlated in the quantity model: total carbohydrates, total calories, and total fat. However, the same set of variables were kept in all of the models for consistency. Finally, the Box–Cox test indicated that the semi-log specification provided the best fit compared to the inverse and linear specifications for both datasets used in the analysis.

First, we describe the results when including quantities of nutrients as independent variables (Table 2). The variables private label and total ounces have the expected signs and are similar in magnitude. For private-label soups in IRI and Gladson, the negative estimated coefficients of −0.381 and −0.480

**Table 2.** Results of Log-Linear Price Regression for Soup including Quantities of Nutrients Using IRI and Gladson Data.

Dependent variable: natural log of cents per ounce

| | IRI | | | | Gladson | | | |
|---|---|---|---|---|---|---|---|---|
| | Parameter estimate | Standard error | *p* Value | % effect | Parameter estimate | Standard error | *p* Value | % effect |
| Health claim variables | | | | | | | | |
| Calorie claim | 0.032 | 0.068 | .634 | 3.0 | 0.052 | 0.064 | .421 | 5.1 |
| Cholesterol claim | 0.11 | 0.136 | .42 | 10.6 | 0.087 | 0.087 | .316 | 8.7 |
| Fat claim | 0.067 | 0.065 | .304 | 6.7 | 0.036 | 0.063 | .566 | 3.5 |
| Saturated fat claim | −0.071 | 0.181 | .697 | −8.4 | 0.002 | 0.07 | .979 | −0.0 |
| Trans fat claim | −0.688** | 0.097 | <.001 | −50.0 | −0.291** | 0.075 | <.001 | −25.5 |
| Fiber claim | 0.144 | 0.096 | .132 | 15.0 | 0.06 | 0.085 | .484 | 5.8 |
| Organic claim | 0.338** | 0.067 | <.001 | 39.9 | 0.458** | 0.063 | <.001 | 57.8 |
| Sodium claim | −0.066 | 0.068 | .331 | −6.6 | −0.065 | 0.066 | .324 | −6.5 |
| Sugar claim | 0.307 | 0.346 | .374 | 28.0 | 0.183 | 0.177 | .299 | 18.2 |
| Whole grain claim | −0.151 | 0.183 | .409 | −15.4 | −0.177 | 0.277 | .523 | −19.4 |
| Nutrition variables | | | | | | | | |
| Amount of calories | 0 | 0.002 | .945 | | 0.001 | 0.002 | .692 | |
| Amount of cholesterol (mg) | 0.015** | 0.003 | <.001 | | 0.019** | 0.003 | <.001 | |
| Amount of total fat (g) | 0.005 | 0.022 | .807 | | 0.01 | 0.024 | .663 | |
| Amount of saturated fat (g) | −0.066* | 0.031 | .037 | | −0.106** | 0.032 | .001 | |
| Amount of sodium (mg) | 0 | 0 | .36 | | −0.001 | 0.001 | .109 | |
| Amount of carbohydrates (g) | 0.003 | 0.008 | .757 | | −0.004 | 0.009 | .694 | |
| Private label | −0.381** | 0.06 | <.001 | −31.8 | −0.480** | 0.062 | <.001 | −38.2 |
| Total ounces | −0.008** | 0.001 | <.001 | | −0.008** | 0.001 | <.001 | |
| Constant | 2.297** | 0.103 | <.001 | | 2.359** | 0.107 | <.001 | |
| $R^2$ | 0.36 | | | | 0.35 | | | |
| *N* | 875 | | | | 875 | | | |

*Note*. * indicates statistically significant at the 5% level; ** indicates statistically significant at the 1% level.

The percentage effect of the binary variables on price was calculated using the formula in Kennedy (1981). The percentage effect is interpreted as relative percentage price differences compared to baseline (i.e., a non-private label soup product with no claims).

**Table 3.** Results of Log-Linear Price Regression for Soup including %DV of Nutrients Using IRI and Gladson Data.

| Dependent variable: natural log of cents per ounce | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | IRI | | | | Gladson | | | |
| | Parameter estimate | Standard error | *p* Value | % effect | Parameter estimate | Standard error | *p* Value | % effect |
| Health claim variables | | | | | | | | |
| Calorie claim | 0.078 | 0.067 | .247 | 7.9 | 0.041 | 0.623 | .513 | −14.2 |
| Cholesterol claim | 0.131 | 0.135 | .333 | 13.0 | 0.088 | 0.084 | .294 | 8.8 |
| Fat claim | 0.068 | 0.065 | .293 | 6.8 | 0.051 | 0.062 | .414 | 5.0 |
| Saturated fat claim | −0.087 | 0.181 | .63 | −9.8 | 0.031 | 0.069 | .651 | 2.9 |
| Trans fat claim | −0.680** | 0.096 | <.001 | −49.6 | −0.227** | 0.073 | .002 | −20.5 |
| Fiber claim | 0.169 | 0.095 | .075 | 17.9 | 0.037 | 0.083 | .655 | 3.4 |
| Organic claim | 0.299** | 0.067 | <.001 | 34.6 | 0.373** | 0.062 | <.001 | 44.9 |
| Sodium claim | −0.077 | 0.068 | .259 | −7.6 | −0.069 | 0.064 | .281 | −6.9 |
| Sugar claim | 0.312 | 0.344 | .365 | 28.8 | 0.109 | 0.172 | .526 | 9.9 |
| Whole grain claim | −0.14 | 0.182 | .442 | −14.5 | −0.108 | 0.27 | .69 | −13.5 |
| Nutrition variables | | | | | | | | |
| %DV cholesterol | 0.032** | 0.006 | <.001 | | 0.053** | 0.008 | <.001 | |
| %DV total fat | 0.012 | 0.011 | .281 | | 0.018 | 0.011 | .105 | |
| %DV saturated fat | −0.014* | 0.006 | .03 | | −0.025** | 0.006 | <.001 | |
| %DV sodium | −0.001 | 0.003 | .661 | | −0.001 | 0.003 | .591 | |
| %DV carbohydrates | −0.001 | 0.01 | .927 | | −0.014 | 0.01 | .147 | |
| %DV calcium | 0.007 | 0.007 | .309 | | 0.038** | 0.007 | <.001 | |
| %DV vitamin A | 0.003** | 0.001 | .001 | | 0.004** | 0.001 | <.001 | |
| %DV vitamin C | 0.004** | 0.002 | .005 | | 0.002 | 0.001 | .234 | |
| %DV iron | 0.001 | 0.004 | .848 | | −0.001 | 0.005 | .791 | |
| Private label | −0.390** | 0.06 | <.001 | −32.4 | −0.495** | 0.061 | <.001 | −39.2 |
| Total ounces | −0.007** | 0.001 | <.001 | | −0.008** | 0.001 | <.001 | |
| Constant | 2.214** | 0.105 | <.001 | | 2.179** | 0.105 | <.001 | |
| $R^2$ | 0.36 | | | | 0.36 | | | |
| *N* | 875 | | | | 875 | | | |

*Note.* * indicates statistically significant at the 5% level; ** indicates statistically significant at the 1% level. %DVs are based on a 2,000 calorie/day diet.

The percentage contribution effect of the binary variables on price was calculated using the formula in Kennedy (1981). The percentage effect is interpreted as relative percentage price differences compared to baseline (i.e., a non-private label soup product with no claims).

($p < .001$) indicate a lower price than brand products and suggest a 31.8% and 38.2% price discount, respectively. These results are similar to Muth et al. (2013), albeit for different products, who found lower prices per ounce for private-label than branded products for breakfast bars (35.7% lower), granola or yogurt bars (61.4% lower), hot cereals (28.5% lower), ready-to-eat cereals (3.0% lower), and granola or natural cereals (39.8% lower). The results for package size are identical between the IRI and Gladson data: each 1 ounce increase in package size is associated with a 0.8% lower price in both datasets ($p < .001$). These results reflect manufacturer pricing strategies in which larger package sizes have a lower price per ounce than smaller package sizes.

Two labeling claim coefficients were statistically significant in both the IRI and Gladson datasets. The presence of a trans fat claim (meaning low or no trans fat) on soup products is significant and negative in both datasets ($p < .001$): the estimated IRI coefficient suggests a 50.0% lower price per ounce for products having a trans fat claim compared with a 25.5% lower price per ounce using the Gladson data. One potential explanation for the difference in magnitude of the coefficients is that Gladson has more products coded as having a trans fat label, and the average product price per ounce of Gladson products with this label is $2.00 higher than the price per ounce for IRI products coded as having a trans fat label. Furthermore, the presence of an organic claim (i.e., 100% organic, organic, or made with organic) is associated with a price premium of the product in both datasets ($p < .001$). The estimated IRI model coefficient suggests a 39.9% higher price per ounce for products having an organic claim, and the Gladson model coefficient suggests a 57.8% higher price per ounce for such a claim.

Two of the coefficients for nutrient values are also statistically significant. In both the IRI and Gladson models, the amount of saturated fat is associated with a lower price per ounce, meaning that consumers place a lower value on products with higher levels of saturated fat, as expected. However, the amount of cholesterol is associated with a higher price per ounce of soup products in both models, which is counterintuitive.

Table 3 shows the results of an alternative specification of the model we examined that uses %DV instead of absolute levels of nutrients as independent variables. These models contain the additional variables calcium, iron, vitamin A, and vitamin C because these nutrients are only included on the label as %DVs unlike the other nutrients. In addition, the label does not include a %DV for calories; therefore, the level of calories in the product is not included in the alternative specification. Results of this alternative specification are consistent with the results in Table 2 with the additional variables of %DV of vitamins A and C as well as calcium being significant in this specification.

Similar to Table 2, the variables private label and total ounces have the expected signs and are within one percentage point of Table 2 results ($p < .001$). Furthermore, the trans fat and organic labeling claims coefficients for both datasets remain statistically significant ($p < .001$) with the same signs and similar magnitudes in the %DV model. For the nutrition characteristics in Table 3, which are now expressed in %DV, several similarities with the results of Table 2 are evident. First, the coefficients for %DV of cholesterol and saturated fat are statistically significant ($p < .001$) with the same signs in both IRI and Gladson as in the models using quantities of these nutrients. The difference is that %DV of vitamins A and C are positively significant in the IRI model ($p < .001$) and the %DV of vitamin A and calcium are positively significant in the Gladson model ($p < .001$). These positive associations imply a higher implicit price per ounce of a soup product with higher %DVs for vitamin A, vitamin C, and calcium.

We also pooled the datasets to test whether the implicit prices of the attributes estimated using Gladson are different than those obtained using IRI. Significant results are displayed in Table 4. For the quantity model, the interaction term on the trans fat claim was statistically significant ($p = .001$), indicating that the implicit price of the trans fat claim estimated using IRI data is statistically significantly different than that obtained using Gladson data. For the %DV model, the trans fat claim ($p < .001$), %DV of cholesterol ($p < .05$), and %DV of calcium ($p = .001$) were also statistically significantly different, indicating that the implicit prices of these variables estimated using IRI are different than those obtained using Gladson data.

Finally, because many consumers may not consider nutrient values when choosing products, we also estimated a version of the model without the nutrition variables. Table 5 shows the results of a log-linear model using only labeling claims variables as independent variables on the natural log of price per ounce. Almost all of the results are similar except that the coefficient for the calorie claim, which was not statistically significant in the prior specification, is statistically significant ($p < .01$). This result likely occurs because the calorie claim and the calorie content are highly correlated; thus, only one of these measures is needed in estimating implicit prices for label information.

**Table 4.** Statistically Significant Results of Log-Linear Price Regression for Soup Using Pooled IRI and Gladson Data.

| Dependent variable: natural log of cents per ounce | | | | | | |
|---|---|---|---|---|---|---|
| | Quantity model | | | %DV model | | |
| | Parameter estimate | Standard error | *p* Value | Parameter estimate | Standard error | *p* Value |
| Data source * trans fat claim Interaction | 0.397** | 0.122 | .001 | 0.453** | 0.121 | <.001 |
| Data source * %DV cholesterol interaction | N/A | | | −0.202* | 0.010 | 0.039 |
| Data source * %DV calcium interaction | N/A | | | −0.031** | 0.010 | 0.001 |
| $R^2$ | 0.36 | | | 0.38 | | |
| N | 1,750 | | | 1,750 | | |

*Note.* * indicates statistically significant at the 5% level; ** indicates statistically significant at the 1% level. %DVs are based on a 2,000 calorie/day diet.

**Table 5.** Results of Log-Linear Price Regression for Soup Using IRI and Gladson Data without the Nutrition Variables.

Dependent variable: natural log of cents per ounce

| | IRI | | | | Gladson | | | |
|---|---|---|---|---|---|---|---|---|
| | Parameter estimate | Standard error | *p* Value | % effect | Parameter estimate | Standard error | *p* Value | % effect |
| Calorie claim | 0.221** | 0.071 | .002 | 24.4 | 0.212** | 0.071 | .003 | 23.3 |
| Cholesterol claim | 0.188 | 0.148 | .203 | 19.4 | 0.244* | 0.096 | .011 | 27.1 |
| Fat claim | 0.039 | 0.069 | .57 | 3.7 | 0.01 | 0.071 | .894 | 0.8 |
| Saturated fat claim | 0.011 | 0.198 | .956 | −0.9 | 0.048 | 0.08 | .547 | 4.6 |
| Trans fat claim | −0.908** | 0.091 | <.001 | −59.8 | −0.628** | 0.074 | <.001 | −46.8 |
| Fiber claim | 0.229* | 0.103 | .026 | 25.1 | 0.089 | 0.094 | .346 | 8.8 |
| Organic claim | 0.443** | 0.071 | <.001 | 55.4 | 0.591** | 0.068 | <.001 | 80.2 |
| Sodium claim | −0.014 | 0.069 | .84 | −1.6 | 0.047 | 0.069 | .493 | 4.6 |
| Sugar claim | 0.592 | 0.375 | .114 | 68.5 | −0.071 | 0.197 | .719 | −8.6 |
| Whole grain claim | −0.257 | 0.199 | .197 | −24.2 | −0.038 | 0.315 | .905 | −8.4 |
| Constant | 2.031** | 0.04 | <.001 | | 1.947** | 0.042 | <.001 | |
| $R^2$ | 0.22 | | | | 0.22 | | | |
| *N* | 875 | | | | 875 | | | |

*Note*. * indicates statistically significant at the 5% level; ** indicates statistically significant at the 1% level.

The percentage contribution effect of the binary variables on price was calculated using the formula in Kennedy (1981). The percentage effect is interpreted as relative percentage price differences compared to baseline (i.e., a non-private label soup product with no claims).

## Discussion and conclusions

The purpose of this study was to develop a better understanding of the effects of product claims and nutrition information on the value of products to consumers and to compare the results between two sources of label information to determine whether the quality of the data is similar. This analysis shows that some labeling statements on soup products are associated with product prices while controlling for the effect of nutrition information and that the associations are consistent across the datasets compared in the analysis. Two labeling claim coefficients were statistically significant in both the IRI and Gladson datasets: the trans fat claim and organic claim. The estimated coefficients for the trans fat claim showed a 50.0% lower price per ounce for soup products in the IRI data compared with a 25.5% lower price per ounce using the Gladson data. These results could indicate that consumers believe that products with these claims are less tasty than products without these claims, or consumers could believe that these products have other negative attributes that are not reflected in the other claims. When we estimated an alternative specification without the nutrition variables, the coefficient for the calorie claim variable was significant and positive as expected.

Consistent with other studies using other data sources, the presence of an organic labeling statement is associated with a higher price in both datasets (Huang & Lin, 2007; Kolodinsky, 2008; Muth et al., 2013). Our results across all six models are consistent in sign, indicating that an organic labeling statement increases the price between 30% and 59% depending on the model. This result reflects consumers' increasing interest in natural and organic products. Because the IRI and Gladson estimates are reasonable and in concurrence with prior studies using other data sources, these datasets appear to be valid sources of information on product labels.

Some coefficients for quantity of nutrients or %DV from the NFL, specifically cholesterol and saturated fat, are statistically significant across datasets, which means that consumers may be responding to information about these nutrients in addition to information provided on labeling claims. The saturated fat coefficient was negative and statistically significant with relatively similar magnitudes, which is expected if consumers place lower value on unhealthier products. However, the cholesterol coefficient was positive and statistically significant with similar magnitudes across models. This result is counterintuitive because one would expect that saturated fat and cholesterol would have the same sign, indicating that consumers respond negatively to unhealthier products. It is advantageous to use %DVs instead of absolute values of quantities as variables in the model because all nutrients values are available as %DVs but only some are available as quantities. Thus, a more complete set of nutrients can be included in a model.

Whether the product is private label is an important price determinant for soups; private-label products have statistically significant lower prices than branded products, which is a result consistent with Muth et al. (2013). Furthermore, the results also reflect pricing strategies in which larger package sizes have a lower price per ounce than smaller package sizes.

Although many of the results of our analyses were similar across models and data sources, differences exist across the data sources. When we pooled the datasets to test whether the differences in the coefficients in the models were statistically significant, we found that the implicit price of the trans fat claim was statistically significantly different in both the quantity and %DV models. We also found that the %DVs of cholesterol and calcium were statistically significantly different in the %DV model. Differences in results across datasets could be due to timing of the data collection and the subjectivity of coding information from the label.

Based on the results of our analysis, the decision regarding whether to use IRI or Gladson data should depend on convenience as both of the nutrition datasets provide similar results. However, we note that IRI data have the advantage of having price information associated with each UPC, but in using Gladson data, an additional source must be used to obtain price information.

This study is subject to several limitations. For example, although we focused on 2012 data for both IRI and Gladson, the precise date when the label information was recorded is unknown. The differences in the dates of data recording likely contributed to some of the discrepancies in our analysis, as did the coding differences between the datasets. For example, the adjustment factors used to calculate total ounces were applied by soup product type (e.g., condensed, dry mix) for both the datasets; therefore, as a result of coding differences for product type, the adjustments made for UPCs in the IRI dataset are not identical to the adjustments made for UPCs in the Gladson dataset. Another limitation is that we cannot distinguish differences in values by demographic groups as can be done in estimating demand curves. A final limitation is that the prices we use represent national average prices; however, actual prices for these products could vary across regions of the country.

In future analyses, it would be useful to analyze the implicit value of labeling statements on additional food product categories. Such research would help determine whether the same differences exist between the IRI and Gladson datasets across food product categories. Also, once the new NFL is included on products, future analyses could focus on whether the changes have affected how consumers value products based on the label information. In particular, changes in the serving sizes of many foods will have dramatic effects on the amount or %DV of nutrients included on the label, and foods may no longer meet the per-serving requirements for including particular health claims on labels.

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