Estimating the Impact of Voluntary Labeling of Trans Fats on the Market Demand for Processed Foods: A Nested PIGLOG Model Approach

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Introduction

Like most Americans, Utahns are getting fatter. According to recent public health statistics assembled by the Utah Department of Health and the Centers for Disease Control and Prevention (CDC, 2002), one-fourth of all Utah children between the ages of 5 and 14 were overweight or at risk of being overweight, and 12 percent of Utah children were obese (Adams). Results from the CDC's 2001-2003 Behavior Risk Factor Surveillance Survey indicated obesity (for all age groups collectively) increased from 11.3% in 1989 to 21.7% in 2002 nationally. Similarly, keeping pace with the national average, obesity in Utah increased from 10.7% in 1989 to 19.0% in 2002. Moreover, 54.4% of Utahns are considered overweight compared to the national average of 57%.

Choices have consequences, and, according to most allied health professionals, poor choices in food consumption may have grave health consequences over the long term (Mokdad et al., 1999, 2001, 2004). This sentiment is echoed in a recent Utah Department of Health publication entitled *Cardiovascular Disease in Utah* (2002). According to their findings, 22% of Utahns were told they had high blood pressure in 1999 compared to a national average of 25%. Similarly, 19% of Utahns were told their cholesterol level was high compared to a national rate of 21%. Moreover, cardiovascular disease is the leading cause of death in Utah, regardless of gender. Approximately 4,000 Utahns die from heart disease annually.

While lifestyle and genetics certainly affect health, the quantity, mix and type of foods we consume are culprits too (Meckler), and food is considered a controllable cardiovascular risk factor (Utah Department of Health, 2002). In particular, increased consumption of trans fats and saturated fats has been linked to a higher risk of heart disease. Although food choice is ultimately the decision of an individual consumer, the domestic food industry, sometimes dubbed Big Food, cannot be completely absolved from responsibility either. The relationship between intense food marketing and health has been the focus of several recent works critical of the powerful U.S. agribusiness industry (Nestle, 2002; Schlosser, 2002).

The domestic consumer watchdog agency responsible for labeling the content of food we purchase in the grocery store is the U.S. Food and Drug Administration (FDA). For roughly a decade the FDA, under the Nutrition Labeling and Education Act of 1990 (NLEA, implemented in May of 1994), has targeted the fat content in food. The food industry responded by supplying a wide variety of low-fat, but high-carbohydrate and high-calorie, products. Waistlines grew as caloric intake rose since we over-ate low-fat foods. With obesity now at epidemic levels, the FDA's stance is shifting to elevate the importance of calories on food product labels and target trans fats and saturated fats. Currently, labeling trans fats is strictly voluntary but soon will become mandatory. Several big agribusinesses have quickly re-engineered their products to reduce or eliminate trans fats, and now label their products as 'healthier' than rival, unlabeled products.

This is a unique and rare opportunity to quantify the impact of this 'natural experiment' in voluntary labeling on the market demand for various foods. Several product categories, such as crackers, salted snacks, cookies and margarine, present before and after comparisons as well as with and without comparisons in market demand. If the labeling is successful from an economic point of view, there will be meaningful and far-reaching policy implications for the allied health profession. For example, product labeling may curb over-consumption tendencies and help mitigate the inevitable serious health consequences of obesity. Similarly, through labeling, it may be cheaper for the government to influence the mix of foods we consume than to subsidize health care and endogenize the economic cost of lost productivity due to obesity-related illnesses (recently estimated by the Bush administration to be $117 billion annually).

The obesity epidemic is a top public health policy issue in the U.S. The President's newly established initiative called HealthierUS, his related Council on Physical Fitness & Sports and the USDA's childhood nutrition programs are carefully orchestrated to help mitigate the problem through changes to both diet and lifestyle. In the economic literature, little is known about the impact of voluntary labeling of trans fats on the market demand for processed foods as the labeling experiments in most cases are only a year along. Clearly, the Utah public health statistics regarding weight, obesity and incidence of heart disease are right in line with the national average. Utah would thus provide a representative case study from which to make inferences regarding national impacts and policy implications. National-level data would likewise be predictive of state-level initiatives.

Literature Review

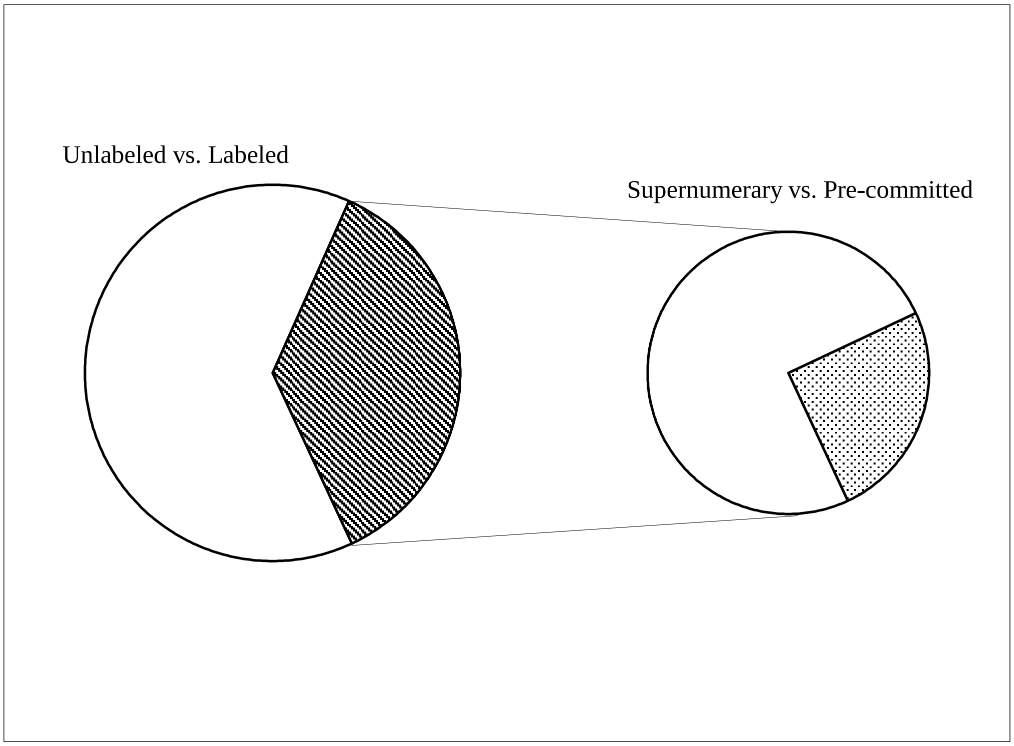
To analyze the market demand response to the introduction of voluntary trans fat labels, we build upon a well-developed microeconomic model of consumer choice that incorporates the role information plays in individual decision-making (Swartz and Strand; Smith, van Ravenswaay and Thompson; Brown and Schrader; Wessells, Miller and Brooks; Piggott; Piggott and Marsh; Kalaitzandonakes, Marks and Vickner; Marks, Kalaitzandonakes and Vickner). Mathios (2000) in particular investigated the impact of NLEA on a processed food market using a random utility model. Teisl, Bockstael and Levy (2001) used the Foster and Just (1989) framework in conjunction with an Almost Ideal Demand System (Deaton and Muelbauer) to investigate the impact of nutrient labeling in a small sample of stores in New England. Both the Mathios and Teisl et al. studies were limited in terms of data quality; lack of a representative sample and low frequency time series limit their findings.

Objectives

The principal empirical objective of this project is to determine how market shares change after voluntary trans fat labels are introduced, and to determine how important labeling information is relative to price in the purchase decision.

Perhaps the best way to understand how voluntary labeling of trans fats could impact the market demand for a processed food product is to visualize the change on shares of consumer expenditures (Figure 1). In the leftmost panel, the pie chart represents all expenditures on salted snacks and the shaded region characterizes the market share of just voluntarily labeled products. As consumers learn of the benefits of low/no trans fat products the shaded region is expected to grow. The rightmost panel describes what fraction of labeled product consumption depends on price (supernumerary) versus information contained on the label (pre-committed, denoted by the shaded region). It is expected that the shaded region in the rightmost panel will grow as well when consumers learn of the benefits of low/no trans fat products. This would imply that non-price information (i.e., the voluntary label), ceteris paribus, drives choice. It is the intent of the public health profession to alter consumption patterns this way. Knowledge gained regarding the voluntary regime would be crucial for the implementation of a mandatory one. Next, a statistical model of demand is proposed to empirically test if trans fat information contained on the voluntary label increases the market share for labeled products and whether the role of the label is more important than price.

Figure 1. Expenditure Shares for Salted Snacks



Procedures and Methods

Once detailed, representative data is purchased for salted snacks and crackers, an empirical demand system will be estimated and labeling hypotheses will be tested. The empirical demand system stems from a well-developed microeconomic model of consumer choice. Let x_i be the quantity consumed of food product *i*, where $i = 1,\ldots,n$. Then $\mathbf{x}$ is a $n \times 1$ vector with elements x_i. Further, let q_i be the elements of the $n \times 1$ vector $\mathbf{q}$, where q_i is the perceived quality of good x_i. Perceived product quality may be influenced by a myriad of non-price factors including, but not limited to, product labels, the media, food safety recalls, advertising, and brand image. Let s_i represent an index characterizing the trans fat content of food product *i* such that $\frac{\partial q_i}{\partial s_i} < 0$; higher levels of trans fat lead to a lower level of perceived quality. More generally, we let $\mathbf{q}(\mathbf{s})$.

As is the case for most applied demand studies, data is typically unavailable to construct a complete demand system. Thus, we assume the consumer's utility function is weakly separable between processed foods and all other goods. In our problem, the individual consumer chooses $\mathbf{x}$ to maximize

$$U(\mathbf{x},\mathbf{q}) \tag{1}$$

subject to the linear budget constraint

$$\mathbf{p'}\mathbf{x} = M \tag{2}$$

where $U(\cdot)$ is the utility function, $\mathbf{p'}$ is a $1 \times n$ vector of prices of food, and M is total expenditure for processed food.

The solution to the consumer's problem results in a vector of n Marshallian or uncompensated demand functions

$$\mathbf{x}^{m}(\mathbf{p}, M, \mathbf{q}) \tag{3}$$

with the usual properties. Because $\mathbf{q}(\mathbf{s})$, we may express the Marshallian demand functions as

$$\mathbf{x}^{m}(\mathbf{p}, M, \mathbf{s}) \tag{4}$$

so that the Marshallian demands now include a vector of shift parameters based on information contained on labels as well as other shifters such as the media, seasonality and a time trend.

Substituting (4) into the utility function $U(\cdot)$, we obtain the indirect utility function $V(\mathbf{p}, M, \mathbf{s})$. Others in the literature (i.e., Teisl, Roe and Hicks, equation (3), p. 344) begin their model development with essentially this expression for the indirect utility function. Inverting the indirect utility function, we obtain the consumer's expenditure function

$$E(\mathbf{p}, u, \mathbf{s}). \tag{5}$$

By applying Shephard's lemma to the expenditure function

$$\frac{\partial E(\mathbf{p}, u, \mathbf{s})}{\partial \mathbf{p}} = \mathbf{x}^{h}(\mathbf{p}, u, \mathbf{s}) \tag{6}$$

we obtain the n Hicksian demand functions and express them in expenditure share form in the $n \times 1$ vector $\mathbf{w}$. The presence of the informational shift variables $\mathbf{s}$ in (6) presents a knotty problem when estimating $\mathbf{w}$.

The use of translating and scaling techniques have long been used to incorporate shift variables such as demographics into singular expenditure systems without violating Closure Under Unit Scaling or CUUS (Pollak and Wales; Lewbel). The notion of CUUS is maintained when the estimated parameters, such as the usual α, γ, and β parameters in the Almost Ideal Demand System (Deaton and Muelbauer), do not depend on the data's scaling, especially the scaling of the data related to the shift variables themselves (Alston, Chalfant, and Piggott; Piggott; Piggott and Marsh). Piggott's (2003) most general nested PIGLOG framework is chosen as it nests 13 different demand systems into a single framework. Rewrite (5) as the sum of pre-committed expenditures and supernumerary expenditures; pre-committed expenditures now resolve the problem of incorporating shift variables in a demand system as given by

$$E(\mathbf{p},u) = \mathbf{p'c} + E^*(\mathbf{p},u) \tag{7}$$

and

$$E^*(\mathbf{p},u) = \exp\left[\frac{\delta + \boldsymbol{\alpha}'\hat{\mathbf{p}} + (1/2)\hat{\mathbf{p}}'\boldsymbol{\Gamma}\hat{\mathbf{p}} + 2\sum_{a=1}^{A}\left\{u_a \cos\left(\lambda \mathbf{k}_{\mathbf{a}}'\hat{\mathbf{p}}\right) - v_a \sin\left(\lambda \mathbf{k}_{\mathbf{a}}'\hat{\mathbf{p}}\right)\right\} + u\beta_0 \prod_{k=1}^{N} p_k^{\beta_k}}{\boldsymbol{\alpha}'\mathbf{i} + \hat{\mathbf{p}}'\boldsymbol{\Gamma}\mathbf{i}}\right] \tag{8}$$

where $\hat{\mathbf{p}}$ is a $n \times 1$ vector of natural logarithms of prices, $\mathbf{k}_{\mathbf{a}}$ is a multi-index, λ is a scale parameter, and $\mathbf{i}$ is a $n \times 1$ vector of ones. The remaining parameters are the usual parameters to be estimated in a demand system, including the unobservable pre-committed quantities $\mathbf{c}$ (i.e., a linear combination of the non-price shift variables). Expressed in share form, we have

$$\mathbf{w} = \left(\frac{1}{M}\right)\boldsymbol{\varphi} + \left(\frac{M^*}{M}\right)\left[\frac{\boldsymbol{\alpha} + \boldsymbol{\Gamma}\boldsymbol{\pi}^* + \boldsymbol{\beta}\left[d(\mathbf{p})\log M^* - \log\tilde{P}\right] - 2\lambda\sum_{a=1}^{A}\left\{u_a \cos\left(\lambda \mathbf{k}_{\mathbf{a}}'\hat{\mathbf{p}}\right) - v_a \sin\left(\lambda \mathbf{k}_{\mathbf{a}}'\hat{\mathbf{p}}\right)\right\}\mathbf{k}_{\mathbf{a}}}{d(\mathbf{p})}\right] \tag{9}$$

where $\log\tilde{P} = \delta + \boldsymbol{\alpha}'\hat{\mathbf{p}} + (1/2)\hat{\mathbf{p}}'\boldsymbol{\Gamma}\hat{\mathbf{p}} + 2\sum_{a=1}^{A}\left\{u_a \cos\left(\lambda \mathbf{k}_{\mathbf{a}}'\hat{\mathbf{p}}\right) - v_a \sin\left(\lambda \mathbf{k}_{\mathbf{a}}'\hat{\mathbf{p}}\right)\right\}$, $\boldsymbol{\pi}^* = \log\left[\left(\frac{1}{M^*}\right)\mathbf{p}\right]$, $d(\mathbf{p}) = \boldsymbol{\alpha}'\mathbf{i} + \hat{\mathbf{p}}'\boldsymbol{\Gamma}\mathbf{i}$, M is total expenditure on the processed foods under investigation in this project, and $M^* = M - \mathbf{p'c}$ represents supernumerary expenditures (i.e., total expenditure less pre-committed expenditure). Consider the i^{th} pre-committed quantity function (i.e., the i^{th} element of $\mathbf{c}$) is given by

$$c_i = c_{i1} + c_{i2}(trend) + c_{i3}(seasonality) + c_{i4}(media) + c_{i5}(trans\ \ fat\ \ label) \tag{10}$$

where c_{i1}, c_{i2}, c_{i3}, c_{i4} and c_{i5} are unknown parameters to be estimated. The pre-committed quantities framework accounts for a linear time trend, seasonality, the media and the presence of a trans fat label.

Econometric Estimation and Autocorrelation Correction

Following Berndt and Savin, with appropriate substitutions and addition of subscripts representing weekly time periods, the nested PIGLOG model of processed food demand given by (9) may be rewritten more compactly as

$$\mathbf{w_t} = \mathbf{\Pi z_t} + \boldsymbol{\upsilon}_\mathbf{t} \tag{11}$$

where $\mathbf{w_t}$ is a $n \times 1$ vector of conditional expenditure shares of processed food, $\mathbf{\Pi}$ is a $n \times K$ matrix of unknown parameters, $\mathbf{z_t}$ is $K \times 1$ vector of explanatory variables, $\boldsymbol{\upsilon}_\mathbf{t}$ is a $n \times 1$ vector of stochastic disturbances governed by the following process

$$\boldsymbol{\upsilon}_\mathbf{t} = \mathbf{R}\boldsymbol{\upsilon}_\mathbf{t-1} + \boldsymbol{\varepsilon}_\mathbf{t} \tag{12}$$

for time $t = 2,\ldots,T$, $\mathbf{R}$ is a $n \times n$ matrix of unknown parameters and $\boldsymbol{\varepsilon}_\mathbf{t}$ is a $n \times 1$ vector of residuals. Further it is assumed $\{\boldsymbol{\varepsilon}_\mathbf{t}\}$ is distributed *iid* $N(\mathbf{0}, \mathbf{\Sigma})$ for $t = 2,\ldots,T$.

Let $\boldsymbol{\iota}'$ be a $n \times 1$ vector of ones. Because the nested PIGLOG model of food is singular (i.e., its shares sum to one), $\boldsymbol{\iota}'\mathbf{w_t} = 1$ for $t = 1,\ldots,T$. The adding up conditions also imply $\boldsymbol{\iota}'\mathbf{\Pi} = [1\ 0\ 0\ \cdots\ 0]$, $\boldsymbol{\iota}'\boldsymbol{\upsilon}_\mathbf{t} = 0$ for $t = 1,\ldots,T$ and, since $\boldsymbol{\upsilon}_\mathbf{t-1}$ and $\boldsymbol{\varepsilon}_\mathbf{t}$ are independent, $\boldsymbol{\iota}'\mathbf{R} = k'$. The final result indicates the *n* column sums of $\mathbf{R}$ equal the same constant.

The autocorrelation correction procedure for singular equation systems as developed by Berndt and Savin is quite flexible and subsumes several interesting special cases. When the $n \times n$ elements of matrix $\mathbf{R}$ are set to zero, this represents the case of no autocorrelation such that $\boldsymbol{\upsilon}_\mathbf{t} = \boldsymbol{\varepsilon}_\mathbf{t}$ and $\mathbf{w_t} = \mathbf{\Pi z_t} + \boldsymbol{\varepsilon}_\mathbf{t}$. For the present data set this assumption is implausible and, hence, introduces an omitted variable bias in the matrix of parameter estimates $\mathbf{\Pi}$. If the *n* elements on the diagonal of matrix $\mathbf{R}$ are restricted to be the same constant and the off-diagonal elements are restricted to all be zeros, this single parameter estimate for serial correlation correction will equal

k' since $\boldsymbol{\iota}'\mathbf{R} = k'$. For the present study $\mathbf{R}$ is kept in its most general form with n^2 unique elements. This model is compared to the null hypothesis of no autocorrelation and the null hypothesis of a single parameter estimate for serial correlation correction (i.e., $\boldsymbol{\iota}'\mathbf{R} = k'$).

In our empirical application, consider the case where we have four processed food products ordered as follows: labeled salted snacks, unlabeled salted snacks, labeled crackers and unlabeled crackers. This results in $n = 4$ conditional expenditure share equations. Since the system is singular as the shares sum to one, the 4th equation is dropped from the estimation. Equations (11) and (12), with the 4th equation dropped may be rewritten as

$$\mathbf{w}_{\mathbf{t}}^{4} = \mathbf{\Pi}_4 \mathbf{z}_{\mathbf{t}} + \boldsymbol{\upsilon}_{\mathbf{t}}^{4} \tag{13}$$

and

$$\boldsymbol{\upsilon}_{\mathbf{t}}^{4} = \mathbf{R}_4 \boldsymbol{\upsilon}_{\mathbf{t-1}}^{4} + \boldsymbol{\varepsilon}_{\mathbf{t}}^{4} \tag{14}$$

for $t = 2,\dots,T$. Since $\mathbf{R}_4$ is now a 3×4, equations (13) and (14) are not estimable. Recognizing $\boldsymbol{\iota}'\boldsymbol{\upsilon}_{\mathbf{t}} = 0$, this is remedied (Berndt and Savin) by the following transformation

$$\overline{\mathbf{R}}_4 = \begin{bmatrix} (R_{11} - R_{14}) & (R_{12} - R_{14}) & (R_{13} - R_{14}) \\ (R_{21} - R_{24}) & (R_{22} - R_{24}) & (R_{23} - R_{24}) \\ (R_{31} - R_{34}) & (R_{32} - R_{34}) & (R_{33} - R_{34}) \end{bmatrix}$$

so that $\overline{\mathbf{R}}_4$ is now a 3×3. Now the $n-1$ column sums in $\overline{\mathbf{R}}_4$ each equal zero. Substituting $\overline{\mathbf{R}}_4$ into (14) we obtain

$$\boldsymbol{\upsilon}_{\mathbf{t}}^{4} = \overline{\mathbf{R}}_4 \boldsymbol{\upsilon}_{\mathbf{t-1}}^{4} + \boldsymbol{\varepsilon}_{\mathbf{t}}^{4} \tag{15}$$

Further substituting (15) into (13), we obtain the estimable, theoretically consistent, conditional nested PIGLOG model of processed food as given by

$$\mathbf{w}_{\mathbf{t}}^{4} = \overline{\mathbf{R}}_4 \mathbf{w}_{\mathbf{t-1}}^{4} + \mathbf{\Pi}_4 \mathbf{z}_{\mathbf{t}} - \overline{\mathbf{R}}_4 \mathbf{\Pi}_4 \mathbf{z}_{\mathbf{t-1}} + \boldsymbol{\varepsilon}_{\mathbf{t}}^{4} \tag{16}$$

for $t = 2, \ldots, T$. Using PROC MODEL routine in the SAS ETS module, we jointly estimate the parameters in $\mathbf{\Pi}_4$ and $\overline{\mathbf{R}}_4$ using nonlinear iterated seemingly unrelated regressions (Gallant). This model is highly nonlinear for several reasons. First, implicit in (16) is the nonlinear functional form given by equation (9). Second, $\mathbf{\Pi}_4$ and $\overline{\mathbf{R}}_4$ not only enter into (16) individually, but as a product as well. When the $\{\boldsymbol{\varepsilon}_{\mathbf{t}}\}$ is distributed *iid* $N(\mathbf{0}, \mathbf{\Sigma})$ for $t = 2, \ldots, T$, it can be shown that the maximum likelihood estimator and the iterated seemingly unrelated regressions estimator are identical (Berndt and Savin; Gallant). Finally, $\overline{\mathbf{R}}_4$ is given in its most general form for first-order autocorrelation correction. The parameter estimates for $\mathbf{\Pi}_4$ and $\overline{\mathbf{R}}_4$ will be reported and thoroughly discussed.

Hypothesis Testing of Consumer Response to Information

Germane to this study is the cross-equation hypothesis test in which the three equations manifested in (16) are estimated with (10) versus the restricted model where (10) is replaced with

$$c_i = c_{i1} + c_{i2}(trend) + c_{i3}(seasonality) + c_{i4}(media) \qquad (17)$$

for $i = 1,\ldots,4$ such that $c_{15} = c_{25} = c_{35} = c_{45} = 0$. The restricted model imposes the null hypothesis that the trans fat label has no impact on the aggregate consumer behavior in the market for food. This test is considered to be superior to an inspection of the parameter by parameter asymptotic *t*-statistics. Gallant outlines a procedure to test this cross-equation restriction using a likelihood ratio test. The likelihood ratio statistic for our model is given by

$$LR = T\left(\ln\left|\Sigma_\infty^R\right| - \ln\left|\Sigma_\infty^U\right|\right) \qquad (18)$$

where *T* is the number of time periods net of any lags, Σ_∞^R is the 3×3 asymptotic covariance matrix for the restricted model and Σ_∞^U is the 3×3 asymptotic covariance matrix for the unrestricted model. Let K^U be the number of estimated parameters in the unrestricted model, K^R be the number of estimated parameters in the restricted model, M be the number of equations in the system, and $F_\alpha = F^{-1}\left(1-\alpha; K^U - K^R; MT - K^U\right)$ be the upper $\alpha \times 100\%$ critical point of the *F*-distribution. If $LR < \left(K^U - K^R\right)F_\alpha$ then we fail to reject the null hypothesis and conclude the restricted and unrestricted models are statistically no different. The outcome of the hypothesis tests would quantify whether or not the trans fat label affected the demand for the labeled products. Referring to Figure 1, the results of the likelihood ratio test would statistically discern whether or not expenditure shares increased for the labeled products (the shaded region in the leftmost panel) and determine the relative importance of the label versus price in the purchase decision (the shaded region in the rightmost panel).

Note: Empirical results will be available prior to the AAEA Annual Meeting in Providence, RI.

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