Buying More than Taste? A Latent Class Analysis of Health and Prestige Determinants of Healthy Food

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Abstract

Healthy foods have gained media attention and prestige among consumers to the point where some foods are called superfoods. In addition to quality and taste, what drives consumption of such products? Is it the product's health benefits or the prestige of buying higher priced differentiated products, or both? Cars, watches, and other luxury goods have long been known to be prestige driven. Prestige driven food consumption has been unexplored in the literature.

To investigate the connection between prestige-seeking tendencies and health benefits in food products, a nonhypothetical and incentive compatible experiment was implemented to elicit willingness to pay (WTP) for several lettuce products. A Latent Class Analysis (LCA) was performed to classify consumers into subgroups based on responses to questions regarding prestige-seeking and health related factors. Each latent class's WTP data from a sealed-bid second-price Vickrey auction were compared using a random parameters tobit model to assess the effects of product attributes within information and blind tasting treatments. Findings revealed consumers respond to

different attributes depending on whether they are motivated by the health benefits or the prestige of food products.

For several decades tremendous efforts by health professionals and government have focused on health and diet. Almost 18 percent of U.S. Gross Domestic Product was spent on health over the 2010-2014 period. Images of healthy, active people are everywhere. The outward visible images of health become a status symbol to many, implying social status and prestige. Outward symbols of health may also signal wealth and superior status for signal conscious individuals.

Human beings are inherently prone to seek prestige or social status under several consumer settings (Berger, Rosenholtz, and Zelditch 1980). In general, theoretical models about social status rely on the assumption that the "social status" itself provides individuals with utility (Veblen 2005). This concept is not new, and Veblen's original idea was first published in 1899 (reprinted in 2005). Veblen (2005) argues that individuals derive utility from showcasing their wealth to others. However, wealth and income are not directly observed by others, and hence it is the visual consumption of goods that displays wealth. The consumption of goods that seeks to demonstrate the purchase capacity and wealth of an individual is known as conspicuous consumption (Charles, Hurst, and Roussanov 2009). The two main motivations for conspicuous consumption are "invidious comparison" and "pecuniary emulation" (Laurie Simon and Bernheim 1996). Invidious comparison refers to higher class individuals seeking to differentiate themselves from lower class individuals; and pecuniary emulation refers to lower class individuals seeking to be thought of members of a higher class. A prestige or social status effect exists if individuals or different classes of individuals are willing to pay a higher price for a functionally equivalent good in order to signal wealth (Laurie

Simon and Bernheim 1996).

In the age of juicing trends and celebrities turning into clean-diet cookbook authors, the connection consumers make between their health status and their food purchasing behavior has become much stronger; however, little is known about the combination of health and prestige-seeking behavior on consumers' valuations of food products. In order for conspicuous consumption to exist, the products need to be purchased in a public setting so that they are observed by others (Laurie Simon and Bernheim 1996). Consumers evaluate conspicuous goods based on quality attributes and the prestige and social status derived from consuming them. Dubois, Rucker, and Galinsky (2012) proposed that even products not typically associated with conspicuous consumption (i.e. non-luxury goods) can be used to signal social status when a hierarchical relationship among people. In this context, it is possible that certain production methods and attributes of food products such as organic and other specialty designations have become fashionable and prestigious. Do consumers derive status utility from consuming those "specialty foods" or perhaps by consuming them at specialty retail outlets with significant price premiums such as Wholefoods? If so, can consumers be segmented into latent classes related to their health and prestige-seeking behavior and food purchases? This article investigates these questions using an experimental economics approach.

Over the last three decades, experimental economic methods have allowed researchers to gather primary data about consumers and their purchasing behavior. Experimental auctions represent a subset of research tools within this field that have been thoroughly used over the past twenty years to elicit consumers' willingness-to-pay (WTP) values for new products and differentiating attributes. These auctions operate off of the institutions of incentive-compatibility and utility theory – that is, real money is used and real economic consequences are enforced to incentivize consumers, through utility maximizing behavior, to reveal their true valuations (Carson and Groves 2007, Lusk, Alexander, and Rousu 2007). Additionally, the ability to induce real markets in a laboratory setting affords economists the opportunity to amplify control, which is not normally found in real markets (Smith 1976). Overall, the elements of incentive compatibility and increased control are the principal differences between experimental methods and more orthodox value elicitation techniques, such as stated preference and observational methods (Lusk, Alexander, and Rousu 2007). Aside from these appealing attributes, experimental auctions have the advantage of allowing researchers to fit the auction mechanism to the scope and objectives of the experiment and directly interpret participants' valuations of the auction goods. Regardless of the type of auction mechanism used, consumers' homegrown WTP values can be directly inferred from their bid values. The effortless interpretation of consumers' WTP values is appealing to researchers who are investigating the market potential for new products or specific differentiating attributes (Hoffman et al. 1993, Lusk and Shogren 2007, Lusk and Hudson 2004).

In addition to intrinsic product attributes and prices, theoretical models of social status include the prestige of the products in the utility function. If prestige or status for a product exists, then for similar products in terms of functionality and with comparable quality, prestige seeking individuals would exhibit a willingness to pay a higher price for the prestigious items. Nelissen and Meijers (2011) conducted a series of experiments to test whether a person wearing a branded-labeled shirt versus a non-labeled shirt would have any effects in the perception of their social status. They found that the conspicuous consumption of the branded shirt resulted in preferential treatment to the point of even generating financial benefits. One of the potential problems in designing an economic experiment for social status or prestige is that quality and price are highly correlated (i.e. higher quality products are usually more expensive). When it comes to food products, the attributes of specialty foods are often associated with quality differentials (Lusk and Briggeman 2009), and the quality variable is confounded with the social status. In the past, in order to disentangle quality and status, experimental methods have used identical products, manipulating the labels with varying prices; thus the quality is controlled in the valuation of willingness to pay, and any differentials are attributed to the social status or prestige. Plassmann et al. (2008) conducted an experiment where subjects tasted wine from identical bottles but labeled at different retail prices. Using functional magnetic resonance imaging (fMRI), they showed that subjects who tasted the wine labeled at a price of $90 not only reported higher flavor ratings compared to the same bottle of wine labeled at a price of $10, but the region of the brain associated with pleasantness had higher activity with the higher-priced bottle of wine. The results of Plassmann et al. (2008) are significant because they show that the perceptions of pleasantness have biological roots and that human beings are inherently prone to derive pleasure from social status. This may provide an explanation as to why consumers report higher taste evaluations when eating more expensive meals (Just, Sığırcı, and Wansink 2014), i.e.- food tastes better at fancy restaurants. Recent wine studies have found that price is a signal for quality and individuals do show higher willingness to pay for the products representing a higher social status (Lewis and Zalan 2014, Mastrobuoni, Peracchi, and Tetenov 2014, Ashton 2014). However, all of the above-mentioned wine studies are considered to use deception in their methods, a practice not allowed in the field of economics (Cooper 2014). We propose a theoretical framework to avoid deception and still account for quality and social status differences. The approach consists of keeping all food products with varying quality constant across all respondents, and separate participants into subgroups or latent classes according to their prestige seeking behavior and evaluate differences in WTP by each prestige-seeking class.

The overall objective of this article is to provide insight into the sources of unobserved preference heterogeneity among consumers and investigate the relationship between consumers' health-prestige-seeking tendencies and their valuations for the marketable attributes of food, specifically information labeling and taste. To accomplish this, individuals will be segmented into latent classes based on their health-prestige-seeking consumption behavior, demographic characteristics, and other lifestyle factors. Following the characterization of the latent classes, data from a second-price Vickrey auction (Vickrey 1961) and a random parameters tobit model estimated each class's WTP for specific food product attributes for lettuce, which included organic, conventional, and hydroponic production methods as well as green, red, and mixed color attributes, and quantified the effect of a labeling information treatment and a blind tasting treatment. Lettuce was used in the study because it is commonplace, familiar to most consumers, available in different product forms and attributes and also to fit budget constraints.

Experimental Procedures

A total of 201 participants (nonstudents) from a mid-size city located at a large University campus participated in the study in late February 2014. There were nine sessions with average participation ranging from n=22 to n=25 subjects per session. While recruiting a sample chock full of college students may have been convenient and albeit less expensive, one of the objectives during the recruitment process was to attract a sample that was representative of grocery shoppers. Toward this end, a series of advertisements were issued in a local newspaper prior to the experiments and email correspondence was established with potential interested parties.

Upon arrival, participants were checked in and were asked to read and sign a consent form. Contingent on the individual signing the consent form, they were next seated and provided with a participant identification number which secured anonymity, a participation packet which included the questionnaire and a description of the auction procedures.

After explaining the procedures and answering any initial questions, two practice rounds of auctions were completed and participants filled out a short quiz that tested their knowledge of the procedures. Next, participants were asked to submit bids for several vegetables in two real rounds of auctions. All subjects submitted bids for a baseline round, where no information was provided about any of the products. Then, a between-subjects design, where half of the subjects participated in a blind tasting as the treatment and the other half of the sample received labeling information about each product. Participants in all sessions bid on eight vegetable products that varied in production method and color: organically produced green lettuce; organically produced red lettuce; conventionally produced green lettuce; conventionally produced red lettuce; hydroponically produced red lettuce; hydroponically produced green lettuce; hydroponically produced red-and-green mixed lettuce; and spinach. Hydroponic mixed lettuce was a red and green variety that had been planted together and grew intertwined with one another to form one head of lettuce. Spinach was used as the control product, as it is often considered a substitute for lettuce. The seven heads of lettuce and one bunch of spinach were laid out on a table at the back of the room and randomly given an identification number.

During the first round of vegetable auctions, the baseline round, all of the products were displayed on the auction table at the back of the room and participants were able to pick up and examine each product before submitting their bids. Participants did not know the name of the product or how it was produced and they were asked to submit their bid such that it was exactly equal to their maximum WTP value for each vegetable product. Bids from this first vegetable auction round were considered the baseline level of bids, against which all subsequent bids were compared. Participants assigned to the blind tasting treatment tasted samples of each of the auction goods and, following the completion of a tasting report, asked to examine the auction products once again and submit bids for the vegetable products. Subjects who received labeling information as the treatment were given a sheet of paper with bullet points about the production methods of the vegetables. While the subjects reviewed the handout, labels that identified the products were placed in front of each of the eight vegetable products on the auction table. Now, participants knew the production method (organic, conventional, or hydroponic production) and color of each lettuce product (red, green, and mixed). After reading the labeling information of the products, participants were asked to examine the auction table as they did in the baseline round and submit bids once again for all eight products.

Following each group's treatment, one of the two vegetable auction rounds in each session was randomly chosen to be binding and the bids for the binding product in that round were sorted from highest to lowest. A second-price Vickrey auction mechanism was used in which the highest bidder became the buyer and paid the market price (which was the second highest bid) for the product (Vickrey 1961). Participants were made aware that the vegetable auction rounds were real and if they became a buyer, an amount equivalent to the market price would be deducted from their compensation fee and they would receive the binding product to take home.

While the buyer and market price of the vegetable auctions were being determined, subjects in all sessions filled out a questionnaire that collected information about demographics (age, income, employment, marital status, race, etc.) and vegetable-buying behavior (purchase outlet, frequency, importance of factors when purchasing lettuce, etc.). In addition, participants answered scale-style questions that related to perceptions of their individual prestige-sensitivity and seeking behavior and their health consciousness. Finally, after the completion of the questionnaire, the buyer(s), the market price, and the binding product and round were announced.

Theoretical Framework

The traditional approach to model the consumption of conspicuous products (Laurie Simon and Bernheim 1996) assumes that an individual *i*, consumes an amount *x* of a conspicuous product which is evaluated according to its quality *q*, where $q \in \left[\underline{q}, \overline{q}\right]$. The individual has resources R, which can be high (H) or low (L), so that $R_L < R_H$and the individual allocates total expenditures on conspicuous goods, denoted by *s*. The total consumption of conspicuous and inconspicuous consumption is denoted by *z*. The individuals face a resource constraint of the form $z \leq \gamma(s, R_i)$, where $\partial\gamma(s, R_i)/\partial s < 0$, expenditures of the conspicuous good reduces total expenditures; and $\partial\gamma(s, R_i)/\partial R > 0$, higher resources allow for higher total expenditures. Total utility for individuals with each type of resources $R_i$is then given by $U_i(x(q), z, W)$, and W denotes all other factor entering the utility function. Note that in the utility specification quality varies in the range $\left[\underline{q}, \overline{q}\right]$, hence the consumption of the conspicuous product is determined by $x \equiv \int_{\underline{q}}^{\overline{q}} x(q)dq$. The prestige or social status would then be found if higher willingness to pay values exist for the same level of quality q. For a non-conspicuous product $y_1$with the same level of quality as the conspicuous product x_1, $WTP(x_1[q^0]) > WTP(y_1[q^0])$.

Traditional experimental methods hold quality at a fixed level q^0, and evaluate WTP based on manipulation of the labels by using different "brands" or prices, which imply higher levels of prestige for some of the products. As discussed before, this construct is considered deceptive, a practice ban in the economics literature (Cooper 2014). We proposed to use several food products with varying quality $q \in \left[\underline{q}, \overline{q}\right]$ and segment individuals into latent classes according to their prestige seeking behavior, and evaluate the WTP for each class. Then, $WTP_{si}(x_1[q], p') > \ WTP_{sj}(x_1[q], p^0), p' > p^0$ and individuals in a latent class s_i who tends to derive more utility for prestige p', would be hypothesized to have higher WTP values for the same products than individuals in a class s_j with lower utility for prestige.

In order to gain information about consumers' health and prestige-related behavior, health conscious and prestige-seeking scales were included in the questionnaire (Eastman, Goldsmith, and Flynn 1999). Consumers indicate the degree to which they agree or disagree, or approve or disapprove with each scale item. The prestige-sensitivity scale is a subscale within the price perception scale, developed and validated by Lichtenstein, Ridgway, and Netemeyer (1993) and also documented in Bearden and Netemeyer (2011). The prestige-sensitivity scale will help identify the individual's proneness to purchase goods for the "feelings of prominence and status" from others (Eastman, Goldsmith, and Flynn 1999, Lichtenstein, Ridgway, and Netemeyer 1993). Health scales included questions on the participant's awareness, involvement, and frequency of questioning their health status. Participants' responses to the prestige scale are used in a Latent Class Analysis to identify and characterize subgroups of different types of consumers within the sample.

A latent class analysis (LCA) operates off the premise that a population can be categorized into subgroups according to certain indicators. It uses a combination of classical regression and Bayesian analysis to estimate the probability of an individual belonging to one of those subgroups, also called a latent class, based on similar observed variables (Lanza, Tan, and Bray 2013, Greene 2012). Individuals are divided into S latent classes $s = 1,\ldots,S$, defined from a number of $j = 1,\ldots, J$ observed variables, also known as the indicators. The number of possible outcomes associated with the variable j is denoted by R_j for individuals $i = 1,\ldots, n$. The observable data is the individual i's observed responses to the J scale-response indicators and behavioral variables and represented by vector $X_i = (X_{i1},\ldots, X_{ij})$, where the possible outcomes of X_{ij} are known as r and $r = 1,\ldots, R_j$. Let $I\left(x_{ij} = r\right)$ act as an indicator function that is equal to 1 if the response to indicator $j = r$, and 0 otherwise. The probability density function of an individual demonstrating a specific membership profile is given as:

(1) $$X_i \sim f_i(x_i;\ \varphi) = \sum_{s=1}^{S} \pi_s f_{i|s}\ (x_i; \theta_s)$$
$$= \sum_{s=1}^{S} \pi_s \prod_{j=1}^{J} \prod_{r=1}^{R_j} (\theta_{jr|s})^{I(x_{ij}=r)}$$

where the distribution and parameters of the indicator variables, X_i, is equal to the probability of individual i qualifying for membership in class s ($\sum_{s=1}^{S} \pi_s$), multiplied by the associated conditional probability density function ($f_{i|s}\ (x_i; \theta_s)$) for all classes. The density function is further defined as the product of the indicator (J) and possible outcome (R_j) vectors. The parameters of the density function, ($\theta_{jr|s}$), represents the indicator-response probabilities of a specific response, r_j to the indicator variable j, given the individual's membership in class *s*. Therefore, if the observed indicators, X, and the number of latent classes, *S*, are known, then the idea is to solve for the parameters $\varphi = (\pi, \theta)$. This can be done through the following likelihood function for φ:

(2) $$\mathcal{L}(\varphi|X) = \prod_{i=1}^{n} f_i(x_i; \varphi).$$

The parameters φ can be estimated through the Expectation-Maximization (EM) algorithm because the individual's class membership is uncertain and thus may be regarded as missing data (Dempster, Laird, and Rubin 1977). The log-likelihood application is specified as:

(3) $$ln\mathcal{L}(\varphi) = \sum_{i=1}^{n} \ln[\sum_{s=1}^{S} \pi_s f_{i|s}(y_i; \theta_s)]$$

the EM algorithm can be used on the $ln\mathcal{L}(\varphi)$ after imprinting random initial estimates of π_s and $f_{i|s}(y_i; \theta_s)$ on a Bayesian calculation of the posterior probability, all in an effort to determine the class membership parameters, φ. The first step is to use a Bayesian approach for determining the class membership probability that individual *i* belongs to class *s*, given the observed *k* indicators:

(4) $$P(s = k|Y_i = y_i) = \alpha_{ik} = \frac{\pi_k \prod_{j=1}^{J} f_{ij|k}(y_{ij}; \theta_k)}{\sum_{s=1}^{S} \pi_s f_{ij|s}(y_{ij}; \theta_s)}$$

Next, applying the random initial estimates yields an estimated value, $\hat{\alpha}_{ik}^{(0)}$, for the unknown class membership probabilities $P(s = k \middle| Y = y_i, \varphi^{(0)}) = \hat{\alpha}_{ik}^{(0)}$. Following this estimation, the second part of the EM algorithm is the maximization of the $E[ln\mathcal{L}(\varphi^{(0)})]$ with respect to φ, subject to $\sum_{s=1}^{S} \pi_s = 1$, $\pi_s > 0$, and $s = 1, \dots, S$. This maximization yields maximum likelihood estimates of π_s and θ_s for $s = 1, \dots S$, useful for recalculating the posterior probabilities.

Because the actual number of existing latent classes is unknown, certain criterion tests are used to gain a more accurate estimation of *S*. In general, Akaike's Information Criterion (AIC) favors larger models (Akaike 1973), and the Bayesian Information Criterion (BIC) accounts for sample size and favors more parsimonious models (Schwarz 1978), and the Adjusted BIC (Sclove 1987) are the primary methods for estimating which level of *S* is most appropriate. The final posterior probability estimates $\hat{\alpha}_{is}$ are used to sort individuals into the *S* latent classes by comparing the highest individual-specific posterior probabilities. For example, individual *i* has membership to class *k* if $\hat{\alpha}_{ik} > \hat{\alpha}_{is}$ for all $s \neq k$.

WTP is then estimated as a function of intrinsic product characteristics and behavioral characteristics of individuals, treatments (either tasting or labeling information) and interaction effects of the latent classes as $WTP^{*}_{isj} = f\left(x_{itj}, \eta, \beta, \theta, S, \varepsilon_{itj}\right)$, where y^{*}_{isj} is the latent value of individual *i*'s bid in treatment t for product *j*, y_{itj} is the observed bid value, x_{itj} is a set of socio-economic characteristics, product characteristics, and treatment indicators, η is a vector of random intercepts, β is a vector of random coefficients, θ is a vector of constant coefficients, S are the interaction effects of the latent classes, and ε_{isj} is a random error term. The WTP is estimated using a random parameters Tobit model, which is specified as:

(5) $$y^{*}_{itj} = a\eta_i + x_{1,i}\beta_i + x_{2,i}\,\theta + \varepsilon_i$$

where y^{*}_{isj} is an $(T \times J) \times 1$ column vector of latent values associated with each bid, α represents an $(T \times J) \times 1$ column vector of 1s, η_i denotes the mean intercept for the pool of observations submitted by individual i, $\bar{\eta}$ takes the form of a scalar that represents the grand mean of observations from all individuals, and μ_i captures the variation or deviation of the mean intercept for individual *i* from the grand mean, $\bar{\eta}$. It is assumed that the random intercepts are distributed with a zero mean and variance σ_μ^2. The coefficients vector β_i is the sum of the grand mean coefficient vector, $\bar{\beta}$, and the respondent deviation, α_i, which captures variation in coefficients between individuals, and the $x_{1,i}$ is a (T *X J*) X *K* matrix of *K* random covariates. Within the same individual, these deviations are distributed with a zero mean vector and a variance-covariance matrix Δ. Consequently, the random coefficients follow a multivariate normal distribution, so that $\beta_i \sim mvn(\bar{\beta}, \Delta)$ and $\mu_i \sim N(0, \sigma_\mu^2)$ if $i = j$. In addition, $x_{2,i}$ represents a (T *X J*) X *L* matrix of *L* fixed covariates, θ is a vector of constant coefficients across individuals, and the term ε_i is a normally distributed random vector with mean zero and common variance matrix σ_e^2. Finally, it is assumed that *α*, *μ*, *e*, and *x* are uncorrelated within and across individuals (Swamy 1970, Moeltner and Layton 2002).

Results and Discussion

The LCA used responses from the health and prestige-seeking scale indicators, weekly exercise behavior, and weekly fruit and vegetable expenditures, and indicators relating health consciousness and awareness to define a number of *S* existing classes where S estimated for a range of 2 to 9 classes. Values for the log-likelihood, AIC, BIC, and Adjusted BIC for each class are included in Table 1. The Information Criteria (IC) produce contradictory results for the optimal number of classes – the minimum BIC suggested a two-class model, while the minimum Adjusted BIC and AIC proposed a four-class model. Dziak et al. (2012) suggested that when ICs differ, AIC frequently tends to favor a large model (overfitting), whereas BIC presents risks because it often supports a smaller model (underfitting). However, for small sample sizes, the error is usually underfitting and the preferred criterion is the one with lower rates of underfitting, in this case the AIC (Dziak et al. 2012).

Table 2 contains the estimated class membership and indicator-response probabilities for the selected four-class model. Participants were categorized based on their responses to questions about their buying behavior as it pertains to feelings of health and prestige. Information about participants' weekly exercise and weekly fruit and vegetable spending habits, health consciousness, awareness, and frequency of health questioning were also used to define the latent classes. About 38% of the participants are members of Class 1, about 24% of the sample is represented by Class 2, 33% are members of Class 3, and another 6% are members of Class 4. Relative to the other classes, consumers in Class 1 were the most active, as they had the highest probability of exercising four times per week or more. They also demonstrated the highest probability of high fruit and vegetable consumption (more than $50 per week). Consumers in this class largely agreed with statements regarding their own perception and consciousness of their health, but low probabilities were observed in the indicators that asked about others perception of their purchases. This class indicated 0 percent probability of "enjoying the prestige of buying a high priced product." The average income of consumers in Class 1, $55,000, was the highest of all classes. Their relatively high-income compared to the other three classes, but low regard toward what others thought of them through their materialistic purchases led to Class 1 being named "High Health, Low Prestige" buyers.

Consumers in Class 2 (24.16% of participants) were concerned about health and prestige when purchasing goods. For instance, there is a 72% probability that individuals in this class believed that people notice when you buy the most expensive brand of product. This class reported over a 90 percent probability of being aware and involved in their health. Their exercising habits were less than class 1 and 4, but more than class 3, while their fruit and vegetable buying behavior was closest to Class 1's habits. Members of Class 2 were labeled as "High Health, High Prestige", referring to the fact that they are concerned about health <u>and</u> prestige.

Individuals in Class 3 (32.6% of participants) were relatively least likely to exercise four or more times per week, and the least likely to spend more than $50 on fruits and vegetables each week. They also exhibited relatively low prestige-seeking behavior and low health consciousness. Class 3 was named the "Low Health, Low Prestige" class"

All individuals in Class 4 (5.85% of participants) were likely to feel an increase in self-esteem and enjoy the garnered prestige after buying high priced products. Additionally, there was an estimated 82% and 91% probability that consumers in this class agreed that "people notice when you buy the most expensive brand" and "it says something to others when you buy the high priced brand," respectively. Compared to the other classes, consumers in Class 4 were most concerned that their friends would think they were cheap if they consistently bought the lowest priced version of a product. As a result of their high regard toward prestige-seeking consumption behavior, Class 4 was named "Low Health, High Prestige."

Table 3 describes the demographics and behavioral characteristics of each latent class, as well as for all participants. As expected according to the theoretical framework proposed, the average WTP across all products was lowest for individuals classified in the Low Health, Low Prestige Class ($1.30/head of lettuce), as they were uninterested in health or prestige. All other classes associated with higher prestige-seeking behavior had higher WTP values. The low-income, high regard for prestige, and low regard for health along with the highest WTP values across all products for the Low Health, High Prestige class provides some evidence that the motivations for their prestige seeking behavior are in line with the concept of pecuniary emulation, or seeking to be thought of as belonging to a higher social status.

Table 4 displays the WTP estimates from the random parameter tobit model. Overall, consumers were willing to pay significant premiums for organic lettuce and significantly discounted red lettuce by nearly $0.29. Few variables were statistically significant with regards to the mean. More information and organic was a significant contributor to a higher WTP for Low Health, Low Prestige shoppers. The standard deviations of the interaction effect of the information treatment was significant for the Low Prestige shoppers, regardless of health preference. High Health, Low Prestige shoppers responded more to tasting and information treatments as indicated by the significance of the standard deviations than did the other classes.

Low Health, High Prestige buyers had the highest willingness to pay ($1.59) followed by High Health, Low Prestige shoppers. Perhaps not surprisingly the Low Health, Low Prestige shoppers had the lowest WTP, but organic lettuce carried a statistically significant premium of them. Those buyers were the only class with a significant effect of organic. Those same buyers also reported a significant effect of the interaction of information and organic.

While few variables had a significant effect on the WTP means, that was not the case for the standard deviations of the random parameters. Information had significant effects on the standard deviation of low prestige shoppers. The tasting treatment was significant for all buyers. Organic was important for the standard deviation of high health shoppers.

Summary and Concluding Remarks

This study investigated how consumers' preferences for health and prestige are related to their willingness to pay for differentiating attributes of food products. The literature shows abundant evidence linking food choices and diet quality with income (Darmon and Drewnowski 2008). Following the conjecture that having a healthy lifestyle may be associated with prestige and social status, individuals in this study were classified into separate latent classes according to their health and prestige preferences. High health, regardless of prestige class, led to a significantly higher WTP than that of Low Health, Low Prestige buyers.

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Table 1. Comparison of Latent Class Models: Combination of Helath-Consciousness and Prestige-Seeking Scales

Number of latent classes (S)	Log Likelihood at convergence	AIC[a]	BIC[b]	Adjusted BIC
2	-1215.0	701.7	784.3	705.1
3	-1158.0	613.7	739.3	618.9
4	-1132.4	588.5	757.0	595.4
5	-1125.7	601.2	812.6	609.8
6	-1112.1	600.1	854.4	610.5
7	-1101.2	604.2	901.5	616.4
8	-1092.8	613.4	953.7	627.4
9	-1081.6	616.9	1000.1	632.6

Note: Boldface type indicates the selected model

[a] AIC (Akaike Information Criterion)

[b] BIC (Bayesian Information Criterion)

Table 2. Latent Class Parameter Estimates for Four-Class Model for Prestige Scale

Variable	Definition	Class 1 *High Health, Low Prestige*	Class 2 *High Health, High Prestige*	Class 3 *Low Health, Low Prestige*	Class 4 *Low Health, High Prestige*
		Latent class membership probabilities (π)			
		37.38%	24.16%	32.60%	5.85%
		Indicator-response probabilities (θ)			
EXER	Exercised 4 times per week or more	0.49	0.36	0.28	0.45
WFVEX	Spend more than $50 per week on fruits and vegetables	0.21	0.17	0.03	0.09
Agree with or are neutral to the following statements:					
PNOTICE	"People notice when you buy the most expensive brand of a product"	0.15	0.72	0.15	0.82
PENJOY	"I enjoy the prestige of buying a high priced product"	0.00	0.47	0.06	0.73
PSAYS	"It says something to people when you buy the high priced version of a product"	0.09	0.72	0.08	0.91
PCHEAP	"Your friends will think you are cheap if you consistently buy the lowest priced version of a pr	0.06	0.43	0.09	0.64
PJUDGE	"I think others make judgements about me by the kinds of products and brands I buy"	0.05	0.60	0.15	0.64
PIMPRESS	"Even for a relatively inexpensive product, I think that buying a costly brand is impressive"	0.00	0.23	0.02	0.18
HSELF	"I'm very self-conscious about my health"	0.91	0.83	0.17	0.18
HCONST	"I'm constantly examining my health"	0.69	0.55	0.02	0.00
HAWARE	"I'm usually aware of my health"	1.00	0.91	0.69	0.09
HINVOLV	"I'm very involved with my health"	0.96	0.98	0.37	0.00

Table 3. Demographic and Behavioral Characteristics of Participants by Latent Class: Combination of Health and Prestige Scales

Variable	Category	All Participants		Class 1 *High Health, Low Prestige*		Class 2 *High Health, High Prestige*		Class 3 *Low Health, Low Prestige*		Class 4 *Low Health, High Prestige*	
		Mean	Percent	Mean	Percent	Mean	Percent	Mean	Percent	Mean	Percent
Age (years)		40.9		43.96		33.38		44.31		31.70	
Household Size (Individuals)		2.54		2.58		2.71		2.37		2.40	
Education	High School Diploma or less		6.74		5.63		0.00		12.73		10.00
	Bachelor's Degree or at least some college		58.43		60.56		64.29		54.55		40.00
	Graduate Courses or more		34.83		33.80		35.71		32.73		50.00
Race	Caucasian		72.83		76.47		65.12		75.00		70.00
	Hispanic		12.14		8.82		11.63		15.38		20.00
	Asian/ Pacific Islander, African American, Native American, or Other		15.03		14.71		23.26		9.62		10.00
Gender	Female		57.59		70.67		40.00		55.74		50.00
	Male		42.41		29.33		60.00		44.26		50.00
Marital Status	Married		43.72		45.45		40.43		45.31		36.36
	Not Married		56.28		54.55		59.57		54.69		63.64
Annual Household Income ($)		51,599		55,000		53,085		48,281		41,363	
Primary Shopper	Primary Shopper		84.08		84.62		78.72		87.69		81.82
	Secondary Shopper		15.92		15.38		21.28		12.31		18.18
Fresh Vegetables on Hand (% of full stock)		35.51		42.51		34.06		28.73		31.59	

Table 4 Random Parameters Tobit Estimates for WTP for Lettuce Products: Combination of Health and Prestige Scales

	Class 1			Class 2			Class 3			Class 4			All Participants		
	High Health, Low Prestige			*High Health, High Prestige*			*Low Health, Low Prestige*			*Low Health, High Prestige*					
E[y]	1.56			1.43			1.30			1.59			1.45		
	Parameter	S.E.	∂y/∂x	Parameter	S.E.	∂y/∂x	Parameter	S.E.	∂y/∂x	Parameter	S.E.	∂y/∂x	Parameter	S.E.	∂y/∂x
Means of Random Parameters															
Constant	1.251 ***	0.066		1.406 ***	0.080		1.034 ***	0.074		2.425 ***	0.283		1.519 ***	0.038	
Organic	0.127	0.083	0.123	-0.012	0.121	-0.012	0.137 *	0.078	0.136	0.209	0.461	0.208	0.099 **	0.047	0.098
Hydroponic	-0.080	0.076	-0.080	-0.073	0.098	-0.073	0.078	0.081	0.077	0.250	0.455	0.249	-0.005	0.046	-0.005
Red	-0.181 ***	0.068	-0.180	-0.291 ***	0.083	-0.291	-0.335 ***	0.068	-0.334	-0.741 ***	0.201	-0.739	-0.292 ***	0.039	-0.290
Mixed	0.069	0.113	0.068	0.152	0.119	0.152	-0.046	0.103	-0.046	0.063	0.464	0.063	0.500	0.062	0.050
Tasting	0.072	0.096	0.071	-0.067	0.109	-0.067	0.126	0.102	0.125	-0.013	0.567	-0.013	0.036	0.052	0.036
Production Information	-0.018	0.126	-0.018	0.078	0.140	0.078	0.051	0.123	0.051	1.564	1.256	1.560	0.069	0.066	0.069
Tasting x Organic	0.018	0.137	0.018	-0.006	0.208	-0.006	-0.224	0.140	-0.223	-0.276	1.198	-0.276	-0.082	0.080	-0.081
Tasting x Hydroponic	0.029	0.130	0.029	-0.014	0.180	-0.014	-0.234	0.144	-0.233	0.072	0.736	0.072	-0.030	0.076	-0.030
Tasting x Red	-0.022	0.105	-0.022	0.076	0.202	0.075	0.055	0.126	0.055	0.219	0.273	0.219	0.034	0.064	0.034
Tasting x Mixed	-0.092	0.186	-0.092	-0.096	0.279	-0.096	0.089	0.186	0.088	-0.269	0.513	-0.269	-0.038	0.112	-0.038
Info x Organic	0.193	0.165	0.192	0.277	0.248	0.276	0.337 **	0.167	0.335	0.038	0.900	0.038	0.209 **	0.091	0.208
Info x Hydroponic	0.067	0.156	0.067	-0.017	0.223	-0.017	0.164	0.161	0.163	-0.125	1.265	-0.125	0.061	0.089	0.061
Info x Red	0.071	0.174	0.071	0.042	0.175	0.042	0.067	0.166	0.067	0.183	1.119	0.183	0.079	0.103	0.079
Info x Mixed	0.322	0.234	0.320	0.159	0.287	0.159	0.298	0.249	0.296	0.507	1.497	0.506	0.284 **	0.137	0.282
Demographics/ Behaviors															
HHSIZE	0.050 ***	0.011	0.501	0.067 ***	0.016	0.067	0.104 ***	0.014	0.103	-0.262 ***	0.077	-0.268	-0.014 *	0.008	-0.014
AWFV	0.002 **	0.001	0.002	-0.002 **	0.001	-0.002	0.000	0.001	0.000	-0.012 **	0.005	-0.012	-0.001 **	0.001	-0.001
Standard Deviations of Random Parameters															
Constant	0.657 ***	0.019		0.644 ***	0.025		0.587 ***	0.019		0.431 ***	0.099		0.642 ***	0.010	
Organic	0.248 ***	0.037		0.427 ***	0.046		0.013	0.039		0.060	0.186		0.221 ***	0.020	
Hydroponic	0.205 ***	0.028		0.110 ***	0.036		0.329 ***	0.029		0.182	0.117		0.187 ***	0.016	
Red	0.222 ***	0.030		0.134 ***	0.036		0.203 ***	0.034		0.231 **	0.116		0.191 ***	0.017	
Mixed	0.062	0.056		0.142 **	0.059		0.103 **	0.052		0.435 *	0.232		0.016	0.032	
Tasting	0.164 ***	0.031		0.237 ***	0.044		0.192 ***	0.029		0.460 ***	0.135		0.148 ***	0.016	
Production Information	0.122 ***	0.040		0.151 ***	0.047		0.090 *	0.047		1.083	0.777		0.001	0.025	
Tasting x Organic	0.246 ***	0.061		0.065	0.088		0.030	0.069		0.066	0.337		0.159 ***	0.038	
Tasting x Hydroponic	0.122 **	0.054		0.057	0.073		0.238 ***	0.046		0.318 *	0.187		0.127 ***	0.029	
Tasting x Red	0.069	0.057		.34153D-04	0.093		0.043	0.051		0.371 **	0.182		0.021	0.035	
Tasting x Mixed	0.037	0.111		0.036	0.141		0.008	0.116		0.025	0.255		0.040	0.064	
Info x Organic	0.295 ***	0.070		0.031	0.112		0.552 ***	0.109		2.197	1.527		0.279 ***	0.047	
Info x Hydroponic	0.538 ***	0.060		0.048	0.089		0.276 ***	0.082		0.894	0.977		0.424 ***	0.035	
Info x Red	0.119	0.077		0.242 ***	0.086		0.019	0.094		0.254	0.675		0.023	0.046	
Info x Mixed	0.451 ***	0.107		0.025	0.189		0.244 **	0.120		0.361	2.411		0.218 ***	0.068	
σ(e)	0.551 ***	0.006		0.515 ***	0.009		0.481 ***	0.007		0.562 ***	0.040		0.554 ***	0.004	
Log-Likelihood	-1142.664			-629.966			-766.270			-173.447			-2804.041		

Note: *, **, ***, indicate statistical significance at the 10%, 5%, and 1% levels, respectively.