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Noisy Information Signals and Endogenous Preferences for Labeled Attributes

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Consumer preferences for labeled products are often assumed to be exogenous to the presence of labels. However, the label itself (and not the information on the label) can be interpreted as a noisy warning signal. We measure the impact of "contains" labels and additional information about the labeled ingredients, treating preferences for labeled characteristics as endogenous. We find that for organic-food shoppers, the "contains" label absent additional information serves as a noisy warning signal leading them to overestimate the riskiness of consuming the product. Providing additional information mitigates the large negative signaling effect of the label.

Key words: demand shifts and rotations, experimental economics, labeling, signaling effect, willingness-to-pay

Introduction

One of the most widely discussed issues in the food industry today is whether labels should be required for certain types of product ingredients or production methods. For instance, twenty-nine U.S. states currently have proposed bills requiring genetically modified organism (GMO) labeling. Most of the ingredients under discussion are classified as credence attributes.[1] An unintended consequence of mandatory labeling of negatively perceived credence characteristics is that it potentially sends a signal to consumers that they should either avoid or be worried about the safety of the product. For example, the label "contains GMO ingredients" may make some consumers reluctant to purchase the GMO-product—not because of objectively definable inherent risks of such ingredients but simply because the label itself signals a warning about the product. A lack of information about products containing GMO ingredients, as well as what specific risks they entail, may lead to the perception that the consumption of such products is much riskier than it actually is. Thus, if consumers perceive the label itself (and not the information in the label) as a warning signal, then the assumption that consumer preferences are exogenous to labeling no longer holds. This paper examines the impact of credence attribute labeling on consumer uncertainty and, consequently, on demand. We do this by modeling the preferences for labeled characteristics as endogenous and by considering the possibility that labels induce noisy signals about the safety of labeled products.

In most theoretical (e.g. Crespi and Marette, 2003; Fulton and Giannakas, 2004) and empirical (e.g. Fox, Hayes, and Shogren, 2002; Hu, Veeman, and Adamowicz, 2005) economic models of food labeling, consumer preferences for labeled food products are assumed to be exogenous to

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[1] Attributes of consumer goods can be divided into three broad categories: search, experience, and credence attributes. Search attributes can be determined by inspection prior to purchase, whereas experience attributes refer to those qualities that are impossible to determine prior to purchase but can be ascertained by the consumer after the purchase (Nelson, 1974). Unlike search and experience attributes, credence attributes generally cannot be verified by the typical consumer, either before or after purchase; such verification is impractical if not impossible (Darby and Karni, 1973). For example, consumers are unlikely to be able to verify whether organic milk was actually produced under the conditions implied by the term "organic" or whether an item actually does contain genetically modified organisms (GMOs).

the presence of labels. In other words, consumers may have preferences for labeled attributes, but mere exposure to a label does not affect preferences. The literature on endogenous consumer preferences is rather sparse. Artuso (2003) develops a theoretical model to examine optimal product regulation in the case of endogenous consumer product acceptance and argues that labeling is only welfare improving when accompanied by measures to assure consumers of the safety of labeled products. Lusk and Rozan (2008) use survey data to show that consumer beliefs about the safety of foods containing GMO ingredients are impacted by the introduction of mandatory labeling policies. However, in an experimental study, Costanigro and Lusk (2014) find little evidence of a signaling effect from exposure to labels.

By contrast, out study treats the label as a potential noisy information signal and suggests that a consumer's willingness to pay (WTP) is influenced by his or her level of uncertainty, which in turn is influenced by the perceived quality of the information provided: noisier information signals give rise to greater uncertainty in consumers' preferences for a product. The main question we address is whether a decrease in WTP caused by a mandatory label reflects existing consumer preferences or whether the label itself induces concern about the labeled ingredients.

Conventional economic demand modeling approaches typically do not specify the precise microeconomic mechanism through which new information might affect demand. However, the theoretical model of Johnson and Myatt (2006) describes how preference heterogeneity and the uncertainty caused by a noisy information signal might affect the shape of the demand curve and how these changes in demand can be disaggregated into shift and rotation components. Our study tests for shift or rotation effects as a result of information by using an empirical model that captures the theoretical effects derived by the Johnson and Myatt model. We use data collected from an economic experiment, which evaluated the impact of the label "contains X" both with and without additional negative information about *X* (where *X* is a credence attribute viewed by at least some consumers as negative). In our empirical model, heterogeneous interpretations of "contains" labels are responsible for how observed demand shifts and rotates.

A number of studies have applied Johnson and Myatt's theoretical model to analyze shifts and rotations of demand. For example, Zheng and Kaiser (2008) use the framework to study advertising effects in a beverage demand systems model, while Rickard et al. (2011) apply it to estimate the effects of commodity-specific and broad-based advertising. Richards and Nganje (2014) estimate the welfare effects of food safety recalls, and Richards, Allender, and Fang (2013) study the demand for cage-free eggs after exposure to political animal-welfare advertisements. However, to our knowledge, no other studies have applied this model in an information-provision and food-labeling setting and, more importantly, none have applied an expanded version of the model to include product idiosyncrasy and information noise, allowing for the identification of labels' signaling effect. The latter is the main contribution of our paper.

There is a wide range in consumers' potential reactions to food labeling. Some consumers are suspicious about the environmental and health effects (on both humans and animals) of biotechnology and other production methods. Some are apprehensive of foods containing GMOs and/or products produced with the use of antibiotics, irradiation, or ingredients perceived to be unhealthy or unnatural in some other way (Fox and Weber, 2002; Lusk et al., 2005; Liaukonyte et al., 2013). These concerns have fueled a movement that calls for stricter food-labeling requirements as well as the provision of often-negative information about such ingredients. At the same time, the level of consumer knowledge about such products' actual production methods remains quite low: only 30% of Americans know that foods produced using biotechnology are available in supermarkets, while only 25% of Americans believe they have ever eaten food containing GMO ingredients (International Food Information Council, 2012; Hallman et al., 2003). Moreover, the information that is available about these production processes and ingredients is usually presented in a variety of sources and is often conflicting (Huffman et al., 2004; Rousu et al., 2007) and alarmist (Sexton, 2012), causing confusion and concern.

A consumer's existing beliefs and the quality of the information signals in question play important roles in how that consumer evaluates the information. Using a Bayesian framework, Huffman et al. (2007) and Lusk et al. (2004) show that people with strong prior beliefs are less influenced by additional information than those with weaker prior beliefs, whereas Hayes et al. (1995) point out that the subjectively perceived quality of information might affect the weight individual consumers place on that information. However, it is unclear from these studies how prior beliefs and information quality interact to determine whether labels might play a signaling role. Our paper addresses this issue explicitly.

The signaling nature of labels helps to explain a seemingly counterintuitive phenomenon: the idea that a consumer's willingness to pay for a product might increase when, in addition to a "contains X" label, negative information is provided about the nature of a disliked credence attribute. The more unbiased and informative the information is perceived to be by the consumer, the less noise it contains, leaving the consumer in a less uncertain state about his or her preferences for the product. We use the theoretical insights on consumer reaction to uncertainty and the nature of labeling in our experiment to identify separately the effects of uncertainty and product idiosyncrasy on both the mean WTP and the dispersion of consumer valuations.

Buyers of organic, healthy, and natural food products tend to be the most outspoken supporters of mandatory labeling policies and tend to have the strongest prior beliefs about biotechnology (Bittman, 2011; Gillam, 2012). However, there is also a large cohort of consumers who can be categorized as indifferent about their foods' ingredients or production practices (Wilcock et al., 2004). Accordingly, we examine the signaling effect of labels on two distinct, self-identified consumer groups: (1) conventional shoppers and (2) those who buy mostly organic products and/or frequently shop in health food stores. This approach is similar to that of Huffman et al. (2007), who use survey questions to exogenously divide consumers into groups and to study labels' effects on each group. Differentiating the consumer cohorts and showing that they react differently to labels allows us to assess the practicality of certain labeling policies and how they might be targeted at different markets depending on each market's consumer composition.

Our results indicate that WTP is negatively impacted by labels with the phrase "contains X," both with and without additional negative information regarding credence attribute X. The organic-food shoppers in our study expressed their largest decrease in WTP when shown a label with no additional negative information (relative to the control group, which was shown products with no labels and no additional information.) By contrast, the conventional-food shoppers expressed their largest decrease in WTP in response to a product that contained a label and additional negative information. We estimate the parameters representing the shifts and rotations of demand for the two consumer types and show that these estimates provide insights into how consumers' prior beliefs are affected by information supplied in a particular treatment. We show that consumers' different uncertainty levels drive the differences in mean WTP and dispersion. Additionally, and perhaps most importantly, we provide empirical and theoretical evidence that the "contains X" label without any additional information serves as a noisy warning signal for the organic-food shoppers, leading them to perceive that the consumption of labeled products is riskier than it actually is. Interestingly, the label's significant negative signaling effect on the organic-food shoppers is largely mitigated by additional information, which ultimately reduces the noise in the information signal. The same result does not hold for conventional food consumers, which suggests that food marketers should consider different marketing strategies for each type of consumer segment should mandatory labeling become law.

Theoretical Framework

Shifts and Rotations of Demand

Our model builds upon the theoretical framework of Johnson and Myatt (2006), who look at the effects of advertising on consumer demand. This framework provides a basis for studying demand curve transformations that stem not only from changes in the mean consumer valuation but also from changes in the dispersion of valuations, which rotate the demand curve. Information about product attributes that are universally attractive to all consumers leads to an outward shift of demand. Rotations of the demand curve, on the other hand, occur due to "real information" (in their terminology) that highlights the actual attributes of the product and allows consumers to find out whether those attributes are consistent with their preferences. If advertising does indeed provide real information, then the dispersion of valuations for the product is likely to rise. Consumers who value the product relatively highly before the advertisement will like it even more after the ad, and those who value it less will like it even less, as demand rotates clockwise.

In our application of Johnson and Myatt (2006), we use a similar model to examine the signaling effect of labels. In our setting, labels and information associated with labels are allowed to shift and rotate the demand curve simultaneously. As more and better quality information about specific labeled attributes is presented, some consumers are turned off by the product, while others' demand increases because they value the highlighted attributes. As a result, such information increases the dispersion of consumers' WTP, thereby rotating the demand curve clockwise. The reveal of information through labels is also allowed to shift the demand inward by alerting consumers about the existence of a generally disliked credence attribute.

More formally, we assume that there is a unit mass of consumers, each willing to pay up to θ for one unit of a particular product. This maximum willingness, θ, is drawn from the distribution $F_s(\theta)$ and is twice continuously differentiable in both s and θ, with support on a $(\underline{\theta}_s, \overline{\theta}_s)$ interval, where $s \in S = [s_l, s_h]$ indexes a family of distributions. Thus, s governs the shape of the valuation distributions, and an increase in s represents a spread in the density of θ, which leads to a clockwise rotation of $F_s(\theta)$ around some point $\breve{\theta}$. The effect of such spread in valuations on the distribution of market demand can be expressed through the inverse demand curve $P_s(q) = F_s(1-p)$, where q is the proportion of consumers willing to purchase the product at price p and is given by $q = 1 - F_s^{-1}(p)$. In this framework, the effect of a change in s is similar to that of the changes in the actual distribution of valuations and rotates the inverse demand curve. If the demand q is below some pivotal point $\breve{q}$, then $\frac{\partial P_s(q)}{\partial s} > 0$; an increase in the spread of valuations causes a rise in the market price and vice versa. In other words, if q is below the pivotal point $\breve{q}$, then greater dispersion in valuations causes the valuation of the marginal consumer, and hence the market price, to rise; if q is above $\breve{q}$, greater dispersion in valuations causes the market price to fall.

Figure 1 presents the changes in the cumulative distribution (CDF) function and corresponding demand functions representing changes in valuation dispersion and means. Specifically, panel (a) illustrates the counterclockwise CDF rotation, which leads to the counterclockwise demand rotation represented in panel (c). Both sets of these rotations are associated with a decreased dispersion in WTP among consumers. Panels (b) and (d) illustrate scenarios in which both shift and rotation effects happen simultaneously. In the theoretical scenarios demonstrated in panels (b) and (d), demand and CDF shift to the left and rotate clockwise, representing a situation where mean valuations decrease, while the standard deviation (dispersion) of valuations increases.

Uncertainty, Product Idiosyncrasy, and Information Signals

The theoretical model outlined above provides insights into how the shape of the demand curve changes in response to varying degrees of information. While these comparative statics by themselves contribute to our understanding of how labels and secondary information might

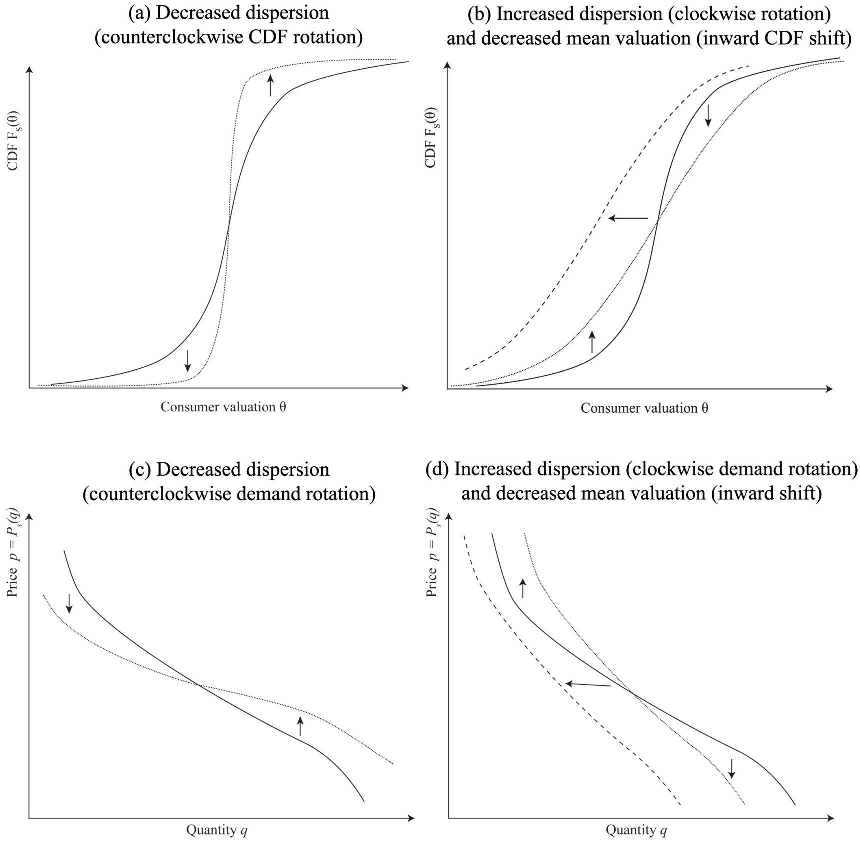

Figure 1. Theoretical Illustration of CDF Rotations and Shifts

impact demand, it does not tell us anything about the underlying microfoundations consistent with such consumer behavior. Accordingly, we expand the theoretical framework presented above by introducing two key parameters: 1) ρ^2, the degree of product idiosyncrasy, and 2) ξ^2, the information signal noise.

Suppose the prior distribution of Bayesian consumers' true monetary utility for a product satisfies $\omega \sim N(\mu, \rho^2)$, where ρ^2 is the dispersion of true consumer payoffs and can be thought of as the degree of heterogeneity or idiosyncrasy of preferences across product attributes. For example, small ρ^2 implies that all consumers value all characteristics similarly, and large ρ^2 represents highly variable valuations implying that consumer preferences for that product are highly divided: some people like the product a lot, while others absolutely hate it. Similar to Johnson and Myatt (2006), we also assume that this valuation distribution can be influenced by additional external information signals. In other words, after receiving an information signal about the product or its attribute, a consumer updates her prior. For example, revealing that a product contains GMO ingredients might allow the consumer to better match product attributes to her preferences; if consumers have heterogeneous preferences for GMO ingredients, the idiosyncrasy of the product will increase, but if all consumers value (or dislike) these ingredients similarly, idiosyncrasy will fall. Therefore, in our setting additional information may increase or decrease ρ^2 depending on whether the additional information signal introduces the existence of universally disliked attribute (decrease in ρ^2, demand rotates counterclockwise, CDF becomes steeper) or an attribute consumers have heterogeneous preferences over (increase in ρ^2, demand rotates clockwise, CDF becomes flatter).

The second parameter introduced is ξ^2, the noise of the information signal. Conditional on the true unknown valuation ω, the information signal is assumed to be noisy and follows the distribution $x \sim N(\omega, \xi^2)$, where ξ^2 can be interpreted as an approximation of noise in the information signal. We can also think about ξ^2 as the level of uncertainty about the product quality that arises due to the information provided: the more (as perceived subjectively) unbiased and informative the information is, the less noise it contains, leaving the consumer in a less uncertain state about her own preferences for the product. For example, when a consumer is provided with a noisy information signal about which she has little factual prior knowledge, her ability to evaluate its validity and implications is low; thus, the level of uncertainty is higher than when no such noisy information is provided. In general, a noisier information signal will increase uncertainty.

Given the information signal x, a Bayesian consumer updates her beliefs to obtain posterior beliefs over ω. Then, with λ being a risk aversion level, consumer's willingness to pay for the product will be the certainty equivalent[2]

$$\theta(x) = \frac{1}{1+\rho^2/\xi^2}\left[\mu - \frac{\lambda\rho^2}{2}\right] + \frac{\rho^2/\xi^2}{1+\rho^2/\xi^2}x. \tag{1}$$

To characterize the CDF of valuations, we consider the distribution of $WTP(x)$ as a function of these parameters. If realized information signals follow the distribution $x \sim N(\mu, \rho^2 + \xi^2)$ and consumer valuations are linear in x, then they satisfy (see Appendix B for more details)

$$WTP \sim N\left(\mu - \frac{\lambda\rho^2}{2(1+\rho^2/\xi^2)}, \frac{\rho^4/\xi^2}{1+\rho^2/\xi^2}\right). \tag{2}$$

As a result, the CDF and inverse demand curve are indexed by both precision signals: ρ^2 and $\frac{1}{\xi^2}$. Below we discuss the comparative statics with respect to these two parameters, examining how changes in the signal's noise, and product idiosyncrasy affect consumer's WTP for an item.

Mean (Shifts of CDF)

Keeping λ constant,[3] the mean valuation, $\mu - \frac{\lambda\rho^2}{2(1+\rho^2/\xi^2)}$, is dependent on two parameters: ρ^2 and ξ^2. For a fixed ρ^2, the mean valuation is decreasing in ξ^2: a noisier information signal that raises more concern and uncertainty lowers mean WTP (higher risk premium from uncertainty). For a fixed ξ^2, the mean valuation is also decreasing in ρ^2: increasing the product idiosyncrasy reduces the mean WTP. If a product is not universally liked, the purchase becomes more of a gamble.

Standard Deviation (Rotations of CDF)

Standard deviation, $\sqrt{\frac{\rho^4/\xi^2}{1+\rho^2/\xi^2}}$, is increasing in ρ^2: the valuation distribution is higher when the product design is more idiosyncratic (higher ρ^2) but decreasing in ξ^2; if information is noisier, the valuation dispersion falls. When the information signal is less noisy, or as the degree of product idiosyncrasy due to the provided information increases, consumers are better able to match ideal product attributes to their own preferences. In such cases, some consumers like a product more because of the new information while other consumers like it less. The higher the noise of the information signal, the more difficult it is for the consumer to identify and evaluate the actual product attributes and to evaluate and place a value on the actual product.

[2] See Appendix B for more detailed derivation of these mathematical relationships.
[3] Note that λ being constant across all treatments is a reasonable assumption, as it is an inherent risk-aversion parameter that is constant for the same group of people across treatments. However, this does not limit us to have different λs (risk-aversion levels) for different consumer groups.

The theoretical model of Johnson and Myatt (2006) describes how heterogeneity in preferences and information noise can explain the phenomenon of demand curve rotation and shifts but does not immediately suggest an empirical test. We show how a test of this theory emerges naturally from an interpretation of changes in consumers' observed WTP in reaction to labels and additional information. Next, we describe the data gathered during an economic experiment that will be used to test the theoretical insights outlined above.

Experimental Design

A total of 169 adult, non-student subjects participated in the economic experiment. Subjects were paid $25 for participating, and they could use part of the cash payment to bid on several food items that were presented in a series of auctions.

Subjects were randomly assigned to one of the three information treatments: T0: control (no label + no information); T1: label "contains X" + no information; and T2: Label "contains X" + negatively framed information about credence attribute X. Negatively framed information in the T2 treatment summarized the views of the critics of the credence attributes. The list of labeled credence attributes and the information presented about them is provided in table A1.[4] The first column indicates the credence attribute revealed in the T1 ("contains X + no info") and T2 ("contains X + info") treatments; the second column notes the auctioned item; and the third column lists the negative information that was provided alongside the label in the T2 treatment.

The credence attributes considered include genetically modified ingredients (granola bar), ingredients that have been exposed to growth hormones (mozzarella string cheese), irradiated ingredients (granola trail mix with dried fruit and nuts), ingredients that have been exposed to antibiotics (beef jerky), high fructose corn syrup (oatmeal cookies), partially hydrogenated oils (oven baked potatoes), and artificial color Red No. 40 (gummy bears). In our econometric specification we control for the attribute type to estimate common, generalizable effects of labeling credence attributes and providing secondary information.

Each session of the experiment began with an explanation of how the auctions and the bidding process worked. To guarantee that subjects understood the mechanism of the auctions, a practice round was included in which each subject submitted a bid for a board game. After the practice round, seven rounds of bidding for seven different food items took place. In the beginning of each round the food item that subjects were bidding on was displayed to them. Since we were auctioning items commonly sold in grocery stores, we removed brand logos to eliminate any brand-image effects. We replicated the nutrition and ingredient list information from the actual labels and presented this brand-free label along with treatment-specific information to the participants on the projector slide and on their individual computer screens.

The Becker Degroot Marschak (1964) (BDM) auction was used to elicit subjects' WTP for the seven items.[5] We expected that subjects would have a range of valuations for the various products, and the BDM is an ideal elicitation method because subjects do not bid against each other but rather submit a sealed bid for each product and then have the chance to "win" a randomly selected food product if their bid exceeded a randomly drawn price (Becker, DeGroot, and Marschak, 1964). Once all bids were submitted in a session, we randomly chose a market price for one randomly selected food item (from a distribution around the retail price of the auctioned item); in cases where a subject's bid was equal to or exceeded the market price, we sold the selected food product to the

[4] While some may question the validity of some of the negative claims presented in the negative information treatment, these claims were taken from peer-reviewed academic articles or from current regulations in place in Europe or the United States. Appendix A includes the list of sources for these claims.

[5] The BDM mechanism is generally considered to be incentive compatible in an expected utility framework, with numerous experimental studies demonstrating the demand-revealing characteristics of the BDM mechanism in induced-value settings (Irwin et al., 1998). BDM auctions, along with alternative commonly used WTP elicitation mechanisms such as Vickrey and *n*th-price auctions, may not be incentive compatible in cases outside of the expected utility model in a private-good context where the price is unknown (Karni and Safra, 1987; Horowitz, 2006).

subject for the randomly chosen market price. Subjects were told at the beginning of the experiment that only one product was randomly picked to be sold at the end of all the auctions and therefore they would only buy one item at most in the auctions. This was done to avoid having subjects bid lower on selected products due to budget constraint or satiation considerations.

After all seven item auctions were completed, participants filled out a computerized questionnaire revealing their nutrition knowledge, attitudes toward food, and some demographic information. Answers from this questionnaire were later used to identify participants as consumers who are either "organic shoppers" or "conventional shoppers." The complete list of questions asked in the computerized survey is presented in table A2.

Econometric Model of Demand Shifts and Rotations

We use the theoretical model presented in a previous section to motivate an econometric model of the impact of information signal in credence attribute labeling setting on consumer choice. We assume a random utility model for consumer utility of the general form $U_{ij} = V_{ij} + \varepsilon_{ij}$ for product j for consumer i, where ε_{ij} is the independent and identically distributed error term and V_{ij} is a deterministic utility, which in turn is a function of product attributes, demographic attributes of the decision maker, and the information provided about the product (Anderson, de Palma, and Thisse, 1992). Rickard et al. (2011) show that willingness to pay by consumer i is an additive function of choice and chooser attributes.[6] Specifically, we write the deterministic part of this utility function as

$$V_{ijm} = \sum_k \beta_k x_{jk} + \sum_n \delta_n z_{in} + \sum_m \gamma_{im} I_m + \varsigma_{ijm}, \tag{3}$$

where i indexes individual consumers, j denotes products, m represents information treatments, x_{jk} are the observable and known attributes for all consumers for product j, z_{in} are the observable demographic characteristics of consumer i, ς_{ijm} is an independent and identically distributed error term, and γ_{im} is the individual-specific impact of information about the credence attribute on indirect utility. This information, I_m differs by treatment ($I_m = \{$*no label + no information; label + no information; label + information*$\}$).

Further, as outlined in our theoretical model, we allow information to have both a direct (shift) and an indirect (rotational) effect. Rotations of demand associated with universally unappealing information and its effect on consumer valuation are modeled through changes in WTP dispersion, while shifts of the demand curve resulting from information heterogeneously evaluated by different consumer types are represented by changes in the mean valuation. As information specific to the treatments is the only signal affecting the universally and heterogeneously evaluated information mix in our experiment from treatment to treatment, we model γ_{im}, recognizing that the information effect will be different across consumers and will depend on, among other things, their prior beliefs and the noise of the information signal (i.e., how concerned they are with the information provided and how uncertain they are given the information available to them):

$$\gamma_{im} = \overline{\gamma_m} + \sigma_m \tau_{im} + Item_j; \tau_{im} \sim N(0,1). \tag{4}$$

We can interpret $\overline{\gamma_m}$ as the common direct effect (shift) due to provided information and σ_m as the indirect effect (rotation) caused by changes in the dispersion of valuations, under information level I_m, while τ_{im} captures unobserved individual heterogeneity (Berry, 1994) and can be interpreted as an unobserved variability in the prior and posterior beliefs relating to credence attributes. Lastly, $Item_j$ controls for item-specific information type. Combining equations (3) and (4) provides an estimable model of the impact of credence attribute labeling on the willingness to pay under each type of information provision.

[6] Appendix B shows how this equation is consistent with a representative utility framework.

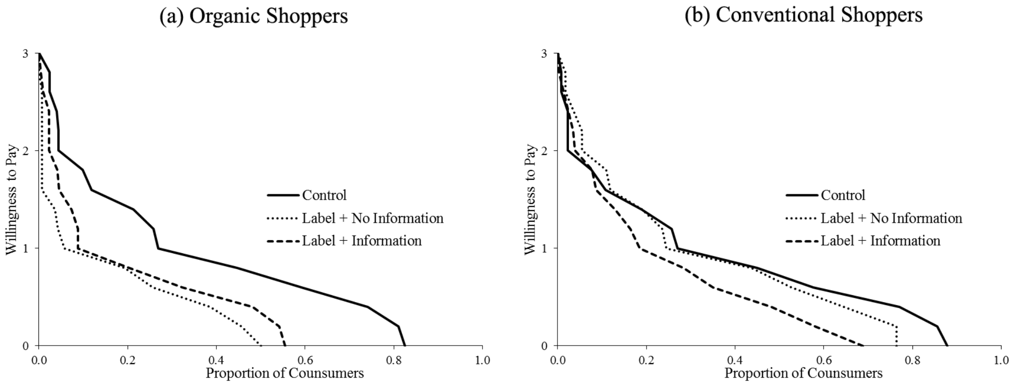

Figure 2. Overall Demand Changes across Information Treatments

Estimation and Results

Descriptive Statistics

In our empirical estimation we distinguish between two types of identifiable demographic groups: (1) conventional shoppers—participants who indicated that they never or very rarely purchase organic food or food at health food stores (N=89), and (2) organic shoppers—consumers who mostly buy organic products and/or frequently shop in health food stores (N=80). This is a self-revealed exogenous division of participants based on their survey answers (specifically answers to questions 14 and 15, see Appendix A). This grouping approach and the model estimates associated with it also lead to policy implications.

The socioeconomic characteristics of the sample are similar across both groups and three treatments. The key demographic information for the subjects in our sample is very similar to data on primary food shoppers in the United States (Food Marketing Institute, 2006). Table 1 presents descriptive statistics for the organic and conventional shoppers. The mean WTP varies quite significantly from one treatment and group to the other, with the control treatment (where items had neither the "contains X" label nor the secondary information about the labeled ingredient) consistently having the highest average bid. It is interesting to note that the relative average WTP in the "label + no negative information" and "label + negative information" is very different for organic and conventional shoppers: for the organic shoppers, the "label + no negative information" treatment has the lowest mean bid, while the conventional shoppers, on average, bid the lowest in the "label + negative information" treatment.

Similar patterns emerge in the graphical representation of demand schedules. Figure 2 plots the demand schedules of these two consumer types across the three experiment treatments. As is evident from these figures, these two consumer groups responded to the same information about credence attributes very differently. Organic shoppers reacted to information presented in T1 ("label + no negative information") more negatively than to information provided in T2 ("label + negative information"), as suggested by a larger inward shift of the demand curve. Conventional shoppers, on the other hand, reacted to information in T2 more negatively than to information in T1. We also note that patterns of change in demand slope and rotation are quite different for the two consumer types.

CDF Shifts and Rotations

We focus on identifying the common, generalizable effects of labeling credence attributes and providing secondary information. To do so, we include attribute fixed effects to control for systematic differences across the attributes and the information nature associated with our analyzed

Table 1. Descriptive Statistics of Demographic Variables by Group and Treatment

	Organic Shoppers			Conventional Shoppers		
	Control	**No Info**	**Info**	**Control**	**No Info**	**Info**
WTP	0.862	0.360	0.467	0.840	0.800	0.577
	(0.696)	(0.479)	(0.585)	(0.612)	(0.717)	(0.680)
Age	42.736	44.45	41.167	41.644	40.191	42.063
	(14.166)	(11.046)	(12.504)	(11.332)	(9.290)	(14.430)
Female	0.756	0.800	0.778	0.556	0.627	0.710
	(0.430)	(0.401)	(0.417)	(0.498)	(0.486)	(0.455)
Children	0.348	0.500	0.449	0.716	0.564	0.633
	(0.478)	(0.502)	(0.499)	(0.452)	(0.498)	(0.483)
Caucasian	0.726	0.800	0.838	0.842	0.627	0.755
	(0.447)	(0.401)	(0.369)	(0.365)	(0.486)	(0.431)
African American	0.030	0.050	0.000	0.032	0.064	0.024
	(0.171)	(0.219)	(0.000)	(0.175)	(0.245)	(0.155)
Asian	0.174	0.100	0.097	0.126	0.064	0.147
	(0.380)	(0.301)	(0.297)	(0.333)	(0.245)	(0.355)
Only High school	0.000	0.000	0.000	0.000	0.000	0.024
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.154)
Some college	0.134	0.100	0.157	0.063	0.245	0.147
	(0.342)	(0.301)	(0.365)	(0.244)	(0.432)	(0.355)
Associate's degree	0.070	0.200	0.098	0.248	0.318	0.098
	(0.255)	(0.401)	(0.297)	(0.433)	(0.468)	(0.298)
College degree	0.348	0.300	0.454	0.378	0.255	0.465
	(0.478)	(0.499)	(0.499)	(0.486)	(0.438)	(0.499)
Master's degree	0.313	0.350	0.259	0.248	0.055	0.171
	(0.465)	(0.479)	(0.439)	(0.433)	(0.228)	(0.377)
Income < \$40,000	0.174	0.150	0.259	0.252	0.127	0.294
	(0.380)	(0.358)	(0.439)	(0.435)	(0.334)	(0.456)
Income \$40,000+\$79,999	0.478	0.600	0.356	0.374	0.500	0.437
	(0.501)	(0.492)	(0.480)	(0.485)	(0.502)	(0.497)
Healthy eaters	0.831	0.900	0.583	0.437	(0.318)	0.315
	(0.376)	(0.301)	(0.494)	(0.497)	(0.468)	(0.465)
Vegetarian or vegan	0.099	0.250	0.162	0.032	0.00	0.024
	(0.300)	(0.435)	(0.369)	(0.175)	(0.00)	(0.155)
Taken a nutrition course	0.279	0.200	0.259	0.369	0.318	0.220
	(0.449)	(0.402)	(0.439)	(0.484)	(0.467)	(0.415)
Usually read nutrient labels	0.930	0.900	0.773	0.622	0.436	0.780
	(0.255)	(0.301)	(0.419)	(0.486)	(0.498)	(0.415)
Require disclosure of	0.896	1.000	1.000	0.815	0.873	0.951
altered ingredients' content	(0.307)	(0.000)	(0.000)	(0.389)	(0.334)	(0.216)
# of bids	201	140	216	222	110	286

Notes: Reported numbers are means; standard deviations are in parentheses below.

credence attributes.[7] To identify the common element of shifts and rotations of CDF after controlling for other observable variables, we estimate combined equations (3) and (4) using simulated maximum likelihood with robust standard errors. The results are presented separately for the

[7] We have also investigated estimating individual, attribute-specific specifications. We generally found that they do not add much additional insight, since we already control for item fixed effects and most of the specifications and empirical CDFs exhibit similar estimates and patterns as the estimated common effects.

Table 2. OLS and Random Coefficients Estimates

	OLS		Random Coefficient	
	Organic	**Conventional**	**Organic**	**Conventional**
		$\overline{\gamma_m}$: **Mean Estimates**		
T0: Control	0.858***	0.972***	0.874***	0.937***
	(0.150)	(0.160)	(0.196)	(0.237)
T1: Label + No Info	0.343**	0.898***	0.359**	0.859***
	(0.150)	(0.169)	(0.192)	(0.276)
T2: Label + Info	0.475***	0.705***	0.490***	0.665***
	(0.146)	(0.160)	(0.194)	(0.243)
		σ_m: **Standard Dev. Estimates**		
T0: Control			0.250***	0.293***
			(0.062)	(0.042)
T1: Label + No Info			0.173***	0.535***
			(0.076)	(0.065)
T2: Label + Info			0.307***	0.408***
			(0.060)	(0.043)
Credence Attribute Type F.E.	yes	yes	yes	yes
Demographic F.E.	yes	yes	yes	yes
Sigma			0.588**	0.556**
			(0.189)	(0.017)
Log-likelihood	−546.67	−647.77	−530.37	−584.04

Notes: Clustered standard errors are in parentheses. Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level.

segments of the sample defined as organic shoppers and conventional shoppers. All of the reported specifications in table 2 also include credence attribute fixed effects to control for the heterogeneity in the value and information type supplied with the auctioned items as well as observed consumer socioeconomic controls, allowing us to estimate robustly attribute demand shift and rotation effects to information treatments. The intercept in table 2 is suppressed, so the inferences about shifts and rotations need to be made while comparing treatment estimates to those of the control.[8]

We conduct a number of specification tests to determine whether the additional structure of our model due to unobserved preference heterogeneity is justified by the data and present ordinary least squares (OLS) estimates for comparison purposes. The likelihood ratio tests and log likelihood function of random coefficient versus linear regression favor the random coefficient model (LR=32.60, P > chi2 = 0.000 for the organic-shoppers subsample and LR=127.44, P > chi2 = 0.000 for the conventional shoppers). Additionally, t-tests of each individual shift and standard deviation parameters show that they are significantly different from zero at least at 5% level of significance. Consequently, we conclude that the random coefficient specification is superior to the constant parameter alternative.

Organic Shoppers (Table 2, Column 3)

Relative to the control treatment (T0) and controlling for the credence attribute type and consumer demographics, the "label + no negative information" treatment (T1) leads to a significant decrease in both the mean valuation and dispersion for organic shoppers. The point estimate of the mean parameter decreases from 0.874 for the control treatment to 0.359 for the T1 treatment, and the estimate for the dispersion of valuations parameter decreases from 0.250 for the control to 0.173.

[8] Additionally, a random coefficient Tobit econometric specification was estimated, with similar results.

These relative changes of estimates imply that when moving from T0 to T1 the empirical CDF shifts inward and rotates counterclockwise, which translates to the corresponding demand schedule becoming flatter and shifting to the left. In the "label + information" treatment (T2) the mean valuation also falls (point estimate 0.490), but less so than in the previous treatment, and the dispersion parameter increases relative to both control treatment and T1 (point estimate of the dispersion parameter is 0.307). These estimates imply that moving from T0 to T2, the empirical CDF shifts to the left (and to the right, relative to T1) and rotates clockwise, corresponding to demand shift to the left and rotating to become steeper.

We can infer that the effects of both, knowledge about a universally disliked attribute—leading to the inward shift in the demand—and heterogeneously evaluated information—rotations of the demand curve—are present within the treatments. For some, the information signal allows consumers to match their heterogeneous preferences toward the labeled attribute, and additional information signal in T2 does just that by providing negative information on both the production processes and possible consequences of consuming the labeled ingredient. These results also suggest that organic shoppers have strong prior beliefs about the credence attributes and they are also the type of consumers who are willing to pay extra to avoid these credence attributes.

Conventional Shoppers (Table 2, Column 4)

Relative to the control treatment (T0), in the "label + no negative information" treatment (T1) the mean valuation falls slightly and the dispersion increases for the conventional shoppers. The point estimate of the mean parameter decreases from 0.937 for the control treatment to 0.859 for the T1 treatment and the estimates for the dispersion of valuations increase from 0.293 for the control to 0.535 for the T1. These results imply that moving from T0 to T1, the empirical CDF for the conventional shoppers shifts inward and rotates clockwise, as the corresponding demand becomes steeper and shifts to the left. In the "label + information" treatment (T2), the mean valuation falls further (decreasing from 0.859 for T1 to 0.665 for T2) and the dispersion decreases relative to T1 (dispersion parameter decreases from 0.535 for T1 to 0.408 for T2). This suggests that in moving from T1 to T2, the empirical CDF shift to the left and rotates counterclockwise and the corresponding demand schedule becomes flatter and shifts to the left.

Similar to the organic shoppers, the universally negatively evaluated nature of the label and additional information decrease mean WTP, shifting the demand inward; however, in this case conventional shoppers don't have strong prior beliefs about the labeled ingredients; while most conventional shoppers dislike the labeled ingredient, the extent to which they dislike it is fairly heterogeneous across consumers. In this demographic group, labels in T1 compared to T0 also shift demand, providing consumers with enough information to update their valuation. In T2, all of the conventional shoppers are provided with the same negative additional information and the dispersion decreases relative to T1, implying that consumers assign label and additional information more to the demand shift role (as more information is provided about the credence attribute (T2), both the mean and the dispersion fall significantly). These results suggest that conventional shoppers have significantly less strong initial beliefs about the credence attributes and that they could be unaware of the widespread existence or possible consequences and traits of these attributes. Finally, it is worthwhile to note that the drop in the mean WTP in both T1 and T2 is substantially larger for the conventional shoppers compared to the organic shoppers. Overall, it confirms the self-revealed preferences of organic shoppers, who routinely pay an organic-foods premium to avoid the labeled ingredients.

The distinctly different response of the organic shoppers when compared with the conventional shoppers within our model implies they treat the same information signals differently based on their priors. While these mean and dispersion results help us identify changes in the shape of the demand functions, they do not provide us with concrete insights into the potential underlying cause for such different reactions to the same information (beyond unobserved consumer heterogeneity within each group). The next step in our analysis involves looking for deeper insights about the relative levels of uncertainty and product idiosyncrasy that would be consistent with the estimated shift and rotation parameters, $\overline{\gamma_m}$ and σ_m. Combining the theoretical characterizations of CDFs with our empirical results, we are able to identify relative levels of uncertainty associated with the information signal, ξ^2, and relative levels of product idiosyncrasy, ρ^2, across the three treatments and two consumer groups.

The experimental nature of our study allows us to trace the relative levels of ξ^2 while observing two levels of ρ^2 across experimental treatments. All auctioned items remain exactly the same across treatments, and their observable attributes objectively do not change. By definition, participants are not able to observe the credence attribute directly. Therefore, we assume that the explicit labeling of such an attribute alerts the consumer to a change in the set of attributes of the product. Thus, ρ^2, the degree of product idiosyncrasy, changes only when consumers are made aware of a new attribute, which they may or may not universally dislike. Next, we describe how ξ^2 and ρ^2 change across three of our experiment treatments.

T0: Control

In the baseline control treatment we do not mention the existence of the credence attributes (i.e., there are no labels). Some consumers might suspect that labeled ingredients exist or are part of the product content, which would affect their level of uncertainty since they lack actual information on whether the product has the credence attribute in question. The baseline degree of product differentiation and level of uncertainty faced by consumers in this treatment are ρ_0^2 and ξ_0^2, respectively.

T1: Label + No Information

This treatment introduces the existence of the credence attribute by providing a label "contains X," alerting consumers to the existence of a credence attribute. We therefore change the idiosyncrasy of product design to ρ_1^2. By providing any type of additional information about the products we are also altering ξ_1^2, the baseline noise of the information signal.

T2: Label + Negative Information

In this treatment we also reveal the existence of the same credence attribute as in the T1 treatment, so the degree of product differentiation stays the same (ρ_1^2). Given that the credence attribute is explicitly labeled in T1 and T2, the known product attributes in those two treatments are the same. However, here we also introduce additional information signal about the credence attribute, which is likely to change the perception of noisiness of the information signal level, ξ_2^2.

Table 3 summarizes the notation for different levels of ξ^2 and ρ^2 across the three treatments and two consumer groups. We distinguish between four different ρ^2 that define the degree of product idiosyncrasy and six distinct ξ^2 that reflect the information noise associated with each of the experiment treatments.[9] This allows us to have different parameter values not only across treatments but also across the organic- and conventional-shoppers groups.

Relative Levels of Idiosyncrasy and Uncertainty: Results

Identifying the relative levels of uncertainty across the labeled treatments is the key to determining whether the signaling effect of the label exists. Intuitively, the main results come from observation that in both treatments T1 ("label + no negative information") and T2 ("label + negative information") consumers know about the existence of the credence attribute: ρ^2 is constant (though

[9] Recall that the degree of product differentiation stays the same in the "label + no information" and "label + information" treatments (ρ_1^2) since both of them reveal the credence attribute. However, T2 introduces additional information about the credence attribute, which is likely to change the perception of noisiness of the information signal level, ξ_2^2.

Table 3. Levels of ρ^2 and ξ^2 for the Organic and Conventional Shoppers

	Organic	Conventional
ρ^2: Degree of Product Idiosyncrasy		
T0: control	ρ^2_{O0}	ρ^2_{C0}
T1: label + no information	ρ^2_{O1}	ρ^2_{C1}
T2: label + information	ρ^2_{O1}	ρ^2_{C1}
ξ^2: Uncertainty Level/Information Noise		
T0: control	ξ^2_{O0}	ξ^2_{C0}
T1: label + no information	ξ^2_{O1}	ξ^2_{C1}
T2: label + information	ξ^2_{O2}	ξ^2_{C2}

it might have different levels for two different consumer groups), whereas the level of uncertainty (due to the fact that different types of information are presented in labeling treatments) is allowed to be different. As shown in table 2, an interesting pattern emerges when we compare treatments T1 and T2 across the two consumer groups. Among organic shoppers, the estimated mean and standard deviation increase when more information is provided, while the opposite is the case among the conventional shoppers. Since the product idiosyncrasy parameter stays constant across the two treatments, this implies that these relative changes are attributable to the noisiness of the information signals in those treatments. More specifically, we find that[10]

1. $\xi^2_{O1} > \xi^2_{O2}$: For the organic shoppers, once the existence of the credence attribute is revealed (which is the case in both treatments T1 and T2), the uncertainty level associated with the information signal is lower in the treatment with more information provided (T2). In other words, for this group of consumers, a label alone without any information (T1) appears to be a highly noisy signal, which is associated with missing information deemed highly relevant by these consumers. Provided with additional, relevant information, the consumer treats it as believable and useful. This is one of the most interesting results of our paper: more information (even though it is negative) softens some consumers' concerns about the meaning of a label. Another, more intuitive way to interpret this result is to note that for most organic shoppers, the "contains X" label without any additional information serves as a noisy warning signal leading them to infer that the consumption of labeled products is riskier than it actually is. This large negative signaling effect of the label is mitigated by additional information, which ultimately reduces the noise in the information signal.

2. $\xi^2_{C1} < \xi^2_{C2}$: Once they are made aware of the existence of the credence attribute, conventional shoppers interpret additional information about the credence attribute as a noisy signal relative to the label alone. The conventional shoppers might not have strong priors about the possible implications of the labeled ingredient or production process, and the additional information provided with the treatment is treated as ambiguous. Similar to Fox and Weber (2002), uncertainty arises in this case from the comparative ignorance context: the conventional shoppers are not sure how to evaluate the information provided compared to how they evaluate the stand-alone label. In other words, when the conventional shoppers see a label by itself, it has less of an impact on their WTP because their priors are such that they are not very concerned. However, if they are shocked with both a label and negative information, this then reduces their WTP more drastically. In this case, additional negative information about the credence attribute raises uncertainty and reduces the WTP as well as the dispersion of bids.

[10] In the Bayesian framework described above, the uncertainty and idiosyncrasy enter the distribution parameters of WTP in equation (2) nonlinearly. By estimating equations (3) and (4) we recover means and standard deviations in equation (2) for each information treatment and use those numbers to infer the relative values of ξ^2. Appendix B shows how the relative values were derived and the mathematical proofs of these results.

Concluding Remarks and Policy Implications

In light of the continuing debate surrounding mandatory labeling policies, the main question this research addresses is whether the decrease in WTP induced by a "contains X" label simply reflects existing consumer preferences or whether the labeling itself induces concern about the labeled ingredients. We test for the effect of information on WTP using an empirical model that captures the theoretical demand shift and rotation effects derived by Johnson and Myatt (2006). The empirical model is estimated using data collected from an economic experiment that evaluated the impact of the label "contains X" both with and without additional negative information about credence attributes X. In the empirical model, heterogeneous interpretations of the "contains" label are responsible for how observed demand shifts and rotates.

There are three main empirical findings of the study. First, and similar to other studies previously discussed, we find that labeling initiatives in individual states and at the federal level could lead to a significant decrease in consumers' WTP for labeled items. This may be an unintended consequence of labeling and one that policy makers need to seriously factor in to the debate. Second, we find that for organic shoppers—who also tend to be the most vocal supporters of mandatory labeling policies—a "contains" label absent additional secondary information serves the noisiest warning signal of all treatments, which increases uncertainty. Thus, a mandatory "contains" label without additional information causes this type of consumer to overestimate the riskiness of consuming the labeled product. Interestingly, the provision of any additional information, even when it is negative, reduces the noise in the information signal to the organic shopper, thereby partially mitigating the negative signaling effect of the label. Finally, unlike the organic shoppers, conventional shoppers do not have strong priors about the possible implications of the labeled ingredients or production processes. As a result, additional negative information presented with the label is the noisiest warning signal of all treatments for them. In other words, for conventional consumers, additional negative information about the credence attribute raises uncertainty and further reduces WTP compared to the label by itself.

The results of this study have direct and immediate implications for the food industry and policy makers who are currently considering requiring mandatory labeling of ingredients and production practices on food products. It should be clear that implementing mandatory labeling will have a negative impact on WTP for at least some consumers. If labeling requirements are imposed, provision of even negative additional information (which is mostly provided to the interested public by consumer groups) can partially mitigate the demand-reducing effects of the label, but only if consumers in the market have preconceived notions and beliefs about these ingredients. However, in markets where the majority of consumers are indifferent or pay little attention to the ingredients labeled (conventional shoppers in our study), the provision of additional negative information would further decrease the WTP for such products. These results suggest that food firms should consider market segmentation strategies should mandatory labeling become law. For example, targeting additional information to organic shoppers might partially mitigate the negative impacts of labeling for these types of consumers.

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Appendix A: Additional Details about the Experiment

Negative Information Presented during the Experiment and its Sources

Table A1. Credence Attributes in "Contains X" Treatment and Information Supplied to Subjects in "Contains + Information" Treatment

Credence Attribute	Item	Additional Negative Information (see sources below)
Genetically modified ingredients	Chewy Granola Bar (with Chocolate Chips)	· GMOs can threaten plant biodiversity because nearby conventional crops are easily contaminated by the growing GMOs in the area. · Some research finds that genetically modified foods can distort natural digestive process and potentially lead to some food allergies. · One study shows that consumption of genetically modified soy can lead to liver problems.
Ingredients that have been exposed to growth hormones	Mozzarella String Cheese	· Growth hormones are used on dairy farms to increase a cow's milk production. · The use of growth hormones substantially increases health problems for cows and causes reproductive disorders in cows · Products containing growth hormones are banned in the European Union but not in the United States
Irradiated ingredients	Granola Trail Mix (with Dried Fruit and Nuts)	· Irradiation exposes foods to radiant energy to prolong shelf life among other uses. · Some studies show that irradiated food can lose 5–80% of their vitamin content, and may damage natural enzymes making it harder to digest the irradiated foods. · Irradiated foods are banned in the EU, but they are not banned in the United States
Ingredients that have been exposed to antibiotics	Beef Jerky (with Natural Smoke Flavoring)	· Some scientific studies show that use of antibiotics will lead to human resistance to antibiotic drugs such as penicillin and bacitracin. · An estimated 14,000 Americans die every year from drug-resistant infections. · The use of non-therapeutic antibiotics is banned in the EU, but it is not banned in the United States
High fructose corn syrup	Soft Baked Oatmeal Chocolate Chip Cookies	· In the United States, HFCS is a processed corn syrup that has largely replaced table sugar as a sweetener in processed foods and beverages. · Studies show that extensive use of HFCS is more harmful to humans than regular sugar, contributing to weight gain by affecting normal appetite functions. · Some research shows that in some foods HFCS may be a source of mercury, a neurotoxin.
Partially hydrogenated oils	Oven Baked Potato Chips	· Partially hydrogenated oils contain trans fats which raise levels of bad cholesterol, and lower levels of good cholesterol leading to circulatory diseases including heart disease. · Food legislation in the United States and the European Union require labels to declare the trans fat content. Trans fats are banned from foods sold in restaurants in New York City.
Artificial color Red No. 40	Gummy Bears	· Red No. 40 is an artificial coloring commonly used in gelatins, puddings, confections, and beverages. · Some research has suggested that artificial dye called Red No. 40, leads to behavioral changes in children diagnosed with ADHD. · Some companies started voluntarily withdrawing products with such artificial dyes.

Sources of Negative Information

Genetically Modified Ingredients:

- Celec, P., M. Kukučková, V. Renczésová, S. Natarajan, R. Pálffy, R. Gardlík, J. Hodosy, M. Behuliak, B. Vlková, G. Minárik, T. Szemes, S. Stuchlík, and J. Turna. "Biological and Biomedical Aspects of Genetically Modified Food." *Biomedicine & Pharmacotherapy* 59(2005):531–540;
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Ingredients that Have Been Exposed to Growth Hormones:

- Current use ban in European Union

- Burton, J. L., B. W. McBride, E. Block, D. R. Glimm, and J. J. Kennelly, J. J. "A Review of Bovine Growth Hormone." *Canadian Journal of Animal Science* 74(1994):167–201;
- Cole, W. J., P. J. Eppard, B. G. Boysen, K. S. Madsen, R. H. Sorbet, M. A. Miller, R. L. Hintz, T. C. White, W. E. Ribelin, B. G. Hammond, R. J. Collier, and G. M. Lanza. "Response of Dairy Cows to High Doses of a Sustained-Release Bovine Somatotropin Administered during Two Lactations. 2. Health and Reproduction." *Journal of Dairy Science* 75(1992):111–123;

Irradiated Ingredients:

- Current irradiation ban in the European Union

- Duodu, K. G., A. Minnaar, and J. R. N. Taylor. "Effect of Cooking and Irradiation on the Labile Vitamins and Antinutrient Content of a Traditional African Sorghum Porridge and Spinach Relish." *Food Chemistry* 66(1999):21–27;
- Ziporin, Z. Z., H. F. Kraybill, and H. J. Thach. "Vitamin Content of Foods Exposed to Ionizing Radiations." *Journal of Nutrition* 63(1957):201–209;

Ingredients that Have Been Exposed to Antibiotics:

- van den Bogaard, A. E., and E. E. Stobberingh. "Epidemiology of Resistance to Antibiotics: Links between Animals and Humans." *International Journal of Antimicrobial Agents* 14(2000)327–335;
- Wegener, H. C. "Antibiotics in Animal Feed and Their Role in Resistance Development." *Current Opinion in Microbiology* 6(2003):439–445;

High Fructose Corn Syrup:

- Parker, K., M. Salas, and V. C. Nwosu. High Fructose Corn Syrup: Production, Uses and Public Health Concerns. *Biotechnology and Molecular Biology Reviews* 5(2010):71–78;
- Stanhope, K. L., and P. J. Havel. "Endocrine and Metabolic Effects of Consuming Beverages Sweetened with Fructose, Glucose, Sucrose, or High-Fructose Corn Syrup." *American journal of clinical nutrition* 88(2008):1733S–1737S;

Partially Hydrogenated Oils:

- Current U.S. and Europe trans fat content labeling regulations, and
- NYC current trans fat in restaurants ban;

Artificial Color Red No. 40:

- Schab, D. W., and N. H. T. Trinh. "Do Artificial Food Colors Promote Hyperactivity in Children with Hyperactive Syndromes? A Meta-Analysis of Double-Blind Placebo-Controlled Trials. *Journal of Developmental & Behavioral Pediatrics* 25(2004):423–434;

Table A2. Survey Questions Asked after the Experiment

#	Question	Answer Options/Description
1	What is your month of birth?	A drop-down list of months is given
2	What your day of birth?	A drop-down list with numbers 1-31 is given
3	What year were you born?	A drop-down list with years 1920 to 2000 is given
4	What is your gender?	·Male ·Female
5	What race are you?	·Caucasian ·African American ·Asian ·Hispanic ·Native American ·Other
6	What is your household income level?	·Less than $40,000 ·$40,000–$80,000 ·$80,000–$120.000 ·$120,000–$160,000 ·Over $160,000
7	What is the highest level of education you have achieved?	·High School ·Some college, but no degree ·Associates Degree ·College Degree ·Master's Degree ·Doctoral Degree
8	Do you have children?	·Yes ·No
9	Are you the primary food shopper?	·Yes ·No
10	Are you a Vegetarian or Vegan?	·Yes ·No
11	Have you ever taken a college course in nutrition or food science?	·Yes ·No
12	Would you describe yourself as a healthy eater?	·Yes ·No ·Maybe
13	Do you usually read nutrition labels?	·Yes ·No
14	How often do you purchase food at health food stores?	·Never ·Very rarely ·Quite frequently ·All the time
15	How often do you buy organic foods?	·Never ·Rarely ·Quite frequently ·All the time
16	On average, how often do you eat snack foods?	·Never ·Less than once a day ·Once a day ·Two to three times a day ·More than three times a day
17	For this question please rank how much weight you place on the following attributes when purchasing snack foods using a scale of 1 (not important) to 10 (very important):	·Price ·Taste ·Convenience ·Healthiness of a snack ·Nutrition Information ·Other information on label ·Organic vs. non-organic ·Fat content ·Existence or lack of particular ingredient
18	If you pay attention to the existence or lack of particular ingredient, what is this ingredient?	This was an open-ended question. A text field was provided for respondents.
19	Do you have any food allergies? Check all that apply.	·None ·Peanuts ·Gluten ·Dairy ·Lactose intolerance ·Other
20	Do you think the government should require disclosure of food ingredients that have been altered from their naturally occurring state?	·Yes ·No

Appendix B: Technical Appendix

Information Noise, Product Idiosyncrasy, and Distribution of WTP

Suppose the prior distribution of Bayesian consumers' true monetary utility for a product satisfies $\omega \sim N(\mu, \rho^2)$. A consumer updates her prior ω given a noisy signal $x|\omega \sim N(\omega, \xi^2)$. Her posterior becomes $\omega|x \sim N\left(\frac{\rho^2 x+\xi^2\mu}{\rho^2+\xi^2}, \frac{\rho^2\xi^2}{\rho^2+\xi^2}\right)$ or, multiplying both numerator and denominator by $\frac{1}{\xi^2}$, we get $\omega|x \sim N(\frac{(\rho^2/\xi^2)x+\mu}{1+\rho^2/\xi^2}, \frac{\rho^2}{1+\rho^2/\xi^2})$.

Under assumed normality, the consumer's WTP is certainty equivalent $E[\omega|x] - \lambda var[\omega|x]/2$. Substituting in the mean and variance obtained above, we get WTP $\theta(x) = \frac{1}{1+\rho^2/\xi^2}\left[\mu - \frac{\lambda\rho^2}{2}\right] + \frac{\rho^2/\xi^2}{1+\rho^2/\xi^2}x$. This expression is a weighted average of the *ex ante* certainty equivalent and the *ex post* information signal realization. The weights depend on ρ^2, which approximates the heterogeneity in consumer preferences for a product, and ξ^2, the information noise, or the level of uncertainty that information signal triggers. As the realized information signal follows the distribution $x \sim N(\mu, \rho^2 + \xi^2)$ and consumers' valuations are linear in x, we obtain the distribution of consumer's WTP, θ.

(B1)
$$WTP \sim N\left(\mu - \frac{\lambda\rho^2}{2(1+\rho^2/\xi^2)}, \frac{\rho^4/\xi^2}{1+\rho^2/\xi^2}\right).$$

Remember that θ is drawn from the distribution $F_s(\theta)$, twice continuously differentiable in both s and θ, with support on the $(\underline{\theta}_s, \overline{\theta}_s)$ interval, where $s \in S = [s_l, s_h]$ indexes a family of distributions. The inverse demand is $P_s(q) = F_s(1-p)$, where q is the proportion of consumers willing to purchase the product at price p and is given by $q = 1 - F_s^{-1}(p)$. $F(\cdot)$ is a continuous distribution with zero mean, unit variance, and strictly positive density, and $P(q) = F^{-1}(1-q)$.

(B2)
$$\begin{aligned} F_s[P_s(q)] &= 1 - q \Leftrightarrow \\ F_s\left[\frac{P_s(q) - \mu(s)}{\sigma(s)}\right] &= 1 - q \Leftrightarrow \\ P_s(q) &= \mu(s) + \sigma(s)F^{-1}(1-z) = \mu(s) + \sigma(s)P(z). \end{aligned}$$

For any choice of ρ^2 and ξ^2, the distribution remains within the normal family. Then, any changes in either ρ^2 or ξ^2 yield a variance-ordered family with a changing mean: $P(q) = \left(\mu - \frac{\lambda\rho^2}{2(1+\rho^2/\xi^2)}\right) + \left(P(q)\sqrt{\frac{\rho^4/\xi^2}{1+\rho^2/\xi^2}}\right)$.

Random Utility Framework

We follow Rickard et al. (2011) in deriving the WTP for auctioned items in a random utility framework in which the distribution of consumer heterogeneity reflects the distribution of marginal valuations in the theoretical model presented in the main text. In the random utility model, consumer utility is the sum of a deterministic and stochastic part such that

(B3)
$$U_{ij} = V_{ij} + \varepsilon_{ij}$$

for product j by consumer i, where V_{ij} is the deterministic component of utility, and ε_{ij} is an *iid* error term. Utility, in turn, is a function of demographic attributes of the individual (x_i) and of the product choice (z_j), a vector of information exposures (I_k), and income (y_i). The marginal value consumer i places on product $j = 1$ is defined as the amount of income that leaves the consumer's utility at least as great with and without the purchase:

(B4)
$$V_{i0}(z_0, I_k, x_i, y_i) + \varepsilon_{i0} \leq V_{i1}(z_1, I_k, x_i, y_i - c_{i1}) + \varepsilon_{i1},$$

where c_{i1} is the marginal value of product 1 by consumer i (Loureiro and Umberger, 2003). We solve for the WTP by consumer i by invoking the random utility assumption and recognizing that

$$Pr(WTP_{il} \geq c_{i1}) = Pr(V_{i0} + \varepsilon_{i0} \leq V_{i1} + \varepsilon_{i1}). \tag{B5}$$

Assuming the error term has a double-exponential distribution with mean 0 and variance $(\pi^2\mu^2/3)$, where μ is the logit scale parameter, and that utility of the non-purchased option is normalized to 1, the WTP becomes

$$Pr(WTP_{il} \geq c_{i1}) = \frac{\exp(V_{i1}/\mu)}{1 + \exp(V_{i1}/\mu)}. \tag{B6}$$

Solving for the WTP from this expression, we write the odds ratio of choosing product 1 relative to product 0 as

$$\frac{Pr(j=1)}{1 - Pr(j=1)} = \frac{exp(V_{i1}/\mu)/[1 + exp(V_{i1}/\mu)]}{1/[1 + exp(V_{i1}/\mu)]} = exp\left(\frac{V_{i1}}{\mu}\right), \tag{B7}$$

where $Pr(j=1)$ is the probability of purchasing good 1. Applying a logarithmic transformation of both sides of the odds ratio gives the expression in equation (B8) for the WTP by consumer i as a function of choice and subject attributes, the type of information, and the scale parameter (which we normalize to 1 without loss of generality in the empirical application shown below):

$$\ln\left(\frac{Pr(j=1)}{1 - Pr(j=1)}\right) = WTP_{i1} = \frac{V_{i1}}{\mu}. \tag{B8}$$

With an appropriate specification for V_{i1} it is possible to test for both the direct (shift) effect of information on the WTP and the indirect (rotational) effect through the dispersion of valuations. Assuming that utility is additive over attribute arguments, we can specify V_{i1} in terms of an empirical, or estimable, model of utility in equation (3), also reprinted here as equation (B9):

$$WTP_{ijm} = V_{ijm} = \sum_k \beta_k x_{jk} + \sum_n \delta_n z_{in} + \sum_m \gamma_{im} I_{im} + \varsigma_{ijm}. \tag{B9}$$

Mathematical Proofs of Main Results

1. $\xi_{O1}^2 > \xi_{O2}^2$. *Proof.* Consider the comparison of estimated means and standard deviations for organic shoppers for treatments T1 and T2 in table 3:

$$\begin{cases} \mu_O - \dfrac{\lambda \rho_{O1}^2}{2\left(1 + \frac{\rho_{O1}^2}{\xi_{O2}^2}\right)} > \mu_O - \dfrac{\lambda \rho_{O1}^2}{2\left(1 + \frac{\rho_{O1}^2}{\xi_{O1}^2}\right)} & \text{(B10)} \\[2ex] \sqrt{\dfrac{\rho_{O1}^4/\xi_{O2}^2}{1 + \rho_{O1}^2/\xi_{O2}^2}} > \sqrt{\dfrac{\rho_{O1}^4/\xi_{O1}^2}{1 + \rho_{O1}^2/\xi_{O1}^2}} & \text{(B11)} \end{cases}$$

Rearranging equation (B10), we have $\frac{\lambda \rho_{O1}^4(\xi_{O1}^2 - \xi_{O2}^2)}{2\xi_{O1}^2\xi_{O2}^2} > 0$. Since $\lambda > 0$, $\rho_{O1}^4 > 0$, $\xi_{O1}^2 > 0$, and $\xi_{O2}^2 > 0$, then it must be the case that $\xi_{O1}^2 > \xi_{O2}^2$. Rearranging equation (B11) leads to $\sqrt{\frac{\rho_{O1}^4}{\rho_{O1}^2 + \xi_{O2}^2}} < \sqrt{\frac{\rho_{O1}^4}{\rho_{O1}^2 + \xi_{O1}^2}}$. This inequality also holds for any given ρ_{O1}^4, and $\xi_{O1}^2 > \xi_{O2}^2$.

Table B1. Means and Dispersions as a Function of Model Parameters

	Mean	St. Dev.	Mean	St. Dev.
T0: control	(1O) $\mu_O - \frac{\lambda\rho_{O0}^2}{2(1+\rho_{O0}^2/\xi_{O0}^2)}$	(4C) $\sqrt{\frac{\rho_{O0}^4/\xi_{O0}^2}{1+\rho_{O0}^2/\xi_{O0}^2}}$	(1C) $\mu_C - \frac{\lambda\rho_{C0}^2}{2(1+\rho_{C0}^2/\xi_{C0}^2)}$	(4I) $\sqrt{\frac{\rho_{C0}^4/\xi_{C0}^2}{1+\rho_{C0}^2/\xi_{C0}^2}}$
T1: label + no information	(2O) $\mu_O - \frac{\lambda\rho_{O1}^2}{2(1+\rho_{O1}^2/\xi_{O1}^2)}$	(5C) $\sqrt{\frac{\rho_{O1}^4/\xi_{O1}^2}{1+\rho_{O1}^2/\xi_{O1}^2}}$	(2C) $\mu_C - \frac{\lambda\rho_{C1}^2}{2(1+\rho_{C1}^2/\xi_{C1}^2)}$	(5I) $\sqrt{\frac{\rho_{C1}^4/\xi_{C1}^2}{1+\rho_{C1}^2/\xi_{C1}^2}}$
T2: label + information	(3O) $\mu_O - \frac{\lambda\rho_{O1}^2}{2(1+\rho_{O1}^2/\xi_{O2}^2)}$	(6C) $\sqrt{\frac{\rho_{O1}^4/\xi_{O2}^2}{1+\rho_{O1}^2/\xi_{O2}^2}}$	(3C) $\mu_C - \frac{\lambda\rho_{C1}^2}{2(1+\rho_{C1}^2/\xi_{C2}^2)}$	(6I) $\sqrt{\frac{\rho_{C1}^4/\xi_{C2}^2}{1+\rho_{C1}^2/\xi_{C2}^2}}$

2. $\xi_{C1}^2 < \xi_{C2}^2$. *Proof.* Consider the comparison of estimated means and standard deviations for conventional shoppers for treatments T1 and T2 in table 3:

$$\begin{cases} \mu_C - \dfrac{\lambda\rho_{C1}^2}{2\left(1+\frac{\rho_{C1}^2}{\xi_{C2}^2}\right)} > \mu_C - \dfrac{\lambda\rho_{C1}^2}{2\left(1+\frac{\rho_{C1}^2}{\xi_{C1}^2}\right)} & \text{(B12)} \\ \sqrt{\dfrac{\rho_{C1}^4/\xi_{C2}^2}{1+\rho_{C1}^2/\xi_{C2}^2}} > \sqrt{\dfrac{\rho_{C1}^4/\xi_{C1}^2}{1+\rho_{C1}^2/\xi_{C1}^2}} & \text{(B13)} \end{cases}$$

Rearranging equation (B12) we have $\frac{\lambda\rho_{C1}^4(\xi_{C1}^2-\xi_{C2}^2)}{2\xi_{C1}^2\xi_{C2}^2} < 0$. Since $\lambda > 0$, $\rho_{C1}^4 > 0$, $\xi_{C1}^2 > 0$, and $\xi_{C2}^2 > 0$, then it must be the case that $\xi_{C1}^2 < \xi_{C2}^2$. Rearranging equation (B13) leads to $\sqrt{\frac{\rho_{C1}^4}{\rho_{C1}^2+\xi_{C2}^2}} < \sqrt{\frac{\rho_{C1}^4}{\rho_{C1}^2+\xi_{C1}^2}}$. This inequality also holds for any given ρ_{C1}^4, and $\xi_{C1}^2 < \xi_{C2}^2$.