Demand for USDA Organic Labeled Junk Food

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Abstract

The USDA organic label, like other labels that make environmental claims, is meant to clearly communicate information about production methods. In theory, these labels allow informed consumers to indicate their willingness-to-pay for an environmental benefit by paying a premium for an eco-labeled item. However, well-established evidence from both surveys and experiments indicate that consumers also perceive a 'health halo' around eco-labeled items, which leads them to both consistently underestimate the amount of calories, and consume more of those items as a result. Existing estimates of willingness-to-pay for USDA organic labeling do not take nutritional quality into account. Utilizing a novel scanner data set, my results for USDA organic labeled chocolate bars and ice cream items show demand for USDA organic labeling is positively associated with calorie content. This interaction effect between calories and USDA label accounts for between 7%-15% of the price of items. This means the USDA organic program's stated informational content, which is limited to production methods, is not driving the entirety of consumer's evaluation of USDA organic labeled items. Further, consumers' evaluations of the informational content of USDA organic labels might have an adverse effect on consumers' health.

Introduction

At the time of the passage of the organic Food and Production act in 1990, pre-existing private organic certification programs like California Certified organic Farmers (CCOF) were almost exclusively for produce items. However, in a series of rulings by the National Organic Standards Board between 1990 and 1997, the USDA tried to balance competing interests between smaller, existing organic producers and larger entrants to the market. In particular, a fierce debate broke out over whether it was possible to have such a thing as an 'organic Twinkie.'[1] The policy USDA chose as a compromise was to make USDA organic certification exclusively about production methods and focused on environmental concerns. Despite this, survey evidence generally indicates consumers believe USDA organic items are healthier. Additionally, in field and lab experiments, when consumers are presented with an eco-labeled an unlabeled version of the same item, they generally estimate the eco-labeled version has fewer calories.[2] Consumers in these studies seem to make a hazy inference from the environmental qualities indicated by the eco-label to nutritional quality. Several studies, like Peloza, Ye, and Montford, (2015), also measure actual calorie consumption, finding participants eat more of eco-labeled items as a result. Providing consumers with more information about the environmental effects of the item's production methods leads consumers to infer the items are healthier, and end up eating more more calories. These results are described in the literature as the 'health halo' effect, and should direct the willingness-to-pay research towards nutritional information as a crucial control. However, very few previous studies estimating the willingness-to-pay for eco-labels have attempted to address the nutritional quality of the items under study.

[1]for an example of the debate, see Gussow, J. D. (1997). Can an organic Twinkie Be Certified? For All Generations: Making World Agriculture More Sustainable, Glendale, CA: OM Publishing, 143-153.

[2]for surveys see, for instance, Hughner, McDonagh, Prothero, Shultz, & Stanton, J. (2007). Who are organic food consumers? A compilation and review of why people purchase organic food. Journal of consumer behavior, 6(2-3), 94-110. for experimental evidence, see evidence on chocolate bars (Schuldt and Schwarz 2010), potato chips and yogurt (Lee et al. 2013) cookies (Schuldt and Schwarz 2012) granola bars and crackers (Peloza, Ye, Montford, 2015).

A key reason existing revealed preference studies have not been able to control for the 'health halo' effect is the choice of items being studied has not allowed the accurate observation of nutritional quality. A great deal of early research on USDA organic labels focused on produce items (Blend and Van Ravenswaay 1999; Loureiro, McCluskey and Mittelhammer 2001; Lin, Smith, and Huang 2008) and eco-labeled seafood items (Roheim, Asche and Santos 2011; Asche, Larsen, Smith, Sogn-Grundvag, and Young 2012; Wessells, Johnston,and Donath 1999; Johnston, Wessells, Donath, and Asche 2001). Although there has been research on nutritional differences between organically produced and conventionally produced seafood and produce items, systematic reviews have found mixed evidence of overall average nutrient quality differences.[3] The lack of clear evidence results from the large number of pre- and post-harvest factors influencing nutrition for harvested and farmed food products. Temperature, light, bruising, irradiation, and the amount of CO2 in storage all can affect the levels of micro nutrients in produce and seafood items. In the wholesale produce and seafood markets, the origin of items can change very quickly, so data taken even over a short amount of time might have a lot of variation in nutritional quality. I benefit from a unique data set that combines traditional scanner data on packaged grocery items with nutritional information unavailable to researchers on produce or seafood. Packaged grocery items are subject to the FDA's Nutrition Facts Label Program, and so provide the opportunity to observe how consumers value USDA organic certification relative to macro- and micro-nutrient density. In general, packaged grocery items have been under-studied in the literature, creating a blind spot in demand estimates of USDA organic labels generally unable to control for a 'health halo'.

The inability to control for nutritional quality helps explain a discrepancy in existing research on the willingness-to-pay for eco-labels between stated preference studies and revealed preference studies. In general, evidence indicates that when presented with a hypothetical

[3]Dangour, A. D., Dodhia, S. K., Hayter, A., Allen, E., Lock, K., & Uauy, R. (2009). Nutritional quality of organic foods: a systematic review. The American Journal of Clinical Nutrition, 90(3), 680-685.

choice in a stated preference survey, consumers tend to overstate the amount they are willing-to-pay for environmental goods (Murphy, et al.2005). For eco-labeled items, this would translate to an expectation that stated-preference estimates of willingness-to-pay would be higher than revealed preference estimates of willingness-to-pay. In the literature, however, many revealed preference estimates of the willingness-to-pay for eco-labeled items are larger than estimates of the same item from stated-preference surveys. For instance, Schollenberg's (2011) hedonic estimate for Fair Trade coffee of 38% on average for consumers in Sweden is much higher than any of the stated preference survey estimates in Lourerio and Lotade (2005), which range from 15 to 20%. Also, the hedonic estimates of a premium for USDA organic certified apples of 34% on average using grocery scanner data in Lin, Smith, and Huang (2009) is much higher than the roughly 5% average premium found in a survey by Loureiro, McCluskey, and Mittelhammer (2002). The 'health halo' effect is a plausible explanation for this difference. Stated preference surveys of willingness-to-pay for eco-labeled items are able to be very explicit about which attributes are and are not included in the profile of a hypothetical product. In market data, however, the 'heath halo' inference consumers make between environmental claims and health claims means explicit controls are needed to avoid inflated estimates.

The study proceeds in five sections. First, a description of the data. Second, a discussion of the analytic framework and underlying model of demand. Third, a description of the estimation procedure, and finally a presentation of the results and discussion with potential avenues of future research in this area.

Data

The data for this study come from a food retailer.[4] Brands, prices, quantities sold, and wholesale costs are observed across grocery items as a panel at weekly intervals over a

[4]Due to the proprietary nature of these data, identifying information here and elsewhere in the analysis is excluded by agreement

four year time span at seven locations in a three-state area. Also, the data indicate when items are put on promotion, which is associated with a lower price, promotional signage, and better placement within the store. Observations are at the item-week level at each location. Price, wholesale cost, and item availability differ very little between locations, since distribution, wholesale purchasing, and price-setting is consistent across locations. Although the proprietary nature of the data limit the ability to report on average differences between price, cost, and quantities sold precisely, in general, the USDA organic items in the data are around 20-30% more expensive than items without a label, and had a smaller share of total sales than items without a label. To the food retailer's data set I added FDA nutritional data and other product characteristics, including flavors, nutritional quality, and labeling.[5] All the items in the data set were successfully matched with the appropriate nutritional and attribute information. Once harmonized, the typical observation in the final data set is an item at a store location in a particular week, with time-varying variables price, cost, and quantity sold, as well as time invariant attributes such as brand, flavor, and FDA nutritional information.

The items fall into two item groups. The first item group consists of the 91 top-selling chocolate bar items described in Table 1.[6] Included in the table are the three nutritional attributes with the most variance between items: calories, total fat, and sodium. For each nutritional attribute, Table 1 presents the total amount in one bar. The chocolate bars in this study had very similar sizes, at around 3.2 oz. Nutrition labels do not necessarily show the amount per bar, but rather show the amount per 'serving,' the definition of which firms have some control over, and which can vary dramatically between brands.[7] Also included are the top two most common flavors, almond and salted, along with "percent dark chocolate."[8]

[5]Collection of these data was conducted both on-location and through vendor-supplied information.

[6]To be included, the items had to pass a minimum threshold (thirty dollars a week) of sales.

[7]Notably, the FDA does not appear to have guidance for industry on the reference serving size for chocolate. see FDA, (2017) Guidance for Industry: Food Labeling: Serving Sizes of Foods That Can Reasonably Be Consumed At One Eating Occasion)

[8]The proportion in question refers to the amount of the non-fat portion of the cocoa bean included (as opposed to the fatty portion of the cocoa bean, known as cocoa butter), relative to milk solids content. I am

Last, Table 1 includes the other eco- and- health labels in the data. These include fair-trade labels, non-gmo ingredient labels, and "natural" labels. Each of these categories is inclusive, meaning all 'fair-trade' labels are included together since, unlike USDA organic labeling, there exists many independent 'fair-trade' and 'non-GMO' labeling organizations, and these labels are typically not subject to regulation. Two important comparisons can be made between USDA organic labeled items and their conventional counterparts, which prefigure the model results presented later.

First, a comparison between chocolate bar items can be made based on the items available to consumers in the data. About 25% of the chocolate bars offered have a USDA organic label. On average, the USDA organic labeled items available to consumers have 20 more calories and 3 more grams of fat per bar, have slightly more salt flavored varieties and slightly fewer almond flavored varieties, and have 3% less dark chocolate. Although the USDA organic labeled items have slightly higher average amounts of calories and total fat per bar, these differences are small in comparison to the spread of the nutritional options available in both categories. The most notable differences between the groups in terms of available items comes in labeling, where 36% more of the USDA organic labeled items also have fair-trade labeling. The USDA organic group has roughly the same proportion of non-GMO labeling and 24% fewer items with gluten free labeling.

This same comparison is much different when made based upon top selling items. Table 1 also presents average attributes for the top five selling items in both groups. For both USDA organic labeled and conventional chocolate bars, the top-selling items have more calories, total fat, and sodium on average. Importantly, the average nutritional differences are much larger when looking at top selling items. On average, the top-selling USDA organic labeled items have 60 more calories and 10 more grams of fat per bar. Of the top five selling USDA organic labeled chocolate bars, none are almond flavored, one is salt flavored, and

not aware of any standard labeling requirements for the categories "dark chocolate" and "milk chocolate" but will note from the data all the bars advertised as "milk chocolate" have less than 50% cocoa content.

four have fair-trade labels. None of the top-selling conventional chocolate bars has eco- or health-labeling. Taken as a whole, these descriptive statistics suggest consumers are buying USDA organic labeled chocolate bars with relatively high levels of fat and calories, even though USDA organic labeled options with fewer calories and less fat are available.

Table 1: Item Average by Label (Chocolate Bars)

	Available		Top 5 Selling	
	Conventional	USDA organic	Conventional	USDA organic
Calories	442	460	490	537
	(70.5)	(60.3)	(57.4)	(71.6)
Fat(g)	31.12	32.50	30.89	38.20
	(5.6)	(6.4)	(6.8)	(5.6)
Percent Dark Chocolate	57%	54%	60%	74%
	(2%)	(2%)	(1%)	(1%)
Almond Flavored	0.20	0.13	0.40	0
Salt Flavored	0.09	0.18	0.20	0.20
Fair-Trade Label	0.31	0.67	0	0.80
Non-GMO Label	0.27	0.31	0	0.20
Gluten Free Label	0.27	0.03	0	0
Observations	68	23	10	10

mean average; sd in parentheses

The second category consists of 77 top-selling ice cream items described in Table 2. For each nutritional attribute, the Table presents the amount per gram. Unlike chocolate bars, ice-cream items are available in several very different sizes (e.g. pints, quarts). Additionally, the churning process of manufacturing ice cream introduces air, so even similar sized containers can have different amounts of actual ice cream.[9] To compare across items, Table 2 reports nutrient density, in terms of calories, total fat and sodium, per gram. Also included are the top two most common flavors in the data, vanilla and chocolate, along with other eco- and

[9]The industry refers to the air content as 'overrun', and can be as high as 50% of the volume. The difference in texture and volume might be familiar to anyone who has tried to re-freeze melted ice-cream.

health- labels. Table 2 presents the same comparison as in Table 1 between the ice cream items available to consumers, and the top selling ice cream items.

About 40% of the ice cream offered by the retailer has a USDA organic label. On average, the USDA organic labeled items available to consumers have 0.2 more calories per gram. A typical pint of ice cream is between 250-350 grams, so on average, a USDA organic labeled ice cream pint would have about 60 more calories. Since total fat is measured in grams, it is the same as a proportion of total grams from fat. The available USDA organic labeled ice cream items have on average 2% more fat. As in the case of chocolate bars, although the USDA organic labeled items have slightly higher average amounts of calories and total fat, these differences are small in comparison to the variance of the nutritional options available in both groups. Table 2 also presents average attributes for the top five selling items in both groups. Unlike the chocolate bar group, the top-selling items have fewer calories and less total fat on average. It is somewhat surprising that top selling ice cream items tend to have fewer calories, in contrast to the chocolate bar group. Intuitively, calories might be preferred by consumers for taste and flavor, but also not preferred for health reasons. The descriptive results in Tables 1 and 2 and in the estimation results presented later suggest that the balance between these competing preferences might be different between the item groups. However, like the chocolate bar group, average nutritional differences between organic and conventional items are much larger when looking at top selling items than when looking at available items. The average difference is about 120 calories for a pint of ice cream, and 4% total fat. Neither the organic nor the conventional top selling items have fair trade labels, and the combination of chocolate flavored ice cream and vanilla flavored ice cream makes up 2 and 4 of the top selling items respectively.

These descriptive statistics suggest with ice cream as with chocolate bars, consumers are buying USDA organic labeled ice cream with relatively high levels of fat and calories. In the next section, I lay out an analytic framework for robust estimates of this relationship.

Table 2: Item Average by Label (Ice Cream)

	Available		Top 5 Selling	
	Conventional	USDA organic	Conventional	USDA organic
Calories(per g)	2.11	2.31	1.74	2.14
	(0.8)	(0.8)	(0.6)	(0.9)
Fat(proportion)	0.11	0.13	0.08	0.12
	(0.1)	(0.1)	(0.1)	(0.1)
Vanilla Flavored	0.33	0.37	0.60	0.40
Chocolate Flavored	0.19	0.29	0.20	0.20
Fair-Trade Label	0.15	0.22	0	0
Observations	46	31	5	5

mean average; sd in parentheses

Analytic Framework

Studies which have used market data to estimate the price premia for eco-labeled items have tended to use hedonic price regressions. These studies have been employed on USDA certified produce (Lin, Smith, and Huang 2008), USDA certified milk (Lin, Smith, and Huang 2009), MSC labeled seafood (Roheim, Asche and Santos 2011), and eco-labeled salmon (Asche, Larsen, Smith, Sogn-Grundvag, and Young 2012). However, a concern with hedonic models in application to market-level scanner data is the difficulty in specifying theoretically consistent functional forms. Ekeland, Heckman and Nesheim (2002) demonstrate the hedonic pricing equations derived from general theoretical approaches are "... intrinsically (generically) non-linear," in this environment. This is a difficult concern to overcome, since no general non-linear specification for the pricing function is available without making assumptions about market structure. An alternative choice is a discrete choice framework. Although the hedonic method and discrete choice share many similarities, discrete choice methods do not place functional form requirements on the hedonic pricing function (Wong 2015).

The discrete choice model of consumer demand is well described and understood, and has a long history of modeling grocery scanner data, even if it has not before been utilized to estimate willingness-to-pay for USDA organic labels. Even so, the selection is worth discussion. Generally, the discrete choice methodology is motivated by the high-dimensionality of modeling in the product space.[10] In these data, controlling for all cross-price elasticities in item-level demand equations would require the estimation of more than 8,000 parameters per item group, which is infeasible. Additionally, at least in the random-coefficients specification outlined later, an attempt is made to model consumer-level heterogeneity to avoid the assumptions placed on individual preferences required to guarantee the theoretical existence of an aggregate demand function (Gorman, 1959).

Whether the discrete-choice framework is appropriate in this case depends on a few considerations. First, the model requires specifying consumer's indirect utility. When derived from a quasi-linear utility function, as in Nevo (2000), this implies no wealth effects. For grocery items like in this study, as in Nevo's study of cereal, it is reasonable to assume wealth effects are small. Even the most expensive item in the data is unlikely to affect many consumer's budget constraints. Second, consumers in a discrete choice model purchase only one item at a time. This is likely to not be true at least some of the time in these data, but if the proportion of consumers buying more than one of an item at a time is small, or if each purchase decision is well modeled as an independent choice, the effect on estimates should be small. Importantly, this would also only bias estimates of the marginal utility of observable attributes, to the extent to which the indirect utility of the marginal choice co-varied with any of the observable attributes. That is, if the decision to buy a second chocolate bar was affected by observable attributes in a way the decision to buy the first chocolate bar was not, estimates would be biased. Last, the discrete choice model assumes all customers are subject to the same prices and product attributes. All of the attributes included in the estimation are those which could have been known by a consumer at the

[10]By modeling in the product space, I mean something in the vein of the linear expenditure model of Stone (1954), or extensions like the AIDS demand system of Deaton and Muellbauer (1980).

point of sale. However, previous research has indicated the salience of various attributes does effect consumer demand. This concern, along with broader concerns about unobservable characteristics, motivate the inclusion of brand, store, and time effects in estimation, as discussed later.

In the discrete choice framework, the indirect utility of consumer i of product j in market m is

$$u_{ijm} = x_{jm}\theta_i + \xi_{jm} + \epsilon_{ijm} \tag{1}$$

,

where x_{jm} is a set of observed characteristics by product and market, ξ_{jm} is a set of unobserved characteristics by product and market, and ϵ_{ijm} is a mean-zero stochastic term. In this formulation, the elements of θ_i are an individual's marginal utilities of the observed attributes. The consumer chooses one unit of item j from a set of $j = 0, 1, 2, 3 \ldots J$ items if and only if $u_{ij} \geq u_{ik}$ for all $k \neq j$ in the item set. Since these data are at the aggregate level, rather than individual, the model's main prediction of interest is the predicted market share,

$$s_{\tilde{jm}}(x_{jm}, \xi_{jm}; \theta) = \int_{m_j} dP^*(v, \epsilon) \tag{2}$$

,

where P^* the market's population distribution as functions of consumer heterogeneity v, and the stochastic error ϵ.

The first specification considered is a logit model, which results from the assumption all consumer heterogeneity is captured in ϵ_{ijm}. This implies $\theta_i = \theta$ in Equation 1 for all i, so the marginal utilities of the observed attributes are the same across all consumers. A second standard assumption for tractability is the stochastic errors ϵ_{ijm} are distributed $i.i.d$ type I extreme value. Without consumer heterogeneity, and with Equation 2 integrated over the extreme value distribution $P^*(\epsilon)$, the expected market share function is

$$\tilde{s_{jm}} = \frac{exp(x_{jm}\theta + \xi_{jm})}{\sum_k^J exp(x_{jm}\theta + \xi_{jm})} \tag{3}$$

.

Importantly, the logit specification imposes a restriction on the cross-elasticities of items in the choice set. The increase in demand for item j resulting from an increase in its attractiveness is drawn from the other items in the choice set in exact proportion to their respective market shares. For example, in the data under consideration here, a increase in price for a non organic-labeled dark chocolate bar would increase demand for both an organic-labeled dark chocolate bar and a non-organic-labeled milk chocolate bar based only on those items' observed market shares. The model does not allow for a relatively larger substitution effect from one item or the other, if consumers treat organic-labeled bars as more similar than dark-chocolate bars, or alternatively treat dark-chocolate bars as more similar than organic-labeled bars. This undesirable feature is a direct outcome of the assumptions on consumer heterogeneity, and motivates the relaxing the assumption, as in the next specification considered.

The second specification, the random coefficients model, relaxes the assumption on consumer heterogeneity. Instead, consumer heterogeneity is modeled as a multivariate normal distribution

$$\theta_i \sim N(\theta, \Sigma v_i) \tag{4}$$

.

This makes the integral in Equation 2 non-tractable analytically, and necessitates solving for θ_i through non-linear optimization in order to describe the model's predicted market shares $\tilde{s_{jm}}$. Σ contains the parameters of consumer heterogeneity, σ_l, describing the variation in consumers' marginal utility. To solve the random coefficients model, I use the algorithm of Berry Levinsohn and Pakes (1994), briefly described in the next section.

Estimation

The goal of estimation in the discrete choice framework is to equate the model's predicted market shares $\tilde{s_{jm}}$ (Equation 2) with the market shares observed in the data as $s_{jm} = q_{jm}/M_m$, for item j's unit sales q_{jm} and market with size M_m. For each of the locations in this study, the potential market for all items M_m, is defined as the number of consumers who visited the store in that week. Using a population-based measure for M_m, as is otherwise common in the literature, does not appreciably change the results reported below. The estimation procedures outlined below can only identify $J - 1$ parameters, so for identification purposes, it is standard to define an "outside good" $s_{m0} = 1 - \sum_j^{J-1} s_{jm}$ as a reference point for the rest of the goods in the choice set, meant to represent the share of consumers who chose not to buy any one of the items. As it true with the discrete choice framework more generally, this assumes each unit sale of an item corresponds to a single consumer.

Estimation of the logit specification is made easier by a linearization of Equation 3,

$$log(s_{jm}) = x_{jm}\theta + \xi_{jm} - log(\sum_k^J exp(x_{jm}\theta + \xi_{jm})) \tag{5}$$

.

If the indirect utility of choosing not to purchase any of the items is set to zero, then $log(s_{j0}) = -log(\sum_{k \neq j}^J exp(x_{jm}\theta + \xi_{jm}))$, so the estimation equation becomes

$$log(s_{jm}) - log(s_{j0}) = x_{jm}\theta + \xi_{jm} \tag{6}$$

.

Identification of the parameters of interest in θ requires the assumption $Cov(x_{jm}\xi_{jm}) = 0$. All of potential observable attributes in x_{jm}, such as price, nutritional quality, or flavor characteristics, could plausibly be correlated with unobservable attributes ξ_{jm}. This motivates three specification choices. First, every specification reported on below includes fixed effects to control for any store-week, or brand-level unobserved attributes. The store-week fixed effects control, for example, unobservable shocks to due to weather, or an individual store's weekly-level retail quality, or the placement of item groups within a store in a particular week. The brand-level fixed effects control, for example, perceptions of quality at a brand level and advertising choices like packaging.

For supply-side unobservables correlated with the mark-up over marginal cost, a natural instrument is wholesale cost c_j. Many scanner-data studies are forced to cleverly design proxies for wholesale price markup, which is thankfully not necessary here. The exclusion restriction is plausible for wholesale cost, since consumers do not observe wholesale cost when making a purchase decision, so adjustments in p_j caused by changes in c_j are not likely to be caused up a firm's knowledge of ξ_{jm}. The fixed effect treatment discussed above also helps narrow the range of potential factors which would lead to a wholesaler mark up. The concern would be a wholesaler increasing an item's own price based on unobserved attributes within brand or store-week. As noted above, purchasing decisions, and therefore wholesale costs, are regional, and very unlikely to vary within a store-week. However, within brand variation is potentially more problematic. For example, if a brand applied the different production process on only some of its items, that could influence both wholesale cost and the item's price in a way not captured by a brand-level effect. Item-level fixed effects would be an ideal way to potentially address those concerns, but are co-linear with the main variable of interest (USDA organic labeling).

However, an instrumental variable approach from Villas-Boas (2007) allows the use of item-level variation in identification. Villas-Boas proposes the interaction of wholesale cost with item-level fixed effects as instruments. Mechanically, these instruments add time variation, allowing for item-level observed attributes. This changes the identification assumption from correlation between input prices and unobserved attributes to correlation between changes in input prices and unobserved attributes. Identification rests on the assumption no brand changes its production process on only some of its items. This is a much more plausible assumption, which is indicative of the strong track record of these instruments in similar research (Draganska and Mazzeo 2003; Hellerstein 2010). So, the OLS estimates of Equation 6 are compared with two-stage least squares estimates with the inclusion of the instruments suggested by Villas-Boas.

It is worth discussing briefly the potential inclusion of the 'standard' instruments in random coefficient estimation from Berry, Levinsohn and Pakes (1995). The BLP instrumental variables rest on the observation, from the discrete choice framework, that consumer i's indirect utility for item j in the model only depends on item j's attributes, making the attributes of other items $k \neq j$, either within brand, or across all competitors, valid instruments. An argument is sometimes made that standard 'BLP instruments' can be used across all product characteristics, including price, based on an argument from theory that unobserved item k attributes affect item j 's price through competitive pressure.[11] These instruments, however have have some limitations. By relying heavily on the discrete choice framework for the exclusion restriction, these instruments make the fairly heroic assumption no unobservable k product attribute correlates with an observed j product attribute. A clear reason to doubt this assumption is observed product attributes often correlate with each other. For instance, in the chocolate bar data, fair trade eco-labels are much more likely to be found on USDA organic labeled items than non-labeled items. A more direct concern, however, for the current study, is the inclusion of the brand-level BLP instruments would exclude the possibility of

[11] see Armstrong (2015) for a longer discussion of this possibility, including conditions under which it might hold.

brand level fixed effects,[12] and the across-competition BLP instrument would be perfectly co-linear with the variable of interest. BLP instruments, while standard elsewhere, are not appropriate in this case.

As with the logit specification, estimation of the random coefficients specification requires predicting market shares $\tilde{s_{jm}}$. However, without the assumption of consumer homogeneity in the marginal utility of observed attributes the integral in Equation 2 can only be approximated, and the parameters must be estimated with non-linear optimization. There exist many in-depth descriptions of the BLP estimation algorithm, so only a brief outline will be discussed here.[13] Recall the model of consumer heterogeneity from the analytic framework,

$$\theta_i \sim N(\theta, \Sigma v_i) \tag{7}$$

.

The random coefficients specification is estimated through Generalized Method of Moments, based on the moment conditions $h(z_{jm}, x_{jm})$, with z_{jm} instruments as described above,

$$E[\xi(\theta)h(z_{jm}, x_{jm})] = 0 \tag{8}$$

.

To form the empirical estimate of Equation 8, we require an estimate of ξ_{jm} for a given value of θ. A way to simplify this problem is based on the assumption, from the discrete choice framework, that the mean indirect utility across all consumers δ_{jm} is linearly related to ξ. This makes it worthwhile to additively separate out indirect utility u_{ijm} into the linear parameters θ_1 of mean indirect utility δ_{jm},

[12] see the discussion in Nevo (2000)

[13] The code used to implement the estimation in R for this study was derivative of routines written Nevo (2000) in Matlab.

$$\delta_{jm} = x_{jm}\theta_1 + \xi_{jm} + \epsilon_{ijm} \tag{9}$$

,

and non-linear parameters θ_2 of heterogeneous consumer-level deviations from mean utility μ_{ijm},

$$\mu_{ijm} = x_{jm}\theta_2 v_i \tag{10}$$

,

so ξ can be defined as the difference between the mean indirect utility implied by the individual-level utility model $x_{jm}\theta_1$, and the mean indirect utility implied by the estimated market shares $\delta(\tilde{s_{jm}}, \theta_2)$

$$\xi_{jm} = \delta(\tilde{s_{jm}}, \theta_2) - x_{jm}\theta_1 \tag{11}$$

.

This leaves the question of estimating mean indirect utility implied by the estimated market shares $\delta(\tilde{s_{jm}}, \theta_2)$, and as an input, estimated market shares $\tilde{s_{jm}}$. Estimated market shares are approximated for given a value for the non-linear parameters θ_2 in an analogous way to Equation 3,

$$\tilde{s_{jm}}(x_{jm}, \xi_{jm}; \theta) = \int_{m_j} dP^*(D, v, \epsilon) \approx \frac{1}{nm} \sum^{nm} \frac{exp(\mu_{jm}(\theta_2) + \delta_{jm}(\theta_1))}{\sum_k^J exp(\mu_{km}(\theta_2) + \delta_{km}(\theta^1))} \tag{12}$$

.

Convergence of iterated estimates of the mean indirect utility implied by the estimated market shares $\delta(s_{\tilde{j}m}, \theta_2)$, is guaranteed by the BLP contraction mapping, in which a step r estimate is constructed as

$$\delta^{r+1} = \delta^r + ln(s) - ln(s_{\tilde{j}}m(x_m, p_m, \delta_m; \theta_2)) \tag{13}$$

.

The GMM objective function based on Equation 8 becomes

$$min_{\theta_2}\xi(\hat{s_{\tilde{j}m}}, x_{jm;\theta_1})Z\Phi^{-1}Z'\xi(\hat{s_{\tilde{j}m}}, x_{jm;\theta_1}) \tag{14}$$

,

where Φ is a consistent estimate of $E[Z\xi\xi'Z']$.[14] The GMM objective function defined by Equation 14 forms the outer loop of the algorithm, and the contraction mapping from Equation 13 forms the inner loop.

Although the convergence of Equation 13 is guaranteed in theory, many practical issues exist. Like any non-linear optimization procedure, results of this estimation are sensitive to starting values. Knittel and Metaxoglou (2008) found own and cross price elasticites estimated from the BLP algorithm could vary by a factor of 100 with different initial values for θ_2. To determine a robust convergence, the estimation here follows a "multi-start" estimation approach with many starting values.[15] Importantly, Knittel and Metaxoglou did not find the multi-start approach solved all of the pathologies of BLP convergence, but it is a necessary condition for robust estimation. Dube, Fox and Su (2012), however, were able to replicate Knittle and Metaxoglou's results with stable estimation by tightening the tolerance on the outer-loop of the estimation. Additionally, Reynaerts, Varadhan, and Nash (2012)

[14] In this case, as is standard, $E[Z'Z]$.

[15] see Varadhan, Ravi, and Paul Gilbert. "BB: An R package for solving a large system of nonlinear equations and for optimizing a high-dimensional nonlinear objective function." Journal of Statistical Software 32.4 (2009): 1-26 for implementation.

found in Monte Carlo simulations the SQUAREM squared polynomial extrapolation method (Varadhan and Roland, 2008) for accelerating the fixed-point contraction allowed for fast estimation with the tighter tolerance level advocated by Dube, Fox and Su.[16] So, based on the 'state-of-the-art' for solving this algorithm, estimation proceeds here with 50 starting values, the SQUAREM acceleration of the contraction mapping, and a solver best suited for large-scale optimization.

Results

The results for the OLS estimates of the logit specification for the chocolate bar group are presented first. Specification (1) includes price, fixed effects for item, store, and week, as well as an indicator for when an item was on promotion. Even though the base specification does not include the variable of interest, it is still an important point of comparison. Recall from the model an item-level unobserved attribute would effect consumer elasticities, and therefore would change the optimal markup the firm could charge. The preferred specification cannot include item-level fixed effects, but if the price coefficient does not change appreciably when item-level fixed effects are replaced by the controls in other specifications, it provides some evidence the unobserved item-level attributes are not overly biasing estimates. In the results below, the sign, relative magnitude, and significance of the price coefficient change very little across the specifications.

The second specification includes indicators for labeling, including fair-trade labels, non-GMO ingredient labels, "natural" labels, and most importantly the USDA organic label. To test the robustness of estimated marginal effect of the USDA organic label, the results in specification (2) are compared to specifications with flavor controls (3) and nutritional controls (4). For the chocolate bar group, the flavor controls are the percent cocoa content,

[16]see Du, Y., & Varadhan, R. (2018). SQUAREM: An R Package for Off-the-Shelf Acceleration of EM, MM and Other EM-like Monotone Algorithms for the implementation of SQUAREM.

and indicators for coconut, caramel, mint, hazelnut, almond, salt, and cherry flavor.[17] Since carbohydrates and fat are linked by an exact relationship to calories,[18] the inclusion of calories as a nutritional control generally precludes separate identification of the effects of carbohydrates or fat. Since most of previous research and lab studies on the 'health halo' focused on calories, estimates are also expressed in those terms here, even though broadly similar results could be found with fat or carbohydrates alone. For the chocolate bar group, calories are included as total grams per bar. Total sodium in milligrams and vitamins A and C, expressed as a percent of daily value, are also included as nutritional controls. Since the descriptive statistics suggested a differential effect of USDA organic labels on consumer's evaluation of nutritional quality, the last variable of interest is an interaction between the USDA organic label indicator and calorie content, presented in the full preferred specification (5).

OLS logit results for the chocolate bar group are presented in Table 3. The interpretation of the coefficients within the discrete choice framework are as parameters of marginal utility, common across all consumers in the market. Marginal willingness to pay for an attribute is a ratio of marginal utility for the attribute to the marginal utility of price. For price, USDA organic label, and the interaction effect between the label and total calorie content in the preferred specification, we can reject a null hypothesis of zero marginal utility at a 5% level. The estimated marginal willingness to pay for a USDA organic label decreases from \$0.32 without nutritional controls to \$0.14 in the full specification. After controlling for calories, the interaction term indicates the estimated additional willingness to pay for USDA organic items for a marginal 100 calories is \$0.20. For a chocolate bar with an average amount of calories, the additional estimated willingness-to-pay is \$0.82.

[17]To be included, the flavor had to be indicated on the front packaging.
[18]Each gram carbohydrates contains four calories, and each gram of fat contains nine calories.

Table 3: OLS Logit results for Chocolate Bars

	(1) Logit OLS	(2) Logit OLS	(3) Logit OLS	(4) Logit OLS	(5) Logit OLS
Price	-0.49^{***}	-0.46^{***}	-0.47^{***}	-0.47^{***}	-0.51^{***}
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
USDA OG Label		0.15^{*}	0.14^{*}	0.10^{***}	0.07^{**}
		(0.08)	(0.08)	(0.03)	(0.03)
Total Calories				0.0013^{*}	0.002^{***}
				(0.0008)	(0.001)
Total Calories and OG Label					0.0011^{***}
					(0.0003)
Brand FE	Yes	Yes	Yes	Yes	Yes
Promotion	Yes	Yes	Yes	Yes	Yes
Store-Week FE	Yes	Yes	Yes	Yes	Yes
Other Labels	No	Yes	Yes	Yes	Yes
Flavor Controls	No	No	Yes	Yes	Yes
Nutrition Controls	No	No	No	Yes	Yes
Item FE	Yes	No	No	No	No
Observations	132,496	132,496	132,496	132,496	132,496

The IV results for the chocolate bar group are presented in Table 4. The first five logit models are estimated with two-stage least squares, and the specification (6) is estimated with random coefficients, as described above. The estimated marginal willingness to pay for a USDA organic label decreases from \$0.40 without nutritional controls to \$0.15 in the full specification. After controlling for calories, the interaction term indicates the estimated additional willingness to pay for USDA organic items for a marginal 100 calories is \$0.16 in the logit IV specification (5) and \$0.13 in the random coefficient specification (6). For a chocolate bar with an average amount of calories, the additional estimated willingness-to-pay would be \$0.48 or \$0.35, respectively.

The random coefficient estimation adds the parameters of consumer heterogeneity σ_x (see equations 4 and 7 above). The estimated heterogeneity of marginal utility for the USDA organic label is large. The estimated marginal willingness-to-pay one standard deviation around the mean ranges from -\$0.07 to \$0.37. Average estimated own-price elasticities vary from -1.76 to -3.88. For all chocolate bar the lowest total estimated WTP is 44% of the average price and the highest total estimated WTP is 179% of the average price. The average total estimated WTP as a percent of the average price is 80%.[19]

[19]Across all chocolate bar items in all weeks and all stores, the standard deviation of price is around 30% of the average price.

Table 4: IV Logit and Random Coefficient results for Chocolate Bars

	(1) Logit IV	(2) Logit IV	(3) Logit IV	(4) Logit IV	(5) Logit IV	(6) Random Coefficient (BLP)
Price	-0.67^{***}	-0.62^{***}	-0.63^{***}	-0.62^{***}	-0.62^{***}	-0.598^{***}
	(0.07)	(0.07)	(0.08)	(0.08)	(0.09)	(0.09)
σ_p						0.16
USDA OG Label		0.25^{**}	0.19^{**}	0.12^{**}	0.09^{**}	0.09^{**}
		(0.09)	(0.09)	(0.05)	(0.035)	(0.04)
σ_{og}						0.13
Total Calories				0.006^{*}	0.002^{**}	0.004^{**}
				(0.004)	(0.001)	(0.002)
σ_c						0.004
Total Calories and OG Label					0.0010^{**}	0.0008^{***}
					(0.0005)	(0.0003)
$\sigma_{og:c}$						(0.0002)
Brand FE	Yes	Yes	Yes	Yes	Yes	Yes
Promotion	Yes	Yes	Yes	Yes	Yes	Yes
Store-Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Other Labels	No	Yes	Yes	Yes	Yes	Yes
Flavor Controls	No	No	Yes	Yes	Yes	Yes
Nutrition Controls	No	No	No	Yes	Yes	Yes
Item FE	Yes	No	No	No	No	No
Observations	132496	132496	132496	132496	132496	132496

The results for the OLS estimates of the OLS logit specifications for the ice cream group are presented next in Table 5. The specifications are largely same as for the chocolate bar group, with the addition of total grams to account for the differences in size. Also accounting for differences in size, calories are included for the ice cream group as calories per gram. Sodium per gram is also included as a nutritional control. The flavor controls are indicators for chocolate, vanilla, mint, and cookie dough. The similarity of the estimate for price between specification (1), which includes item-level fixed effects, and specifications (2)-(5) suggests item-level unobservables are not overly biasing estimates in the preferred specification.

For price, USDA organic label, and the interaction effect between the label and total calorie content in the preferred specification, we can reject a null hypothesis of zero marginal utility at a 5% level. The estimated marginal willingness to pay for a USDA organic label decreases from \$1.91 without nutritional controls to \$1.50 in the full specification. The interaction term indicates the estimated additional willingness to pay for USDA organic items for a marginal 10 calories per gram is \$0.04. For a chocolate bar with an average amount of calories per gram, the additional estimated willingness-to-pay is \$0.25. As was indicated above by the descriptive statistics, the estimated marginal utility of calorie density is negative, unlike the chocolate bar group.

Table 5: OLS Logit results for Ice Cream

	(1) Logit OLS	(2) Logit OLS	(3) Logit OLS	(4) Logit OLS	(5) Logit OLS
Price	-0.27^{***}	-0.23^{***}	-0.23^{***}	-0.22^{***}	-0.22^{***}
	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
USDA OG Label		0.44^{***}	0.48^{***}	0.37^{***}	0.33^{***}
		(0.06)	(0.11)	(0.12)	(0.08)
Calorie Density				-0.0062^{*}	-0.0068^{*}
				(0.0034)	(0.0032)
Calorie Density and OG Label					0.00094^{***}
					(0.00032)
Total Grams	Yes	Yes	Yes	Yes	Yes
Brand FE	Yes	Yes	Yes	Yes	Yes
Promotion	Yes	Yes	Yes	Yes	Yes
Store-Week FE	Yes	Yes	Yes	Yes	Yes
Other Labels	No	Yes	Yes	Yes	Yes
Flavor Controls	No	No	Yes	Yes	Yes
Nutrition Controls	No	No	No	Yes	Yes
Item FE	Yes	No	No	No	No
Observations	112112	112112	112112	112112	112112

The IV results for the ice cream group are presented in Table 6. The first five logit models are estimated with two-stage least squares, and the specification (6) is estimated with random coefficients. The estimated marginal willingness to pay for a USDA organic label decreases from \$2.21 without nutritional controls to \$1.06 in the full specification. After controlling for calories, the interaction term indicates the estimated additional willingness to pay for USDA organic items for a marginal 10 calories is \$0.013 in the logit IV specification (5) and \$0.04 in the random coefficient specification (6). For an ice cream item with an average amount of calories per gram, the additional estimated willingness-to-pay would be \$0.45 or \$0.16, respectively. For the random coefficient estimate the estimated marginal willingness-to-pay for the USDA organic label one standard deviation around the mean ranges from \$0.15 to \$1.97.

Table 6: IV Logit and Random Coefficient results for Ice Cream

	(1) Logit IV	(2) Logit IV	(3) Logit IV	(4) Logit IV	(5) Logit IV	(6) Random Coefficient (BLP)
Price	-0.14	-0.20^{**}	-0.20^{*}	-0.27^{**}	-0.31^{*}	-0.33^{*}
	(0.08)	(0.08)	(0.09)	(0.11)	(0.14)	(0.16)
σ_p						0.10
USDA OG Label		0.44^{***}	0.44^{***}	0.44^{***}	0.45^{***}	0.35^{**}
		(0.15)	(0.15)	(0.15)	(0.14)	(0.15)
σ_{og}						0.30
Calorie Density				-0.018^{*}	-0.022^{**}	-0.021^{*}
				(0.008)	(0.009)	(0.012)
σ_c						0.013
Calorie Density and OG Label					0.0004^{***}	0.0014^{***}
					(0.0001)	(0.0004)
$\sigma_{og:c}$						0.0008
Total Grams	Yes	Yes	Yes	Yes	Yes	Yes
Brand FE	Yes	Yes	Yes	Yes	Yes	Yes
Promotion	Yes	Yes	Yes	Yes	Yes	Yes
Store-Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Other Labels	No	Yes	Yes	Yes	Yes	Yes
Flavor Controls	No	No	Yes	Yes	Yes	Yes
Nutrition Controls	No	No	No	Yes	Yes	Yes
Item FE	Yes	No	No	No	No	No
Observations	112112	112112	112112	112112	112112	112112

Discussion

The most notable difference between the two item groups in the results is estimated marginal willingness-to-pay for calories is positive for the chocolate bar group and negative for the ice cream group. As discussed above, the expectation for consumer's willingness-to-pay for marginal calories is ambiguous, since calories are associated with better flavor in higher fat and carbohydrate content, but also negatively associated with healthiness. One potential explanation for the difference is diminishing marginal utility in calories overall. The chocolate bar group items have many fewer total calories on average than ice cream group items. For ice cream, already loaded with calories, consumers' desire not to eat too unhealthily might outweigh flavor for marginal calories, whereas for chocolate bars, with lower levels of calories, consumers might be willing to add marginal calories for the benefit of additional fat and sugars.

The estimated effect sizes also seem to differ quite a bit between the junk food categories. The estimated willingness-to-pay for a USDA organic label in the preferred specification was $1.06 for ice cream items and only $0.15 for chocolate bar items. However, the total willingness-to-pay for an USDA organic labeled item with an average amount of calories looks very similar between the two categories if expressed as a percent of the average price. It is possible consumers treat their willingness-to-pay for the USDA organic label as a rough percentage, as in a tip on a check. However, the results for chocolate bars and ice cream also share many common features. In both, the estimates for the effect of price is robust to the inclusion of controls, most importantly in the case of item-level fixed effects. Also for both, the specifications without nutritional controls estimate a higher willingness-to-pay for the USDA organic label than in the specifications with full controls. This suggests previous revealed preference research, by focusing on categories of items where observing nutritional quality is difficult, might have over estimated consumer's willingness-to-pay for USDA organic labeling. Estimates from stated preference studies are less likely to suffer from this overstatement, since those studies have tended not to present consumers with nutritional differences when evaluating their willingness-to-pay. The results might help explain the discrepancy between revealed preference and stated preference studies of USDA organic labels.

The results also indicate USDA organic labels and calories tend to be bought together in the packaged junk food category, as predicted by the survey and experimental evidence on the 'health halo' effect. If consumers behave in a market context as they have in experimental studies, they would be expected to buy USDA organic labeled items with relatively more calories, indicated in the results by the positive additional marginal willingness-to-pay for calories for organic items. This means, at the least, the USDA organic program's stated informational content, which is limited to production methods, is not driving the entirety of consumer's evaluation of USDA organic labeled items. Further, consumers' evaluations of the informational content of USDA organic labels might be perversely affecting consumers' health, which has interesting implications for the policy effectiveness of the USDA organic certification program.