Articles

Predicting Consumer Preferences for Fresh Salmon: The Influence of Safety Inspection and Production Method Attributes

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A rank-ordered logit model is estimated using data collected by a mail survey of consumers in the northeastern and mid-Atlantic United States. The methodology, based on conjoint analysis, determines the average relative importance and value of three product attributes for fresh salmon (seafood inspection, production method, and price), and estimates the relative attractiveness of particular products to consumers. When used in combination with demographic data and responses to questions on perceptions, the analysis suggests market segmentations and potential marketing strategies based on the heterogeneity in preferences among consumers.

In today's marketplace, consumers face choices between competing food products that may appear quite similar. Consumers often rely on product information provided on packaging or labels to evaluate the attributes of different products. Prices may weigh heavily in product choice, but the price itself may influence perceived quality of the product. Safety and quality inspections (e.g., USDA inspected or FDA approved) and production methods (e.g., organically grown) also may affect consumer choices.

In this paper, consumer preferences for attributes of fresh salmon are investigated. In particular, we focus on three key attributes: inspections that attest to product safety and quality; production methods that may influence the consumer's perception of product quality; and price.

Beginning in 1997, all seafood producers selling product in the United States and abroad must be certified as complying with the Hazard Analysis of Critical Control Points (HACCP) program administered by the FDA. This program was promulgated in response to increasing criticism of the seafood industry for its lack of mandatory inspection programs. However, many consumers are unaware of the regulatory changes occurring in the seafood safety policy arena. Thus, communicating to the consumer that the seafood product has been inspected is important to the seafood industry as it hopes to increase demand for products and raise prices to cover the increased costs due to regulations. Relevant questions to answer are: (1) How important to consumers is an inspection that verifies that seafood products are safe and of high quality? (2) Does it matter to consumers which agency of the government is in charge of the program?[1]

Among seafood industries, the salmon industry has experienced a 97% increase in world production of salmon over the past ten years, from 1.65 million pounds in 1986 to 3.26 million pounds in 1995 (Johnson 1996). A significant portion of this is due to the increased production of farmed salmon. However, landings of wild salmon in the Pacific have also greatly increased. Marketing strategies have been employed by both the wild harvest sector and the farmed sector aimed at increasing market share and overall consumer demand for salmon. Groups promoting wild Alaskan salmon often emphasize that Alaskan salmon are

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[1] At the time of the preparation of the survey, both the USDA and the FDA were being proposed as administering agencies of the U.S. government for a mandatory seafood HACCP inspection program.

harvested from the cold, clean waters of the Pacific. Groups promoting farmed salmon note that the salmon have been farmed in sites selected by growers for their clean waters. Given this propensity by the industry to differentiate farmed salmon from wild salmon, it is of general interest to determine whether knowledge of production method will influence consumer evaluation of the product, and which production method is preferred.

The purpose of this paper is to answer the above questions. To do so, we rely on a data set collected via a mail survey of randomly selected households in the northeastern and mid-Atlantic states. One of the questions presented in this survey asks respondents to rank their preferences for fresh salmon products with different attributes using a conjoint experiment (Green and Srinivasan 1978). The different attributes pertained to price, inspection, and production method.

Conjoint analysis is often used in market studies when, as in this case, new or hypothetical products or product attributes are being assessed, and when market data are not available. The conjoint question can be used to determine the average relative importance and value of the three product attributes, and to estimate the relative attractiveness of particular products to consumers. Used in combination with demographic data and responses to questions on perceptions, conjoint analysis can suggest market segmentations and potential marketing strategies based on the heterogeneity in preferences among consumers. However, tastes and preferences can rarely be explained fully by demographic groupings or even by information about consumer awareness and perceptions of product attributes. We also estimated individual preference models and used information from these models to improve the performance of the aggregate models where the entire data set is used. These individual-level models proved to be critical in avoiding misinterpretations of the results of the aggregate models.

The Data

A sample of over 1,500 consumers in the northeastern and mid-Atlantic states[2] completed a mail survey in which they provided information about their preferences and consumption patterns for fresh fish, their beliefs about safety and quality of fish, and their individual demographic characteristics. One major focus of the study was to determine consumer perceptions of and preferences for farmed fish versus fish caught in the wild. Another important focus was to assess consumer perceptions of seafood quality and safety, and to determine the economic value of a mandatory quality inspection program.

The data collection process was administered between April and August 1993. Five thousand surveys were mailed to randomly selected households dispersed across the states according to each state's share of total population for the region.[3] Surveying began with a personalized, hand-signed letter sent to each household with information on the impending arrival of the survey and the importance of responding. Also the household was thanked for its cooperation. This was followed a week later by the survey and an accompanying letter. The letter accompanying the survey asked that the individual chiefly responsible for the retail purchase of seafood complete the survey. A week later a postcard was sent to remind households to complete and return the survey. Two weeks later a follow-up survey was sent, followed again by a postcard reminder.

Just over 1,500 surveys were returned (a 30% response rate). It is notable that 64% of respondents were male. In addition, 97% of the respondents were consumers of fresh seafood. The proportion of people who are consumers of fresh seafood seems much higher than would be expected of the general population, suggesting that seafood consumers were much more likely to return the survey. Thus the response rate for seafood consumers, the focus of the study, is likely much greater than 30% but is difficult to assess given a lack of data on the population of fresh seafood consumers. A particular difficulty with mail surveys is that not all respondents answer all the questions. In this survey, out of the 1,529 respondents, 756 (or 15% of the sample) answered the conjoint question and all of the demographic and perception questions used in the models estimated in this paper, and 968 (or 19% of the sample) answered all demographic and perception questions. The descriptive statistics of the variables used in estimation based on the subsample and those from the overall group of respondents are given in table 1. The variables enter the econometric models as binary variables that indicate membership in that particular category.

[2] The states include Maine, Vermont, New Hampshire, Massachusetts, Connecticut, Rhode Island, New York, Pennsylvania, New Jersey, Delaware, Maryland, and West Virginia, as well as Washington, D.C.

[3] The list was generated by a private list service firm in Delaware.

Table 1. Descriptive Statistics of Survey Respondents and Observations Used in Estimation

	Full Sample (n = 968)	Sample Used (n = 756)
Demographics		
Age of head of household:		
Greater than 65 (yes = 1, no = 0)	0.06	0.05
Between 21 and 40 (yes = 1, no = 0)	0.33	0.36
Female respondent (yes = 1, no = 0)	0.35	0.34
Household income		
Less than $25,000 (yes = 1, no = 0)	0.18	0.15
Less than $35,000 (yes = 1, no = 0)	0.34	0.31
Presence of children (age 1–15) in household (yes = 1, no = 0)	0.36	0.37
Region of residence:		
Northeast (NY, PA, NJ, DE) (yes = 1, no = 0)	0.54	0.54
New England (CT, ME, NH, VT, MA, RI) (yes = 1, no = 0)	0.23	0.23
Mid-Atlantic (WV, DC, MD, VA) (yes = 1, no = 0	0.23	0.23
Coastal (within 50 miles of coast) (yes = 1, no = 0)	0.47	0.46
Other characteristics		
Frequent salmon consumer (1x/mo. or more) (yes = 1, no = 0)	0.21	0.21
Frequent seafood consumer (1x/mo. or more) (yes = 1, no = 0)	0.50	0.50
Shop for seafood at:		
Supermarket (yes = 1, no = 0)	0.47	0.47
Seafood market (yes = 1, no = 0)	0.19	0.17
Beliefs		
Agree that farmed finfish is of higher quality than wild (yes = 1, no = 0)	0.30	0.31
Agree that farmed finfish is safer than wild (yes = 1, n = 0)	0.51	0.52
Aware of farmed salmon (yes = 1, no = 0)	0.37	0.38

Modeling Preferences for Multiattribute Goods

For over a quarter of a century, marketing researchers have been using conjoint analysis to evaluate the consumer appeal of potential products and services based on their attributes (Green and Srinivasan 1990). By observing a sample of consumers' relative rankings or ratings of a set of multiattribute products (e.g., fish of various sizes, colors, textures, and prices), the relative importance and value of these attributes are estimated. This information can be used to design products and services to maximize consumer appeal, or can be used to estimate market share of competing products. Originally used in the fields of psychometrics and marketing, conjoint analysis is now widely used in economic research to evaluate consumer preferences and demand for market goods (see, for example, Manalo 1990; Anderson and Bettencourt 1993; Wirth, Halbrendt, and Vaughn 1991) and, increasingly, to determine public preference and willingness to pay for multiattribute and/or multiuse public goods such as recreation, hunting, or landfill siting (MacKenzie 1990, 1993; Swallow et al. 1994; Desvousges, Smith, and McGivney 1983; Rae 1983).

The conjoint question for this analysis is shown in figure 1. Respondents were asked to rank nine different salmon products in order of preference, with a rank of 1 assigned to the most preferred product and a rank of 9 assigned to the least preferred. The question design varied three attributes (origin, price, and inspection) with three possible levels for each attribute.[4] By observing a sample of consumers' relative rankings or ratings of a set of multiattribute products, the relative importance and value of these attributes can be estimated. The estimation of the parameters that model these preferences can be done in a variety of ways, but it is commonly referred to as conjoint analysis (Green and Srinivasan, 1978). The attribute combinations for the nine products represent a full profile, orthogonal Addleman design that eliminates multicollinearity and resulting bias in parameter estimates (Addleman 1962).[5]

Accounting for Heterogeneity of Groups and Individuals in Conjoint Analysis

Conjoint applications in the economics literature have been based mostly on aggregate models for

[4] The three price levels chosen were consistent with prevailing retail prices at the time of the survey. The mid-level price was equal to the average price in supermarkets from Narragansett, R.I., Newark, Del., and Durham, N.H. The price levels were $4.49, $4.99, and $5.49/lb.

[5] While this allows a reduction in the number of comparisons each respondent has to make, it assumes that the attributes are completely separable. This could be problematic if, for example, an inspection has relatively more value to consumers when they know fish is wild as opposed to farmed.

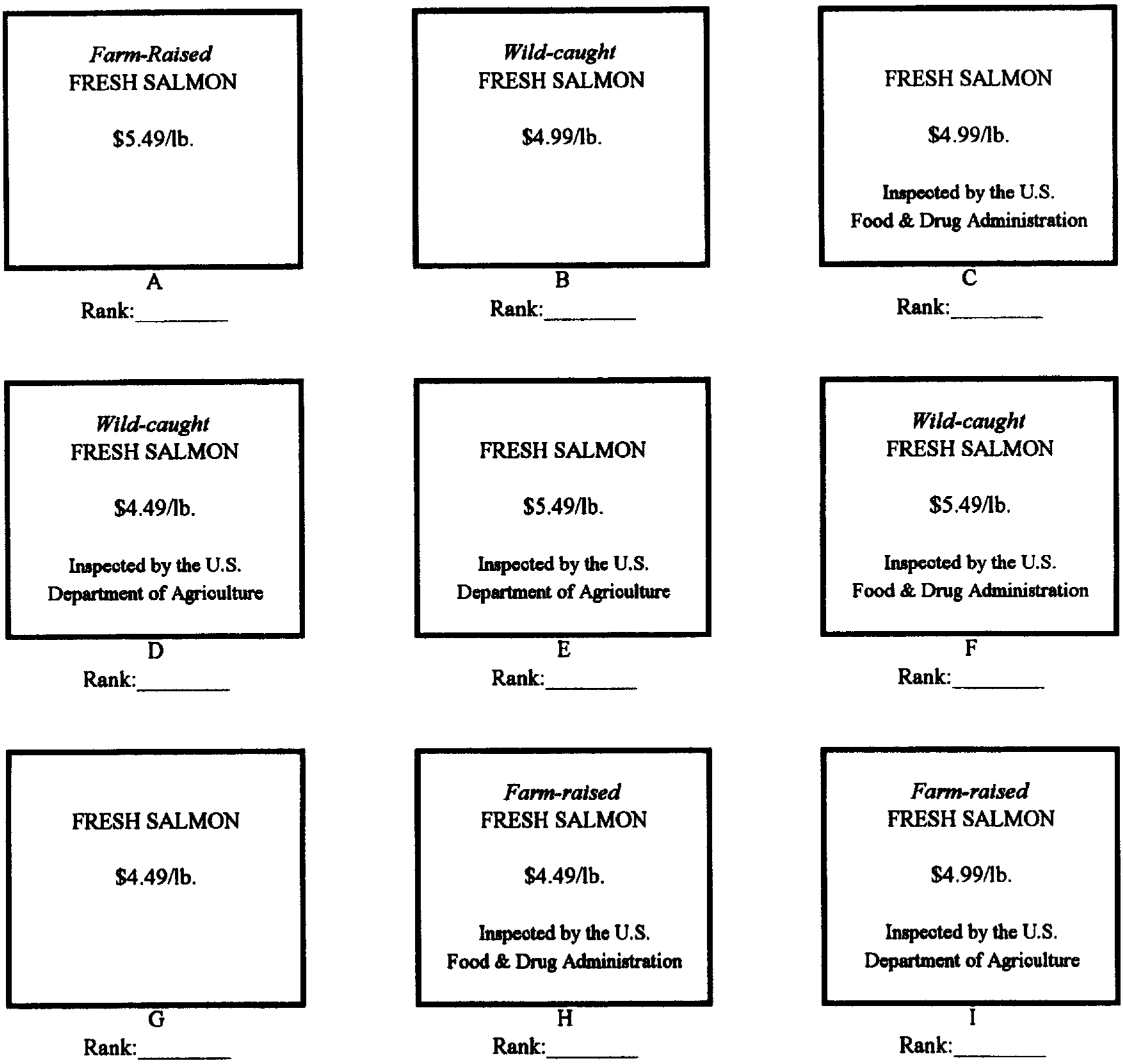

Figure 1. Label Choices for Fresh Salmon

which model parameters (attribute importance weights) are estimated using the responses of all survey participants. A single utility function is estimated and assumed to be representative of all consumers. In some cases, demographic variables are interacted with attribute variables to distinguish heterogeneous preferences along demographic lines (Swallow et al. 1994). By contrast, commercial conjoint applications most often estimate preference models at the individual level and use these individual preferences to simulate consumer choices.

An aggregate model with main effects only provides estimates of the average relative utility to the respondents of the various attributes, which can be used to estimate their relative preferences for products with any combination of attributes. We refer to this as a representative consumer model. While these estimates offer the benefits of easy calculation of probabilities or confidence intervals around parameters or rankings, their predictive validity tends to be low because of the diversity of preferences across individuals.[6] The representative consumer model may also be subject to problems of aggregation if the utility model is not linear (Stoker 1993) and may be subject to a majority fallacy (e.g., an aggregate model might indicate that a mid-size car was the most preferred level when in

[6] By using a representative consumer model, we are implicitly assuming that preferences across individuals are identical and that differences in observed rankings or ratings are caused by error in observing preferences.

fact most people preferred either a large or a small car) (Moore 1980).

Various methods are used to account for heterogeneity among consumers when estimating aggregate models. Componential segmentation, by adding terms to the model that capture interactions between attribute preferences and individually specific variables, accounts for heterogeneity based on observable characteristics of individuals. These may be demographic variables or responses to questions about perceptions or preferences. The componential model can be useful in identifying market segments that differ in preferences and consumption patterns.

Much of the diversity in individual preferences is not tied to observable characteristics of individuals, however. Cluster analysis, which separates the sample into groups of respondents based on similar preferences, is able to account for some diversity in preferences that cannot be tied to observed personal characteristics.[7] Predictive validity has proved higher with cluster analysis than the componential model in some studies, though it typically remains lower than individual level models (Moore 1980; Green and Helsen 1989). Both types of aggregate models confound the choice process at the individual level with heterogeneity in the process across individuals (Elrod, Louviere, and Davey 1992).

In early applications of conjoint analysis in the psychometric and marketing literature, a separate utility or preference model was estimated for each individual (Moore 1980). The form of the preference model (composition rule) is assumed to be the same for all individuals, but the parameters are allowed to vary across the sample of individuals (Green and Srinivasan 1978). The use of individual models is pervasive in commercial conjoint applications (Wittink and Cattin 1981; Green and Srinivasan 1990). Individual-level models have high predictive validity in terms of the correlation between predicted and observed ranks, and have also been shown to perform well in predicting ranks of a sample of observations withheld when estimating parameters (Elrod, Louviere, and Davey 1992). A number of studies have compared predicted choices with actual market behavior observed at a later date and have indicated a high correlation between predicted and actual behavior (Levin et al. 1983; Louviere 1988). Individual-level estimations have the disadvantage of requiring enough information collected from each individual to estimate his or her utility function. This can require a large number of observations when the number of attributes and attribute levels is large. Additionally, tests of statistical significance of attribute parameters or dependent variable predictions are cumbersome (Elrod, Louviere, and Davey 1992), and in some cases cannot be calculated.

For this study, we estimate a "representative consumer" model as well as componential models that contain interactive terms between product attributes, demographic, and perceptions variables. We also estimate individual-level models to differentiate respondents into groups. We compare and contrast the results provided by these different models.

[7] This tends to limit its use in identifying useful market segmentations.

Random Utility Models and Rank-Ordered Logit Estimation

The conjoint question asked respondents to rank nine different products in order of preference, with 1 being the most preferred and 9 the least preferred. A question format requiring an ordinal ranking, as opposed to a rating scale, was chosen because it is believed to be more reliable (Green and Srinivasan 1978), particularly in surveys administered by mail. This seems rather intuitive, as people are unused to providing a rating or willingness to pay for a product, but they are used to choosing between different products that vary according to price and other attributes. A referendum or paired comparison format would have the same advantages but requires a greater number of questions to derive the same amount of information.

The theoretical foundation for the rank-ordered logit estimation of the conjoint question is based on random utility theory. The respondent ranks the product with the highest level of utility of the nine choices presented as number one, then chooses the second most preferred from the remaining choices, and so on. The consumer would choose product one over product two if

$$U(\textit{Inspection}_1, \textit{Production Method}_1, \textit{Price}_1) > U(\textit{Inspection}_2, \textit{Production Method}_2, \textit{Price}_2),$$

where $U(\bullet)$ represents the individual's utility function. The random utility specification (Beggs, Cardell, and Hausman 1981) results in the consumer selecting product one over product two if

$$V(\textit{Inspection}_1, \textit{Production Method}_1, \textit{Price}_1) + \varepsilon_1 > V(\textit{Inspection}_2, \textit{Production Method}_2, \textit{Price}_2) + \varepsilon_2,$$

where $V(\bullet)$ is the measurable or observable component of utility and is estimated statistically, and ε is the unobservable, or random, component.

Using rank-ordered data imposes limitations on the estimation methods that can be used reliably. Because the ranks are ordinal rather than cardinal, and because the nine ranks given by each respondent are not independent, neither an OLS, ordered probit nor logit specification would provide consistent estimates.[8] Beggs, Cardell, and Hausman (1981) developed a model that they refer to as rank-ordered logit; it accounts for both the ordinal nature of the data and the lack of independence between observations for each respondent.

As above, let U_{ij} represent the random utility that individual i derives from alternative j with an observable deterministic component V_{ij} and a random component ε_{ij}. The observable V_{ij} component includes attributes of both the decisionmaker and the alternative in the choice set. V_{ij} is assumed to be a linear function of the variables X_{ij} such that:

$$(1) \qquad V_{ij} = X_{ij}\beta.$$

Consider individual i's ranking of J choices as $\mathbf{R_i} = (r_1, r_2, \ldots, r_J)$ so that the probability of the observed rankings using the logistic distribution is:

$$(2) \qquad \pi(R_i) = pr[U_{r_1} > U_{r_2} > \ldots > U_{r_J}] = \prod_{h=1}^{J-1}\left[\exp(X_{ir_h}\beta) \Big/ \sum_{m=h}^{J}\exp(X_{ir_m}\beta)\right].$$

For an independent sample of N individuals the log-likelihood function is:

$$(3) \qquad L(\beta) = \sum_{i=1}^{N}\log\pi(R_i) = \sum_{i=1}^{N}\sum_{h=1}^{J-1}X_{ir_h}\beta - \sum_{i=1}^{N}\sum_{h=1}^{J-1}\left[\log\sum_{m=h}^{J}\exp(X_{ir_m}\beta)\right].$$

The maximum likelihood estimates of β are those with the maximum probability of resulting in the observed sets of ranks. The log-likelihood function is globally concave and provides unique estimates of β which are consistent, asymptotically normal and asymptotically efficient. The rationale of the model is that individuals compare all the choices, select the most preferred—independent of the rankings of the remaining choices—then make their next choices out of the remaining subset of choices, and so on until all are ranked. Thus the standard independence of irrelevant alternatives assumption necessary for the multinomial logit model is assumed to hold at each level of ranking.[9]

From a Representative Consumer to a Componential Model

We estimated a representative consumer model as well as several componential models that contained interactive terms between product attributes and demographic and perception variables. The parameter estimates and summary statistics for these models are shown in table 2. The results in table 2 are from models using standard binary coding of attributes incorporating one level of each attribute into the intercept to avoid perfect multicollinearity. A somewhat better fit is achieved when contrast coding is used;[10] however, the interpretation of the coefficients is less clear. The specification for the model with interactive terms was chosen by testing down from models with additional variables.[11] Models were estimated with additional variables, including distance of households from the coast, discrete age of head of household categories, and household income less than $25,000. The inclusion of these variables did not significantly improve the model.

The vector of coefficients from these models, multiplied by a corresponding vector of explanatory variables, yields a predicted in-sample ordinal measure of utility that can be used to compare individuals' relative preferences for products with different attributes. Table 3 shows the results of some comparisons of different products for different consumers. In this table, there are six hypothetical consumers, three female and three male. Each is faced with three sets of hypothetical products. For example, in the first set the products presented are all high priced ($5.99) and USDA inspected, but the information on production method varies. One salmon portion is farmed, one is caught

[8] We did estimate OLS, ordered probit, and ordered logit models, and found the results to be consistent with the rank-ordered logit model in terms of predicted rankings of products and the relative magnitudes of parameters. It is quite possible that OLS model might have a higher predictive accuracy despite the sacrifice of unbiasedness and consistency. Wittink and Cattin (1981) found OLS estimation to be pervasive in commercial conjoint applications even though data were often nonmetric.

[9] Our estimations were done with LIMDEP version 7, which estimated this model in its discrete choice module.

[10] Contrast coding allows us to represent all three levels with two variables. For instance, a low price would be coded 0 and 1, a high price 1 and 0, and a medium price −1 and −1. The sum of each variable across levels must be zero. The part-worth for a particular level is calculated by multiplying the coefficients on the two variables by the values for that level and adding this to the intercept (i.e., simply −1*beta1 + −1*beta2 + alpha for medium price). See Cohen and Cohen (1975) for a more thorough explanation.

[11] Nested models were compared using likelihood ratio tests to assess the significance of groups of variables (i.e., models including and excluding all terms interacting with gender).

Table 2. Estimation Results for Label Attributes

Variable	Full Sample		Model with Main Effects Only	
	Coeffecient	t-ratio	Coefficient	t-ratio
Intercept	−0.937	−21.51	−0.935	−21.73
Main Effects				
Farmed	0.179	1.78	0.584	15.77
Wild	0.290	2.43	−0.039	−0.83
Price low	0.049	0.48	0.050	1.31
Price high	−0.461	−4.43	−0.646	−16.05
USDA	2.077	20.72	1.900	48.34
FDA	2.153	20.57	1.660	39.08
Interaction terms				
Farm* farmed higher quality	0.514	5.76		
Wild* farmed higher quality	−0.287	−2.77		
Farm* aware of farmed salmon	−0.006	−0.09		
Wild* aware of farmed salmon	0.234	2.70		
Farm* freq. salmon consumer	0.003	0.04		
Wild* freq. salmon consumer	−0.108	−1.06		
Farm* farmed safer than wild	0.397	4.96		
Wild* farmed safer than wild	−0.362	−3.89		
Farm* Northeast	0.215	2.40		
Wild* Northeast	0.003	0.03		
Farm* New England	0.016	0.15		
Wild* New England	0.179	1.48		
Farm* shop seafood market	−0.031	−0.33		
Wild* shop seafood market	0.423	3.81		
Farm* female	0.191	2.50		
Wild* female	−0.459	−5.13		
Farm* income less than 35K	−0.258	−3.31		
Wild* income less than 35K	−0.126	−1.38		
Farm* kids	0.015	0.20		
Wild* kids	−0.137	−1.60		
Price low* farmed higher quality	0.021	0.24		
Price high* farmed higher quality	−0.383	−4.22		
Price low* aware of farmed salmon	0.003	0.05		
Price high* aware of farmed salmon	0.176	2.30		
Price low* freq. salmon consumer	−0.061	−0.68		
Price high* freq. salmon consumer	−0.037	−0.41		
Price low* farmed safer than wild	−0.006	−0.08		
Price high* farmed safer than wild	−0.205	−2.50		
Price low* Northeast	0.002	0.02		
Price high* Northeast	−0.100	−1.09		
Price low* New England	0.051	0.48		
Price high* New England	0.017	0.16		
Price low* shop seafood market	−0.028	−0.29		
Price high* shop seafood market	0.267	2.72		
Price low* female	−0.052	−0.68		
Price high* female	−0.159	−2.04		
Price low* income less than 35K	0.028	0.35		
Price high* income less than 35K	0.204	2.55		
Price low* kids	0.028	0.38		
Price high* kids	−0.234	−3.07		
FDA* farmed higher quality	−0.038	−0.42		
USDA* farmed higher quality	0.127	1.46		
FDA* aware of farmed salmon	−0.217	−2.84		
USDA* aware of farmed salmon	−0.130	−1.77		
FDA* freq. salmon consumer	−0.325	−3.62		
USDA* freq. salmon consumer	−0.308	−3.57		
FDA* farmed safer than wild	−0.152	−1.84		
USDA* farmed safer than wild	0.185	2.36		

Continued on next page

Table 2. *Continued*

	Full Sample		Model with Main Effects Only	
Variable	Coeffecient	t-ratio	Coefficient	t-ratio
FDA* Northeast	−0.163	−1.78		
USDA* Northeast	−0.045	−0.52		
FDA* New England	−0.243	−2.27		
USDA* New England	−0.313	−3.06		
FDA* shop seafood market	0.223	2.28		
USDA* shop seafood market	0.097	1.03		
FDA* female	0.107	1.38		
USDA* female	0.373	4.99		
FDA* income less than 35K	−0.278	−3.49		
USDA* income less than 35K	−0.352	−4.61		
FDA* kids	−0.138	−1.81		
USDA* kids	−0.130	−1.79		
N	756		756	
Log-likelihood:				
At convergence	−8,018		−8,196	
Initial	−9,678		−9,678	
Lambda (d.f. = 67)	3,320*		2,964*	

*Indicates significant equations at the 5% level.

in the wild, and for one there is no information. When attributes of inspection and price are held constant, but the attribute of production method is varied, the in-sample predictions show that all the male and female consumers would rank the farmed product first, with the highest utility level. Ties are indicated in the rankings, where the ties represent those instances where the predicted utilities were not statistically different from one another.[12]

Similarly, when production method and price are held constant (the second set of three products), products with a USDA inspection achieved the highest utility. However, when production method and inspection are held constant and price is varied (the third set of products), there was a statistical tie between the low and medium priced product for all cases.

Accounting for Individual Heterogeneity

As mentioned above, only some of the heterogeneity in tastes and preferences can be captured by including observable demographic variables and revealed perceptions. While individual level models have often proven to have higher predictive validity, they require a relatively greater amount of data per individual. The scarcity of observations per individual limits our ability to construct individual-level preference models from our data. To construct linear additive individual-level models, we had nine observations per individual and seven parameters to estimate (including an intercept dropping one level of each attribute to avoid perfect multicollinearity). This allowed us to estimate individual OLS models, but with only two degrees of freedom and violations of the assumptions of cardinal data and independence of observations, the statistical reliability of these estimates in prediction is unclear.[13]

Given these limitations, we chose to rely primarily on the aggregate componential models discussed above. Nevertheless, the individual-level models uncovered an important factor in determining preferences that was hidden with aggregate models and was not explained by inclusion of the demographic or perceptions variables available. According to the parameter estimates from the individual preference models, over 46% of the individuals in the sample appeared to prefer a salmon product priced at \$4.99/lb. (medium price) over a product priced at \$4.49/lb. (low price) when all other attributes were identical. A somewhat smaller proportion still preferred the higher-priced

[12] The significance of the difference between utility scores for two products is determined by a two tailed t-test. The t statistic is computed as the difference between utility scores over the standard deviation of the estimate of the utility score. The standard deviation of the estimate is calculated as X′Cov(b)X, where X is the difference between the vectors of explanatory variables for the two products being compared and Cov(b) is the covariance matrix for the parameter estimates computed during estimation.

[13] OLS models for each respondent were estimated using SHAZAM. Individual parameter estimates were then used in a choice simulator constructed with Excel spreadsheets. We did not estimate the significance of the parameters for each individual or confidence intervals around individual-level predictions.

Table 3. Ranking of Alternative Products by Person Based on Predicted Utility Scores

		Female, with children, household income >$35,000, from New England, and		
		Frequent consumer of salmon, aware of farmed salmon, believes farmed fish is safer, believes farmed fish is higher quality, shops for seafood at seafood market	Frequent consumer of salmon, unaware of farmed salmon, believes farmed fish is safer, believes farmed fish is higher quality, shops for seafood at supermarket	Infrequent consumer of salmon, unaware of farmed salmon, does not believe farmed fish is safer, does not believe farmed fish is higher quality, shops for seafood at supermarket
	High price, USDA inspected	2	2	2
Product Set I	Farmed, high price, USDA inspected	1	1	1
	Wild, high price, USDA inspected	2	3	2
	Farmed, high price	3	3	3
Product Set II	Farmed, high price, FDA inspected	2	2	2
	Farmed, high price, USDA inspected	1	1	1
	Farmed, low price, USDA inspected	1	1	1
Product Set III	Farmed, medium price, USDA inspected	1	1	1
	Farmed, high price, USDA inspected	2	2	2

		Male, with children, household income >$35,000, from New England, and		
		Frequent consumer of salmon, aware of farmed salmon, believes farmed fish is safer, believes farmed fish is higher quality, shops for seafood at seafood market	Frequent consumer of salmon, unaware of farmed salmon, believes farmed fish is safer, believes farmed fish is higher quality, shops for seafood at supermarket	Infrequent consumer of salmon, unaware of farmed salmon, does not believe farmed fish is safer, does not believe farmed fish is higher quality, shops for seafood at supermarket
	High price, USDA inspected	3	2	2
Product Set I	Farmed, high price, USDA inspected	1	1	1
	Wild, high price, USDA inspected	2	3	1
	Farmed, high price	3	3	2
Product Set II	Farmed, high price, FDA inspected	2	2	1
	Farmed, high price, USDA inspected	1	1	1
	Farmed, low price, USDA inspected	1	1	1
Product Set III	Farmed, medium price, USDA inspected	1	1	1
	Farmed, high price, USDA inspected	2	2	2

NOTE: Highest ranked = 1; second highest ranked = 2; lowest ranked = 3. Tied rankings indicate no statistical difference in predicted utility scores.

product when the prices were \$5.49/lb. and \$4.49/lb. This seemingly "irrational" behavior may have been due to the artificiality of the data-gathering mechanism, but it may be representative of actual consumer behavior. It may be that an important quality attribute was missing from product descriptions, and that some respondents assumed that this attribute was represented at least partially by price. The survey question had specifically told respondents to assume that the nine products were identical *in appearance*, but it seems likely that many assumed that the quality of the fish was correlated with its price, and that these beliefs may carry over to actual purchasing decisions.

We tested whether this "price preference" could be attributed to observable variables, suggesting group rather than individual heterogeneity. A simple correlation matrix showed no strong correlations between the individual price preference parameter and the demographic and perceptions variables. A regression of the price parameters against these variables yields an adjusted R^2 of only .027. However, this regression did identify two significant variables. The parameter for consumers that purchased seafood at supermarkets was significant ($p = .00001$) and had a positive sign suggesting more "price rational" preferences. The parameter on frequent seafood consumption was also significant ($p = .001$) and had a negative sign, suggesting an unexplained preference for higher-priced fish. The fact that frequent seafood consumers were more likely to fall into the "irrational" category lends some support to the conclusion that an important attribute may have been missing from the product descriptions and was consequently associated with price. In future surveys, it would be useful to ask consumers if they think that price is an indicator of quality.

The sample was then divided into two groups on the basis of the parameter estimates for low and medium price. For simplicity, the group with a preference for the higher priced product is referred to as "irrational" and the others as "rational," though in fact there is reason to believe that the preference for higher-priced fish may have had a rational basis. We then estimated rank-ordered logit models for the two groups. The parameter estimates for both groups are shown in table 4. Likelihood-ratio tests confirm that these separately estimated models were superior to both the aggregate model and to a model that included the "rational" variable as a dummy interacted with attributes variables.

Given a sample set of individuals with different combinations of demographic and perception characteristics, we can determine the proportion of consumers that would choose one product or another if given the choice between two. Table 5 provides some choice share estimates for different product comparisons. When presented with two choices (for example farmed, USDA-inspected salmon priced at \$4.49/lb. versus wild, USDA-inspected salmon priced at \$4.49/lb.), 81% of the people within our sample are predicted to choose the farmed product over the wild product. Also, 63% of the people within our sample are predicted to choose fresh salmon that is FDA inspected and priced at \$5.49/lb. (but has no production method information) over farmed fresh salmon that is priced at \$4.49/lb. (but has no inspection information). Finally, 97% of the people within our sample are predicted to choose the inspected product with no information on production method priced at \$4.99/lb. over the farmed salmon product that has the same price but no inspection information.

The representative consumer model performs differently than the models accounting for individual heterogeneity caused by the price "rationality." Given a particular choice of products, some consumers will choose one product, and some another, but these predicted choice shares vary somewhat depending on whether the full sample of data is used, or if the individuals in the data set are separated according to price "rationality." Thus, we are given estimated choice shares (or vote share if we were comparing policies subject to a vote), rather than simply an indication of the winning choice preferred by the majority.

Calculations of choice shares of pairs of products based on in-sample predictions presented in table 5 reiterate the findings that farmed product is preferred to wild product, regardless of price preferences. In addition, the comparisons of choice shares show that the heaviest weighting in preferences relates to inspection. This attribute dominates product choice even if a lower-priced alternative is available.

Some caveats are in order. The results from the simulation are representative only of the choice share from a larger population to the extent that the heterogeneity in preferences of the sample is representative of the population. While we believe that our sample may be representative of seafood consumers in the northeastern and mid-Atlantic United States, we suspect that results might vary considerably elsewhere. For example, it is likely that the preference for wild versus farmed may be reversed on the West Coast given the dominance of the wild fisheries in the Pacific. Heterogeneity in preferences tied to observable demographic characteristics can be accounted for by weighting the sample appropriately, but individual heterogeneity

Table 4. Estimation Results for Label Attributes with Sample Separation

	Full Sample		"Rational" Respondents		"Irrational" Respondents	
Variable	Coefficient	t-ratio	Coefficient	t-ratio	Coefficient	t-ratio
Intercept	−0.937	−21.51	−1.239	−20.47	−0.659	−10.24
Main Effects						
Farmed	0.179	1.78	0.356	2.43	0.016	0.11
Wild	0.290	2.43	0.594	3.43	0.043	0.25
Price Low	0.049	0.48	0.867	5.88	−0.491	−3.35
Price High	−0.461	−4.43	−0.837	−5.48	−0.202	−1.36
USDA	2.077	20.72	2.375	16.29	2.157	14.97
FDA	2.153	20.57	2.611	16.95	2.000	13.46
Interaction Terms						
Farm*farmed higher quality	0.514	5.76	0.503	3.99	0.632	4.77
Wild*farmed higher quality	−0.287	−2.77	−0.255	−1.73	−0.309	−2.04
Farm*aware of farmed salmon	−0.006	−0.09	−0.082	−0.79	0.044	0.39
Wild*aware of farmed salmon	0.234	2.70	0.154	1.29	0.329	2.52
Farm*freq. salmon consumer	0.003	0.04	−0.112	−0.91	0.070	0.53
Wild*freq. salmon consumer	−0.108	−1.06	−0.203	1.42	−0.009	−0.06
Farm*farmed safer than wild	0.397	4.96	0.334	2.97	0.509	4.27
Wild*farmed safer than wild	−0.362	−3.89	−0.378	−2.89	−0.420	−3.06
Farm*Northeast	0.215	2.40	0.247	1.89	0.160	1.24
Wild*Northeast	0.003	0.03	0.153	1.00	−0.143	−0.96
Farm*New England	0.016	0.15	−0.034	−0.23	0.035	0.22
Wild*New England	0.179	1.48	0.243	1.43	0.089	0.49
Farm*shop seafood market	−0.031	−0.33	0.028	0.20	0.000	0.00
Wild*shop seafood market	0.423	3.81	0.421	2.71	0.428	2.64
Farm*female	0.191	2.50	0.201	1.88	0.090	0.78
Wild*female	−0.459	−5.13	−0.414	−3.36	−0.562	−4.24
Farm*income less than 35K	−0.258	−3.31	−0.198	−1.82	−0.347	−2.95
Wild*income less than 35K	−0.126	−1.38	−0.170	−1.35	−0.011	−0.09
Farm*kids	0.015	0.20	0.194	1.87	−0.154	−1.38
Wild*kids	−0.137	−1.60	−0.218	−1.82	−0.123	−0.97
Price low*farmed higher quality	0.021	0.24	0.157	1.25	−0.068	−0.51
Price high*farmed higher quality	−0.383	−4.22	−0.319	−2.48	−0.567	−4.23
Price low*aware of farmed salmon	0.003	0.05	−0.063	−0.60	0.110	0.95
Price high*aware of farmed salmon	0.176	2.30	0.120	1.12	0.348	3.02
Price low*freq. salmon consumer	−0.061	−0.68	−0.001	−0.01	−0.124	−0.92
Price high*freq. salmon consume	−0.037	−0.41	−0.013	−0.11	−0.045	−0.33
Price low*farmed safer than wild	−0.006	−0.08	−0.118	−1.04	−0.027	−0.22
Price high*farmed safer than wild	−0.205	−2.50	0.013	0.11	−0.478	−3.94
Price low*Northeast	0.002	0.02	−0.138	−1.06	0.028	0.22
Price high*Northeast	−0.100	−1.09	0.007	0.05	−0.125	−0.96
Price low*New England	0.051	0.48	−0.170	−1.16	0.041	0.25
Price high*New England	0.017	0.16	0.031	0.20	0.148	0.92
Price low*shop seafood market	−0.028	−0.29	−0.072	−0.52	−0.016	−0.11
Price high*shop seafood market	0.267	2.72	0.397	2.86	0.057	0.40
Price low*female	−0.052	−0.68	−0.152	−1.44	−0.041	−0.36
Price high*female	−0.159	−2.04	−0.010	−0.09	−0.299	−2.55
Price low*income less than 35K	0.028	0.35	0.001	0.01	0.046	0.40
Price high*income less than 35K	0.204	2.55	0.181	1.62	0.269	2.26
Price low*kids	0.028	0.38	−0.067	−0.64	0.067	0.61
Price high*kids	−0.234	−3.07	−0.304	−2.85	−0.176	−1.55
FDA*farmed higher quality	−0.038	−0.42	0.089	0.69	−0.146	−1.11
USDA*farmed higher quality	0.127	1.46	0.255	2.08	0.000	0.00
FDA*aware of farmed salmon	−0.217	−2.84	−0.241	−2.25	−0.275	−2.39
USDA*aware of farmed salmon	−0.130	−1.77	−0.173	−1.71	−0.196	−1.77
FDA*freq. salmon consumer	−0.325	−3.62	−0.550	−4.36	−0.001	0.00
USDA*freq. salmon consumer	−0.308	−3.57	−0.389	−3.23	−0.211	−1.64
FDA*farmed safer than wild	−0.152	−1.84	−0.279	−2.38	−0.092	−0.76
USDA*farmed safer than wild	0.185	2.36	0.023	0.21	0.363	3.12
FDA*Northeast	−0.163	−1.78	−0.193	−1.45	−0.239	−1.82

Continued on next page

Table 4. *Continued*

	Full Sample		"Rational" Respondents		"Irrational" Respondents	
Variable	Coefficient	t-ratio	Coefficient	t-ratio	Coefficient	t-ratio
USDA*Northeast	−0.045	−0.52	−0.053	−0.41	−0.062	−0.49
FDA*New England	−0.243	−2.27	−0.506	−3.35	−0.006	−0.04
USDA*New England	−0.313	−3.06	−0.489	−3.39	−0.117	−0.76
FDA*shop seafood market	0.223	2.28	0.190	1.30	0.222	1.56
USDA*shop seafood market	0.097	1.03	0.039	0.29	0.152	1.11
FDA*female	0.107	1.38	−0.052	−0.48	0.275	2.35
USDA*female	0.373	4.99	0.296	2.84	0.427	3.80
FDA*income less than 35K	−0.278	−3.49	−0.288	−2.61	−0.239	−1.97
USDA*income less than 35K	−0.352	−4.61	−0.104	−0.98	−0.708	−6.18
FDA*kids	−0.138	−1.81	−0.180	−1.68	−0.084	−0.74
USDA*kids	−0.130	−1.79	−0.129	−1.27	−0.161	−1.48
N	756		355		401	
Log-likelihood:						
At convergence	−8,018		−3,710		−5,134	
Initial	−9,678		−4,545		−4,031	
Lambda (d.f. = 67)	3,320*		1,670*		2,206*	

*Indicates significant equations at the 5% level.

cannot.[14] Thus, the reliability of out-of-sample predictions is difficult to assess.

Implications for Industry and Policymakers

According to this sample of seafood consumers, the strongest preferences are related to seafood inspection. Products indicating an inspection by either the USDA or the FDA are preferred to products with no inspection. Table 4 shows that for the "rational" respondents, the importance of seafood inspection is significantly higher than price or method of production. Of the two agencies, the main effects coefficients indicate that the FDA is preferred to the USDA as an inspection agency. However, when these coefficients are modified by the interaction terms of the attributes with demographics and beliefs, the total effect is that the USDA is the preferred agency over the FDA. This may be because consumers associate the USDA with meat and poultry inspection and feel comfortable with the USDA acting as a seafood inspector as well.

Similarly, while the main effects results seem to indicate that wild salmon is preferred to farmed, modifying these effects by the coefficients of the dummy interactions with farmed and wild results in farmed being the preferred method of production. The interaction terms with the respondents' agreement with statements that farmed finfish is of higher quality and safer than wild finfish were par-

[14] In fact, weighting the sample to match the demographic make-up of the population may nullify the randomness of the sample that is necessary to make probability estimates.

Table 5. Predicted Choice-Shares of Hypothetical Fresh Salmon Products
(based on within-sample predictions of preference between two product profiles)

Product	Total Sample	Accounting for Individual Heterogeneity
	Choice Share	
Farmed, low priced, USDA inspected	81%	76%
vs.		
Wild, low priced, USDA inspected	19%	24%
High-priced, FDA inspected	63%	50%
vs.		
Farmed, low priced	37%	50%
Medium price, FDA inspected	97%	96%
vs.		
Farmed, medium price	3%	4%

ticularly important to this result. It is worth repeating that this particular result may be heavily influenced by the location of the respondents. It is likely that repetition of the survey with West Coast consumers would result in the opposite outcome.

These results imply that the current public policy of implementing HACCP by the FDA will be viewed positively by consumers, as they become aware of it and as they become familiar with the FDA as an inspection agency. The salmon industry's strategy of labeling product as to what method of production is used, farmed or wild, seems to favor farmed salmon more than wild salmon in the northeastern and mid-Atlantic states. This may be the result of the perception that farmed salmon is higher quality and safer than wild, possibly because a farmed product is connected with a product over which the harvester has some degree of control, unlike wild salmon.

Conclusions and Directions for Future Research

Conjoint analysis has proved itself a useful tool in measuring preferences for multiattribute goods and services including both private and public goods. It provides an alternative to standard demand analysis when market data are not available or when assessing new or hypothetical products or product attributes jointly. Our application demonstrates the usefulness of conjoint analysis to marketing professionals and producers in evaluating pricing policies and marketing strategies for seafood, and suggests that public policies (namely, an inspection program) can provide benefits to seafood consumers.

Applications of conjoint analysis in the economics literature have been limited mostly to representative consumer models. Because of the heterogeneity in tastes and preferences between individuals, the predictive ability of these models is often quite low. In this paper we discussed and demonstrated a number of ways to account for heterogeneity of tastes and preferences between groups and individuals, including some of the advantages and disadvantages of each. Componential models, which include interactive terms that capture the heterogeneity attributable to observable demographic characteristics, greatly improve model performance. Further improvements are made by including information derived from questions about individual perceptions. However, much of the heterogeneity in preferences is not correlated with observable characteristics. Marketing applications have often modeled choice behavior at the individual level. Individual-level analysis typically results in higher predictive ability and can identify important heterogeneity in preferences that may not be revealed by aggregate models. Individual-level analysis requires a large amount of data per individual, and out-of-sample predictions are reliable only to the extent that the sample is a truly random probability sample.

For reasons discussed above, we presented results from componential models as opposed to individual preference models. We did estimate individual-level models and found them useful in developing aggregate models and interpreting the results of these models. We found that many individuals apparently preferred to pay more rather than less for a given piece of fish, suggesting that they may associate price with quality. With an aggregate model this is not apparent: it had the effect of reducing the estimated importance of price and provided invalid predictions of choices for many consumers.

It is common practice to use price (or the change in taxes in the case of comparison of public goods) as a metric to compare the value of different attributes. A willingness to pay (WTP) for changes in attribute levels can be estimated for the representative consumer. In contrast, in marketing studies price is often considered just another attribute. WTP estimates may be inappropriate if respondents are assuming an implied relationship between the cost and the quality of market products or public goods. Even when this is not the case, one must be careful with the interpretation and use of average coefficients. Aggregate analysis of responses, when there is a high degree of heterogeneity in preferences either in the magnitude or direction (as above), may suggest moderate preference (and a low statistical significance) for or against an increase in that attribute level, which may lead to false predictions of choice behavior of groups. If market analysts or policymakers are concerned with the percentage of people who will favor a product, service, or policy, a positive willingness to pay at the aggregate level may have little meaning. Vatn and Bromley (1994) provide a number of other arguments that suggest caution in trying to reduce preferences for multiple attributes down to a common metric of monetary values.

We suggest that too often heterogeneity is not sufficiently accounted for in contingent choice studies done by economists. Accounting for both group and individual heterogeneity can improve the performance of models in predictions as well as provide valuable added information to industry or policymakers. Our own experience also provided us with an important lesson concerning survey design. The amount and type of data collected (i.e., ordinal ranks versus scaled ratings) may limit the acceptable estimation procedures, and one should have this in mind when designing the survey.

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