Valuing Attributes of Fluid Milk Using Choice-Based Conjoint Experimental Design

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Abstract

A choice-based conjoint (CBC) experiment was employed to analyze Chinese consumers' preferences for fluid milk defined by four choice attributes: production processing method, fat content level, taste, and price. The results from two analysis approaches (counting and multinomial logit models) indicated that Chinese consumers are willing to pay a premium for pasteurized, low fat content, and natural tasting milk, but that they require a discount for choosing ultra high temperature (UHT), high fat content, and flavored milk. In addition, this study estimated the trade-offs among attributes' levels and simulated the effects of income on the probabilities of choosing attribute-specified milk.

Key words: China, choice-based conjoint, consumer economics, milk attributes, multinomial logit model

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I. Introduction

Consumption of dairy products in China, particularly fluid milk, has experienced record growth over the last decade, especially in urban areas (Fuller *et al.*, 2006). Statistics from the National Bureau of Statistics of China (NBSC) show that per capita annual demand for fluid milk in urban households in 2004 reached 18.8 kilograms, up from 6 kilograms in 1995. In three metropolitan cities, Beijing, Shanghai and Guangzhou, annual per capita fluid milk consumption reached 56, 51, and 27 kilograms, respectively, in 2002, according to Fuller *et al.* (2004). Total sales of milk products in China in 2005 were $9.5 billion, of which $4.1 billion resulted from sales of fluid milk (USDA, 2006). This is in sharp contrast to twenty years ago, when consumption of milk products was essentially non-existent.

Whether or not China's domestic production can meet the growing milk demand is unknown since there is a lack of understanding of this newly emerged market. There is little information on consumers' preferences for certain milk attributes. More specifically, there is little knowledge about how the preferences of urban Chinese consumers will influence their purchasing behavior today and over time. Specific questions include: Will Chinese consumers choose milk on the basis of quality and other factors in addition to price? Which and how attributes of milk products affect their preference? Are they willing to pay a premium for a specified attribute? How they make their trade-offs decision between attributes? Lack of knowledge about these questions is an important problem for milk producers and traders seeking to access to China's milk market and for policy makers and analysts in China and around the world. Until greater knowledge of consumer preferences is

acquired, evidence-based development of marketing strategies, trade policy, and even R&D for new products to better fit the world's fastest growing economy will remain scarce.

Previous studies have not adequately addressed these questions. Generally, they have ignored milk's attributes and focused on estimating various demand elasticities for generic milk by implicitly assuming that milk is a homogeneous commodity. For example, based on survey data from Jilin, Inner Mongolia, Shangdong, Jiansu, Sichuan, and Guangdong, Wang *et al.* (2004) indicated that the income elasticity of fluid milk was 0.32. Based on NBSC household income and expenditure data, Ma *et al.* (2004) estimated expenditure and own-price elasticities for seven animal products in urban China. Their results showed that the conditional expenditure elasticity for dairy products, including fresh milk and milk powder, were significantly decreased from 2.17 in the early 1990s (1991-1993) to 1.07 in the late 1990s (1999-2001). The estimated own-price elasticities for the two periods were -0.96 and -1.00, respectively. Zhou *et al.* (2002) and Yang *et al.* (2004) also discussed dairy product consumption, production and trade opportunity in China and influential factors. However, their studies are largely descriptive.

Besides implicitly assuming a homogeneous product, many recent demand studies pay insufficient attention to the selection bias that might be caused by the large number of zero consumption households. However, two recent studies of milk consumption in China analyzed several influential demand factors while also addressing the zero-consumption problem. In 2002, Fuller and colleagues conducted a survey of 314 households in three metropolitan cities (Beijing, Shanghai and Guangzhou) in China. Using this data, a Tobit model and a double hurdle model were estimated to determine the factors affecting Chinese consumers' purchasing

behavior (Fuller *et al*., 2004). Using large-scale individual consumer survey data, Bai *et al.* (2006) also identified and analyzed individual and household determinants on fluid milk market participation and consumption level in Qingdao, China. However, while these two studies addressed the zero consumption problem and improved information on consumer characteristics, both these studies examined the generic, aggregate milk commodity, hence implicitly assuming homogeneity of milk products. These studies of the aggregate milk commodity assumes that consumers' preferences and purchasing behavior are independent from product attributes such as fat content, flavorings and taste. Hence, the results from these studies are limited, especially for the development of marketing strategies.

It seems likely that the causes of the increase in fluid milk consumption are at least partly linked to the rapid and sustained economic growth of China, and the social and cultural transformation that has occurred in China over the past two decades. For instance, part of the increase may be due to the appeal of milk as a "modern," western-style food. Deeper causes might be found in the possibility that increases in income, information, and broader experiences have allowed Chinese consumers to increasingly choose milk on the basis of quality, safety, product diversity, and other attributes. Thus, some observers suggest that, fluid milk has become an important component of breakfast in many urban locations due to its convenience and nutrition. Demand may be stimulated by information (whether valid or not). For example it is said that some fashion-conscious city women like to drink a small amount of milk before going to sleep, believing that they will be more beautiful when they wake up the next morning. Higher incomes also allow consumers to indulge preferences for diversity. Thus, flavored milk products are attracting the younger generation with special flavors. However, while these ideas

are interesting, they are simply speculations until they are investigated systematically and tested in a well designed empirical analysis. Once confirmed, knowledge of such consumption patterns can be useful to policy and marketing entities.

The purpose of the current study is to demonstrate how a choice-based conjoint (CBC) experimental technique can be used to isolate milk attributes to better understand consumers' preferences. The application to Chinese milk consumption will serve both to generate useful information about Chinese consumers and to provide the necessary data to illustrate the choice-based conjoint experiment technique. Our CBC experiment investigated four fluid milk attributes: production processing method, fat content level, taste, and price. The results indicate that Chinese consumers are willing to pay a premium for pasteurized, low fat content, and natural tasting milk, but that they require a discount for choosing ultra-high-temperature (UHT), high fat content, and flavored milk. In addition, this study also shows how the CBC approach allows us to estimate the trade-offs among attribute levels and to predict the income effects on the probabilities of choosing attribute-specified milks.

This paper is organized as follows. In the next section, the CBC analysis and modeling issues are reviewed. In the third section, the experimental design, the survey, and the sample summary are discussed. The CBC data will then be analyzed using two approaches in the fourth section. The predictions of probability of choosing, trade-offs, and income effects will then be presented. The paper concludes with a summary of our main findings.

II. Choice-based Conjoint Analysis

Choice-based conjoint analysis is a stated preference value revelation technique that is based on allowing consumers to make choices from a set of

experimentally designed products defined by a bundle of a product's attributes (Louviere, 1988). Conjoint measurement has been widely used in the marketing research and health care research (Lazari and Anderson, 1994; Miguel, Ryan and McIntosh, 2000; Bryan and Parry, 2002; Kim, Lee and Koh, 2005). Compared to traditional ratings- or rankings-based conjoint analysis, the CBC approach has become an attractive alternative for measuring preference structures (e.g., Elrod, Louviere and Davey, 1992; Louviere and Gaeth, 1988; Louviere, 1991), particularly in the marketing research field. There are several reasons for the increasing popularity of this approach, according to previous studies (e.g., Sawtooth Software technical paper series, 1999). First, the task of choosing a preferred product is similar to what buyers actually do in the marketplace. Second, compared to most other conjoint analysis studies using "main effects only" assumptions, the CBC approach can generally quantify main effects and most interaction effects as well, depending on the experimental design. Third, it is possible to measure alternative specific effects on consumers' preferences for the products in the CBC analysis. Finally, the analysis of CBC data is much simpler relative to other conjoint analyses such as ratings- or rankings-based conjoint data.

Formally, the basic problem is the estimation of a utility function $U = f(X_1,...,X_k)$ where U denotes utility for the good in question and ($X_{1,...,}X_k$) represent the k attributes of the good. Consider an individual faced with a set of alternatives from which to choose, each of which consists of a different combination of levels of a set of multiple attributes. Suppose individual i faces J alternatives, indexed $j=1,...,J$ and described by vectors of attributes X_j. The individual i has a utility function that can be written in the linear form

(1) $$U_{ij} = X_j\beta + \alpha_i + \varepsilon_{ij}$$

where X_j is the attribute vector of the j^{th} alternative, and β is coefficient vector representing the weight of attribute in the valuation of alternative *j*. The variable α_i is an individual specific component, and ε_{ij} is stochastic and reflects the idiosyncracies of individual *i* in tastes for the alternative *j* (McFadden, 1974). Then, the probability of an individual *i* choosing the m^{th} alternative is

$$(2) \qquad P_i(m \mid C, \beta) = P(X_m\beta + \alpha_i + \varepsilon_{im} > X_j\beta + \alpha_i + \varepsilon_{ij} \quad \forall j \in C \,\&\, j \neq m)$$

where *C* denotes the choice set. In the case of independently and identically distributed extreme value disturbance of ε, the probability of alternative *m* being chosen can be expressed as follows:

$$(3) \qquad P(m \mid C, \beta) = \frac{\exp(X_m\beta)}{\sum_{j \in C} \exp(X_j\beta)}$$

This equation can be estimated from the consumer choice data generally collected in surveys.

III. Experimental Design, Survey, and Data Description

CBC Experimental Design

Experimental design and questionnaire construction are the most fundamental, but also the most challenging parts of choice-based conjoint analysis (Anderson and Wiley, 1992; Lazari and Anderson, 1994; Miguel, Ryan and McIntosh, 2000). In the present study, these tasks were undertaken using focus groups and pretests. Based on literature, informal focus groups and discussion with professional colleagues, ten potential attributes of fluid milk were selected for preliminary examination -- including milk processing technology, brand, package category, production place, taste, protein, fat, calcium, vitamin content, and price. A pretest was constructed in which respondents were required to rank these attributes from 1 to 10 by their importance for making a purchase decision. This pretest (in

Chinese) was sent to 50 individuals in China for the first pretest. The pretest also contained questions about prices and fat information of fluid milk that these informants currently purchased. Based on statistical results from this pretest, as well as the literature and discussions with experts and other knowledgeable Chinese informants, four attributes (processing technology, fat content, taste, and price) were chosen for the final survey instrument. In addition, preliminary judgments were made concerning the levels of the attributes that should be included. Careful analysis was required in choosing the final number of attributes and the number of levels of the attributes because the larger the number of attributes and levels, the more complex the decision problem for the respondent and the statistical problem for the analyst.

A second pretest was undertaken at the site before the final survey was conducted. During the second pretest, interviewers also collected milk price information from ten randomly selected stores to adjust the price levels in the design to better represent the local market price of fluid milk. The selected attribute levels are shown in Table 1.

An 18-run (or "profile") fractional factorial design was used in construction of the CBC experimental questionnaire. Statistically, a full factorial design would have required 2x3x2x3=36 unique combinations of milk attributes. However, asking respondents to select their most preferred attribute combination from 36 possibilities would have given them a difficult, perhaps impossible, task and the resulting decision costs and biases might have compromised results. Comparisons between the 18-run fractional factorial design and a 36-run full factorial design indicated that the 18-run design reduced potential profiles by half, and hence significantly improved operational ability, while sacrificing only minor design efficiency and

balance (See Table A.1-A.3 in Appendix).

Six choice sets resulting from the design of 18-run with six blocks were assigned and used to construct four fixed versions of the questionnaire instrument for the CBC experiments with the following criteria: Version I consisted of set 1, set 2, and set 3; Version II consisted of set 4, set 5, and set 6; Version III consisted of set 1, set 3, and set 5; and Version IV consisted of set 2, set 4, set 6[1]. Respondents were randomly assigned one of the four versions to answer. In each choice set, there were three alternatives from which respondents were asked to choose their preferred selection in the survey. Table 2 shows a sample question. In addition to the CBC questions, a series of questions about respondents' socio-demographics, their milk consumption, and milk shopping behaviors were presented in the survey.

Survey and Data Description

[1] Although ideally respondents should each see exactly one choice set, showing them more than one is economical. In practice, most researchers show more than one choice set to each respondent (Kuhfeld, 2005). One danger in showing too many choice sets is that it might cause respondent fatigue and lead to less thoughtful responses to the questions hence the number of choice sets offered must be limited (Louviere and Woodworth, 1983). When presenting multiple choice sets to respondents, researchers might either assign choice sets randomly to each respondent or assign a fixed version of choice sets to groups of respondents. Which method is better depends on balancing ideal procedure (random assignment) against operational concerns which depend on the interviewing approach: computer-administered interviews permitting random assignment, while paper-administered interviewing usually uses fixed assignment.

The data in this study were collected from 838 in-person interviews. The survey instrument was administered in Qingdao, China in the summer of 2005. Qingdao is one of 14 coastal cities that were first opened to the foreign market in 1984. This city is on the southern tip of the Shangdong Peninsula along the Yellow Sea. It is currently divided into 7 urban districts. In 2003, the total population was 2.24 million. Annual per capita disposable income in 2005 was 12,920 Yuan. This is about 2,000 Yuan higher than the national level (10,493 Yuan) and the Shandong provincial level (10,744 Yuan), but it is lower than that of main metropolitan cities such as Beijing (17,653 Yuan) and Shanghai (18,645 Yuan) in the same period.

The surveys were conducted in four stores (one hypermarket, two supermarkets and one convenience store) located in four of seven urban districts (one store in each district). These locations were chosen to ensure representative of a cross section of the Qingdao population. Also, conducting the surveys at sites that are the same time and place where actual purchasing decisions are made should better elicit true preferences. Four graduate students from a university were hired and trained to conduct the survey.

To avoid potential selection bias from individual sampling, the interviewers were instructed to solicit the third adult consumer (18 years and older) who came into the survey area following completion of the previous interview. To improve data quality, contracts were signed with the selected food stores, and 200-400 Yuan per day was paid to each store for use of the survey area. As a reward for participating in the survey, every respondent was given a gift card (worth U.S. $1.8), redeemable at the participating store.

The sample statistics indicate that our selected sample is representative of most of the characteristics of the population in the study area (see the last two

columns in Table 3) – adjusted for expected shoppers. The average family size and monthly per capita disposable income in the sample show no significant differences from their corresponding population levels. Although women (66.3 %) and unemployed respondents (6.1 %) are over-represented in the sample, we believe that these sample characteristics are expected and appropriate representatives of the household for the purposes of this survey. The higher share of female respondents is expected, since women typically play a larger role in family food shopping in China. The unemployment rate in the sample is higher than the *official registered unemployment rate*. However, the sample may be representative of the true unemployment rate, because there is "unregistered" urban unemployment (Wolf, 2004).

Table 3 also shows that the surveyed sample had a relatively wide range of consumers. The monthly household disposable income for more than 60% of the sample ranged between 2,000 and 5,000 Yuan (or between $250 and $625). Forty-three percent had children under 18 years old. More than 90% of households owned a refrigerator. The majority of the total surveyed respondents were in their late 30s or early 40s, with an average age of 38 years. Nearly three-fourths of respondents had a high school education level or higher, and were the primary food shoppers in their households. Fifty percent were employed full-time.

IV. Empirical Analyses

In this section, the collected CBC experimental data will be analyzed by two methods: a counting approach and a multinomial logit model (MNL) approach. In the second approach, three MNL models are estimated. Model I takes only main effects into consideration. Model II adds interactions between attributes and respondent demographic characteristics to Model I. Model III further adds two-way

attributes interactions to Model II.

Approach One: Counting

The counting approach calculates a proportion for each level of each attribute. The choice frequency is computed by dividing the number of times a milk profile which includes that level (value) of the attributes is chosen by the number of times that level is presented in the entire CBC experimental survey. This approach provides a direct, descriptive measure of all main effects and most two-way interaction or higher-way interaction effects. These descriptive statistics provide basic and intuitive knowledge for most effects for the survey data.

We present an example to help understand how this method works. Suppose the choice set shown in Table 2 is the only set from which each respondent is asked to choose their preferred milk option. We see that the level, *pasteurized,* occurrs twice among the three choices for each respondent. Specifically, products 1 and 2 have the value *pasteurized*; whereas product 3 has the value *UHT* for the attribute, "processing technology." Multiplying the total interviewed respondents N, we get $2N$, meaning that "pasteurized level" occurred $2N$ times in our CBC experiment. Also suppose that there were m and n respondents who chose milk product 1 and 2, respectively, as their preferred milk product – the two choices which include this attribute. In this case, the main effect of pasteurized level can be expressed by $(m+n)/ 2N$. Thus, if all respondents had chosen either product one or two and none had chosen 3, the frequency for the *pasteurized* value of the "processing technology" attribute would have been 100%. Similarly, we can count two-way (bivariate) and higher-way interaction effects. Table 4 reports only main effects and two-way interaction effects.

Significant main effects for the survey data are presented on the diagonal in

Table 4. The proportion choosing pasteurized milk was 40%, which is about 15% higher than that for UHT milk (26%). (For our data, the frequencies for pasteurized and UHT milk do not add up to 100% because not all questions involved these choices.) Free fat milk was the most popular, with a 54% rate, which is about double that for 1.5% fat content milk (28%), and triple that of milk with 3.8% fat level (18%). There is about a 40% probability that milk with natural taste would be chosen as the preferred alternative, while 27% chose flavored milk in the experiment. Similar to fat content, the price of milk obviously has a negative effect on the probability of choosing a milk alternative.

The frequencies for two-way interaction effects vary differently across levels of attributes. For example, consumers were more likely to choose low fat content milk, no matter what the price of the milk was. The probability of consumers choosing pasteurized milk was higher than for UHT for free fat and the 3.8% fat level while they are tied for the 1.5%. But, we also noticed that there was a 43% probability that flavored milk would be chosen as the most preferred milk at 1.3 yuan/250ml price level, which was almost 10% higher than that of natural taste milk. However, when the price level increased to 1.6 yuan/250ml and 1.9 yuan/250ml levels, natural taste milk was more likely to be chosen than the flavored one. This suggests a possible interaction between taste and price. Figures 1-4 provide visible and intuitive interaction effects. For example, there might be no interaction effects between taste and fat content level, and between fat level and processing method (see Figures 1 and 2), but interaction effects might exist between price and fat level, and between price and taste (see Figures 3 and 4).

Approach Two: Multinomial Logit Models (MNL)

The frequency approach gives some basic intuition, but for deeper analysis

multivariate methods are better at uncovering interactions while incorporating statistical "controls" on the other variables. In particular, one often wants to "control for" demographics – determine tastes conditional on the demographic variables. However, in the multinomial logit model, consumers' demographic characteristics will fall out of the probability of choosing an alternative, since they do not vary across the choices among milk alternatives (Greene, 2003). One method to modify the basic MNL model is to create a set of dummy variables for the choices and multiply each of them by the individual specifics (Greene, 2003). Also, demographics can be imposed into the MNL model by multiplying them by the product attributes (e.g., Morrison et al., 2002). The former method is widely applied in common CBC brand-specified studies, while the latter has been mainly adopted in a purely generic choice design[2].

Thus, the utility U for the individual i from choosing fluid milk m can be empirically expressed as a function of milk attributes, interactions between a pair of attributes, and interactions between attributes and demographics, as follows:

$$\begin{aligned} U_{im} &= \beta_1 process + \beta_2 fat + \beta_3 taste + \beta_4 price \\ &+ \gamma_1 processXfat + \gamma_2 processXtaste ... + \gamma_5 tasteXprice \\ &+ \lambda_1 processXgender + ... + \lambda_k fatXincome + ... + \lambda_{k+l} priceXincome + ... + \varepsilon_{im} \end{aligned} \quad (4)$$

where $\beta, \gamma, and \lambda$ are parameters to be estimated, and X indicates that term is an interaction between the variable before it and after it. These interaction items show how other attributes and individual characteristics modify the effect of the multiplied attribute on the probability of choosing. Definitions for the variables in final model specification are presented in Table 5.

[2] In a purely generic choice experiment, the alternatives are not brand-specified, but are defined by the bundles of a product's attributes, as in this study.

The estimated results from three MNL models are presented in Table 6. The statistical significance of the models is examined by using likelihood ratio tests of the null hypothesis that all slope estimates are zeros. The LR Chi-square values in models I through III are 1031.74, 1245.12, and 1461.18, respectively. The probability that the LR Chi-square is greater than the corresponding critical value is less than 0.01 in each model, meaning that we can reject the null. Except for interaction *processXfat* in model III, all estimates are significant at the 1% or 5% levels.

Estimated results in model I represent milk attributes' main effects. Results are generally consistent with the results obtained from the previous counting choice analysis. Qingdao urban consumers are more likely to choose pasteurized milk than UHT. As expected, fat content level and price have negative effects on the probability of an alternative being chosen. Also, the probability of choosing natural taste milk is greater than that of choosing flavored milk.

Estimates for the four attributes in model II and model III do not exactly represent the effects of attributes on the response variable, since they are modified by respondents' characteristics and other attributes. More exactly, to derive an estimate for the impact of a particular attribute one must set the interacting variable at a particular value. In order to compute a figure corresponding to the "main effects," in the frequency method a simple mathematic computation is needed where the interacting values are set at their means. For example, the effect of fat content on consumers' probability of choice in model II can be expressed as $\hat{\beta}_2 + \hat{\lambda}_3 senior + \hat{\lambda}_4 income$, which equals -0.444 when the variables *senior* and *income* are set at their means. Similarly, we can recover the main effects of processing method (-0.6082), taste (0.6293), and price (-1.120). Compared to the

corresponding main effects from model I estimation, they are nearly the same.

The estimates for interaction between attributes and respondents' demographic characteristics in model II and model III reflect the disparities of the preferences for milk attributes across consumer groups. For example, in model II, the negative significant estimate of the coefficient for *incomeXfat* means that richer consumers are more likely to choose lower fat milk than others (or, equivalently, that poorer consumers are likely to choose higher fat levels). Similarly, the positive estimate for interaction *genderXtaste* and the negative estimate for *youngXtaste* imply that male consumers are more likely to prefer natural tasting milk to flavored milk than females, and that young buyers significantly prefer flavored to natural milk. This is probably because flavored milk is treated as fashion consumption item by the young generation, and especially by females. Also, the estimated results indicate that senior consumers are more sensitive to fat content level than other consumers. The fact that many senior's health problems (e.g., high blood pressure) are related to fat intake may contribute to this finding.

The estimates for five of six possible interactions between a pair of attributes are statistically significant, implying significant two-way interaction effects on the probability of an alternative being chosen. These interaction effects measure how one attribute modifies the effects of its interacted attribute on the probability of an alternative to be chosen. For example, the negatively significant estimate of interaction *processXtaste* means that milk taste will weaken the effect of processing method on the probability of choice, and *vice versa*. The positive coefficient of interaction *tasteXprice* implies that price will strengthen the effect of taste, and *vice versa.*

Predictions for Utility and Probability of Choice

Predictions for the utility of choosing milk combination *j* and the probability of choosing it from the choice set that it belonged to are computed using the predicted forms of equation (3) and (4). Table 7 presents the predicted results for the18-profile set contained in our CBC experiment based on model I-model III[3]. Three profiles (alternative 1 in choice set 5, alternative 3 in choice set 3, and alternative 1 in choice set 1) consistently obtained the highest utility over the 18-profile set. All of these were pasteurized and free fat content milks (in **Bold** in Table 7). The probability of being chosen as the most preferred milk in the corresponding choice set that they belonged to was 87.6%, 67.4%, and 60.9%, respectively, in model I-based predictions. Except for alternative 3 in choice set 3 in model 3, the predicted probabilities of choice of these three highest utility profiles did not change significantly across three models.

The three alternatives with the least utility are alternative 2 in choice set 5, alternative 1 in choice set 3, and alternative 3 in choice set 1 sequentially (in *italics* in Table 7). Also notice that these alternatives all contain the highest fat level and are favored milks. The corresponding probabilities to be chosen are 2.6%, 5.1%, and 8.8%, respectively, in model I-based predictions. Again, the results are the same in the model II- and model III-based predictions. The utilities and probabilities were also predicted for the nineteen milk profiles that were not included in the design. To save space, these results are not presented here, but are available on request.

Predictions for Income Effects

The above discussions about probability of choice are based on an average individual. However, the CBC approach allows us to predict the effects of individual

[3] The 18-profile actually includes 17 unique products, since one profile was duplicated in the design.

characteristics on the probability of choosing any alternative in a given choice set by setting the demographic variables at different levels. Figures 5.1(2)-10.1(2) show the predicted income effects for each designed choice set based on model II (III). There is almost no difference between model II and model III results. The major exception is the case of choice set 4, where the probability of alternative 2 to be chosen in model II is less than that of alternative 3, no matter the income level, whereas the result is the opposite in model III -- until the per capita monthly income is greater than 1,900 yuan, or about 230 US dollars. Meanwhile, except for choice set 5, one of three alternatives in other choice sets will achieve near 100% of probability of choice, while the other two will gradually lose consumers' interest as income increases. Taking choice set 1 as an example, the probability of choosing alternative 2 (pasteurized, 1.5% fat, natural taste, and 1.9 yuan price) will gradually near 100% as income increases, although it is obviously lower than that of alternative 1 (pasteurized, free fat, flavored, and 1.3 yuan price) at the mean level of current income (monthly 1,078 yuan per capita, or 135 US$ in this study)[4]. To better understand these figures, it is useful to refer to Table 7 for a profile level specification.

Trade-offs within Attributes

Including a value variable into the CBC design has a particular advantage of measuring the trade-offs among levels of other attributes. Taking model II as an example, the prediction form of the utility function in equation (4) can be written as

[4] Notice that the discussion about income effects on probability of choice did not consider price changes. However, it just changes in magnitude if price inflation rate is not greater than income growth rate.

$$\hat{U}_{ij} = \hat{\beta}_1 process + \hat{\beta}_2 fat + \hat{\beta}_3 taste + \hat{\beta}_4 price$$
$$+\hat{\lambda}_1 genderXtaste + \hat{\lambda}_2 youngXtaste + \hat{\lambda}_3 seniorXfat + \hat{\lambda}_4 incomeXfat + \hat{\lambda}_5 incomeXprice$$

Assuming an average individual, we then take total differential to get[5]

$$d\hat{U}_j = \hat{\beta}_1 dprocess + \hat{\beta}_2 dfat + \hat{\beta}_3 dtaste + \hat{\beta}_4 dprice$$
$$+\hat{\lambda}_1 \overline{gender} * dtaste + \hat{\lambda}_2 \overline{young} * dtaste + \hat{\lambda}_3 \overline{senior} * dfat$$
$$+\hat{\lambda}_4 \overline{income} * dfat + \hat{\lambda}_5 \overline{income} * dprice$$

Then, the trade-offs among levels of one attribute can be calculated by assuming the predicted utility and the levels of other attributes, with the exception that price does not change. For example, the trade-off of changing processing method from pasteurization to UHT can be expressed as

$dprice = -[\hat{\beta}_1 / (\hat{\beta}_4 + \hat{\lambda}_5 \overline{income})] * dprocess = -0.543$. This means that the price of the alternative has to reduce by 0.543 yuan per unit (250ml) to keep the utility unchanged if the processing method switches from pasteurization to UHT. Table 8 presents all trade-offs based on model II (trade-offs based on model III are available on request).

Two points are worth mentioning. The first point is that the estimated trade-offs are identical to the marginal Willingness-To-Pay (WTP)[6]. The positive sign

[5] To do so, we assumed that all attributes have continuous levels. In magnitude, this assumption does not affect our trade-off calculation for attributes with discrete levels, such as taste and processing methods in this study.

[6] For fat content, the marginal WTP is equal to the trade-off from adding fat content of 1%. The marginal WTP for fat content is -0.397 in RMB, or about 5 cents in US currency. For continuous variables such as fat content, we may actually calculate

means that consumers are willing to pay a premium for gaining utility, while the negative sign means that consumers want a discount for compensating lost utility. The second point is that the trade-offs are a function of respondents' demographic characteristics, such as income. Thus, technically, we also can simulate income effects on the trade-offs. However, we can intuitively know that the trade-offs will go up as income increases, because as income increases, consumers tend to choose the higher priced milk, as we showed earlier.

V. Summary and Conclusions

In this study a choice-based conjoint experimental technique was applied to estimate consumers' preferences for fluid milk by taking milk attributes into consideration. The suitability of the CBC technique arises from its capacity to support the analysis of changes in milk-specific attribute levels in conjunction with differences in individual socioeconomic characteristics. When appropriate statistical tools are applied, the choice-based conjoint analysis enables analysts to examine consumers' preferences for fluid milk and specifically the effects of demographic characteristics on the probability of choosing a specified type of milk. Moreover, one can employ methods for estimating the trade-offs among the attribute levels of the milk types.

The main results of this study show that all four of the selected attributes have significant main effects on the preferences of Qingdao urban consumers for fluid milk. Also, the study also shows that most of two-way interactions and higher level the interactions between attributes and respondents' demographics are significant. In general, Qingdao consumers were found to be willing to pay a

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price elasticity instead of the marginal WTP. In this case, the estimated price elasticity with respect to fat content is -0.438.

premium for pasteurized, low fat content, and natural tasting milks, while they tended to require a discount before they would consider purchasing UHT, high fat content, and flavored milks. Turning to the interaction between milk attributes and consumer characteristics, our results indicate that female consumers are more likely to prefer flavored milk to natural tasting milk than males, and that young generation consumers significantly prefer flavored to natural milk compared to others. Also, as we expected, senior consumers are more sensitive to fat content level than other consumers.

This study also estimated the effect of income on the probability of choosing the attribute-specified milk. The results show that Qingdao consumers tend to be more likely to choose pasteurized, lower fat, and natural tasting milk at higher income levels (and to chose UHT, high fat and flavored milk at low income levels). Assuming that changes in income will have the same impact as the cross-sectional data show, it can be predicted that an increase in income will weaken the negative effects of milk price, which will lead to consumers to have more interest in higher priced milks. Other unspecified quality-related attributes, such as whether the product is organic or fiber-enriched, might be the reason.

In conclusion, this study sheds light on some aspects of China's economic, social and cultural transformation and its link to the changing consumption patterns for food products. Chinese consumers' diets are changing to include more western-style foods (Curits *et al.*, 2007). Increasingly, prosperous Chinese consumers are not only consuming more foods, but also increasingly choosing foods on the basis of quality, safety, and other factors in addition to price. The entry and rapid spread of western-style fast food establishments (e.g. McDonald's, KFC, and Pizza Hut) and multinational retail giants (e.g. Wal-Mart and Carrefour) in China provide important

accesses to this increasingly emerging market. However, China's rich history and culture imply that Chinese consumers will have their own, unique path of changing food consumption patterns. With China's vast population and rapid and sustained economic growth, this change may be creating new market and trade opportunities. In particular, fluid milk is gaining popularity in most Chinese urban areas, where it is becoming an important proportion of breakfast and health diets. However, there has been little information on consumers' preferences for milk attributes. The results of this study will help reveal market and trade opportunities in fluid milk and provide a basis for policy and investment in creating and developing national and international market capacity.

Acknowledgments

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Tables

Table 1. Selected Attributes and Levels Used in CBC Experiment

Attributes	Levels
Processing Technology	Ultra-High Temperature (UHT), Pasteurized
Fat Content	Fat Free, 1.5%, and 3.8%
Taste	Natural, Flavored (e.g., chocolate or fruit)
Price	1.3, 1.6, and 1.9 RMB yuan/250ml

Table 2. Example of a Choice Set from CBC Experimental Questionnaire

Q: If you are planning to buy milk today, and the following alternatives are available, please mark "√" in your most preferred product from each choice set.

Product Attributes	**Milk 1**	**Milk 2**	**Milk 3**
Processing Technology	Pasteurized	Pasteurized	UHT
Fat content	Fat Free	1.5%	3.8%
Taste	Flavored	Natural	Natural
Price (yuan/250ml)	1.3 yuan	1.9 yuan	1.6 yuan
□ I would likely choose Milk 1 □ I would likely choose Milk 2 □ I would likely choose Milk 3			

Table 3. Sample Statistics and Representative Tests

	Sample Mean	Std. Dev.	Population Mean	P-value[a]
Age (years)	38.05	13.64		
Under 30	0.377	0.485		
31-50	0.401	0.490		
Older than 50	0.222	0.416		
Female	0.663	0.473	0.495 b	Pr>t=0.0000
Unemployed	0.061	0.239	0.030 c	Pr>t=0.0001
Education Level (binary; yes=1)				
Primary school or illiteracy	0.039	0.195		
Middle school	0.230	0.421		
High school or equivalent	0.370	0.483		
2-year college or equivalent	0.228	0.420		
4-year college	0.126	0.333		
Advanced degree	0.006	0.077		
Monthly Per Capita Income (1000 Yuan)	1.078	0.566	1.077 c	Pr>|t|=0.9483
Less than 2000	0.210	0.408		
2001-4000	0.498	0.500		
More than 4000	0.292	0.455		
Household Size (persons)	3.248	1.092	3.191 b	Pr>|t|=0.1298
Total Observations	838			

a. Null Hypothesis, Ho: sample mean=population level.

b. 2003 data as population level since 2005 data are unavailable. The household size is from 2004 Qingdao Statistical Yearbook. The share of female is calculated based on the data from 2004 Shandong Statistical Yearbook. We believe there are no significant differences for these data between 2003 and 2005.

c. Data are from Qingdao 2005 Economic and Social Development Annual Report released by Qingdao Bureau of Statistics.

Table 4. Counted Main and Two-way Interaction Effects

Attributes		Process		Fat			Taste		Price		
	Levels	UHT	Past.	0%	1.5%	3.8%	Natl	Flvd	1.3	1.6	1.9
Process	UHT	26.0	---								
	Past.	---	40.6								
Fat	0%	38.9	68.8	54.1	---	---					
	1.5%	27.9	27.8	---	27.8	---					
	3.8%	11.5	24.6	---	---	18.0					
Taste	Natural	25.7	50.9	66.4	28.5	24.3	39.7	---			
	Flavored	26.2	27.7	41.8	27.2	11.8	---	26.9			
Price	1.3	23.3	52.7	63.4	25.5	24.5	33.6	42.5	38.0	---	---
	1.6	27.6	46.0	58.9	23.9	27.0	44.8	28.5	---	36.7	---
	1.9	27.2	23.5	39.6	34.0	2.9	40.8	9.9	---	---	25.3

Table 5. Definitions of Variables

Variable	Definitions and Coding
process	Milk processing method (UHT=1, Pasteurized=0)
fat	Milk fat content
taste	Milk taste (Natural=1, Flavored=0)
price	Milk price
gender	Respondent's gender (male=1, otherwise=0)
young	Whether respondent's age is less than or equal to 30 years (yes=1; no=0)
senior	Whether respondent's age is greater than 50 years (yes=1; no=0)
income	Monthly per capita disposable income

Table 6. Estimated Results from Multinomial Logit Models

	Model I		Model II		Model III	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Attributes:						
process	-0.5923***	0.0507	-0.6082***	0.0515	-4.2936***	0.4455
fat	-0.4280***	0.0178	-0.2267***	0.0408	0.6261***	0.1722
taste	0.6179***	0.0534	0.7863***	0.0773	-3.3896***	0.4217
price	-1.1186***	0.1058	-2.7428***	0.2340	-5.7268***	0.4038
Interactions with demographic characteristics:						
genderXtaste			0.3565***	0.1116	0.3569***	0.1126
youngXtaste			-0.7343***	0.1083	-0.7769***	0.1100
seniorXfat			-0.0985**	0.0423	-0.1030**	0.0419
incomeXfat			-0.1791***	0.0343	-0.1552***	0.0342
incomeXprice			1.5057***	0.1953	1.5170***	0.2000
Interactions with other attributes:						
processXfat					0.0160	0.0507
processXtaste					-1.5046***	0.1460
processXprice					2.9527***	0.2984
fatXtaste					0.1414***	0.0417
fatXprice					-0.5365***	0.1170
tasteXprice					3.1246***	0.2753
Observations	7542		7542		7542	
Log Likelihood	-3197.15		-3117.06		-2988.33	
LR chi2	1031.74		1191.93		1449.4	
Prob > chi2	0.0000		0.0000		0.0000	
McFadden Adj R^2	0.1389		0.1605		0.1952	

*, **, and *** denotes statistically significant at the 10%, 5%, and l% levels, respectively.

Table 7. Predicted Utilities and Probabilities of Choice for 18-profile[a] with Six-block in the CBC Design

		Attributes				Based On Model I			Based On Model II[b]			Based On Model III[b]		
Set	Alt	Process	Fat	Taste	Price	Uj	Exp(Uj)	Pr(cj|Set)	Uj	exp(Uj)	Pr(cj|Set)	Uj	exp(Uj)	Pr(cj|Set)
1	1	0	0	0	1.3	**-1.454**	**0.234**	**60.9%**	**-1.456**	**0.233**	**61.4%**	**-5.319**	**0.005**	**61.5%**
	2	0	1.5	1	1.9	-2.150	0.117	30.4%	-2.164	0.115	30.3%	-6.067	0.002	29.1%
	3	1	3.8	1	1.6	*-3.391*	*0.034*	*8.8%*	*-3.458*	*0.031*	*8.3%*	*-7.201*	*0.001*	*9.4%*
2	1	0	1.5	1	1.9	-2.150	0.117	45.5%	-2.164	0.115	46.0%	-6.067	0.002	43.9%
	2	1	3.8	1	1.3	-3.055	0.047	18.4%	-3.122	0.044	17.7%	-7.185	0.001	14.3%
	3	1	0	0	1.6	-2.382	0.092	36.1%	-2.400	0.091	36.3%	-6.116	0.002	41.8%
3	1	0	3.8	0	1.9	*-3.752*	*0.023*	*5.1%*	*-3.815*	*0.022*	*4.8%*	*-10.001*	*0.000*	*0.6%*
	2	1	1.5	1	1.3	-2.071	0.126	27.5%	-2.101	0.122	26.8%	-6.939	0.001	13.7%
	3	0	0	1	1.6	**-1.172**	**0.310**	**67.4%**	**-1.162**	**0.313**	**68.4%**	**-5.110**	**0.006**	**85.6%**
4	1	1	0	1	1.9	-2.100	0.122	47.8%	-2.106	0.122	48.6%	-5.588	0.004	59.5%
	2	0	3.8	0	1.3	-3.081	0.046	17.9%	-3.143	0.043	17.2%	-6.323	0.002	28.5%
	3	0	1.5	0	1.6	-2.432	0.088	34.3%	-2.458	0.086	34.2%	-7.184	0.001	12.0%
5	1	0	0	1	1.3	**-0.836**	**0.433**	**87.6%**	**-0.826**	**0.438**	**88.2%**	**-4.819**	**0.008**	**85.4%**
	2	1	3.8	0	1.9	*-4.344*	*0.013*	*2.6%*	*-4.423*	*0.012*	*2.4%*	*-8.624*	*0.000*	*1.9%*
	3	1	1.5	0	1.6	-3.024	0.049	9.8%	-3.066	0.047	9.4%	-6.729	0.001	12.7%
6	1	1	0	0	1.9	-2.718	0.066	33.9%	-2.736	0.065	34.5%	-6.457	0.002	27.2%
	2	1	1.5	0	1.3	-2.689	0.068	34.9%	-2.730	0.065	34.7%	-6.146	0.002	37.1%
	3	0	3.8	1	1.6	-2.798	0.061	31.2%	-2.850	0.058	30.8%	-6.187	0.002	35.6%

[a] : The 18-profile actually includes 17 unique products, as one profile was duplicated in the design; [b] : Utility values are predicted at means of the demographics.

Table 8. Estimated Trade-offs in CBC Design (based on Model II)

Attributes	Trade-off Directions	Trade-offs	
		in RMB	in US$[a]
Process	Pasteurization→UHT	-0.543	-0.068
Fat content	0%→1.5%	-0.595	-0.074
	1.5%→3.8%	-0.912	-0.114
	0%→3.8%	-1.507	-0.188
Taste	Flavored→Natural	0.562	0.070

[a] : exchange rate used is 1 US$=8RMB.

Figures

Figure 1. Interaction Effects Between Tastes and Fat Levels

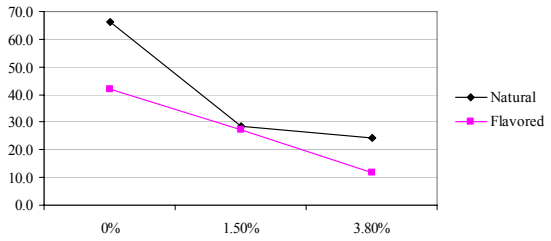


Figure 2. Interaction Effects Between Fat Levels and Processes

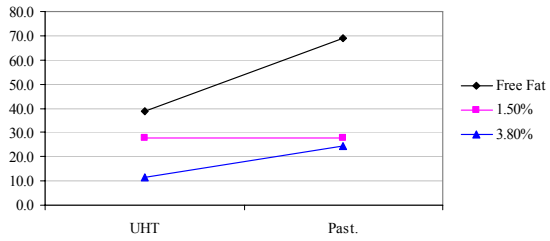


Figure 3. Interaction Effects Between Prices and Fat Levels

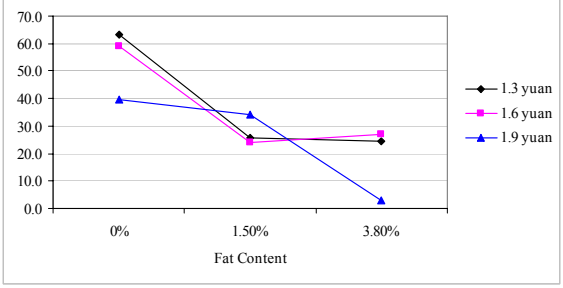
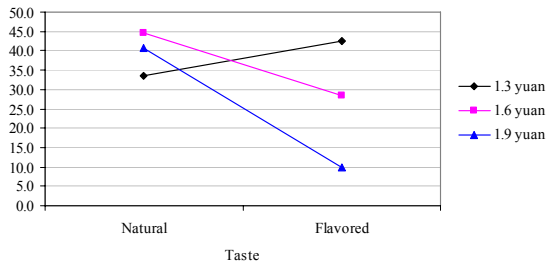


Figure 4. Interaction Effects Between Prices and Tastes



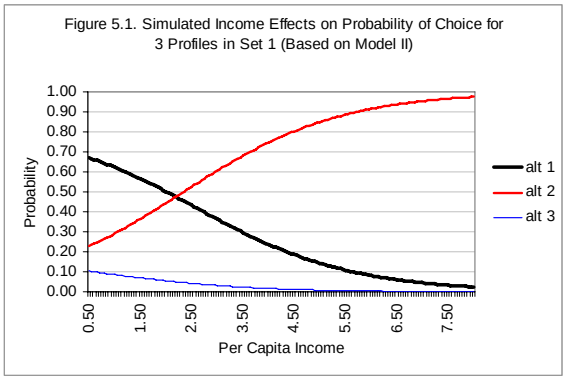


Figure 5.1. Simulated Income Effects on Probability of Choice for 3 Profiles in Set 1 (Based on Model II)
Probability
1.00
0.90
0.80
0.70
0.60
0.50
0.40
0.30
0.20
0.10
0.00
0.50
1.50
2.50
3.50
4.50
5.50
6.50
7.50
Per Capita Income
alt 1
alt 2
alt 3

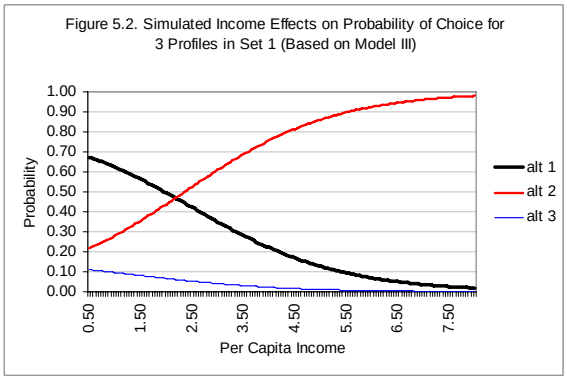


Figure 5.2. Simulated Income Effects on Probability of Choice for 3 Profiles in Set 1 (Based on Model III)
Probability
1.00
0.90
0.80
0.70
0.60
0.50
0.40
0.30
0.20
0.10
0.00
0.50
1.50
2.50
3.50
4.50
5.50
6.50
7.50
Per Capita Income
alt 1
alt 2
alt 3

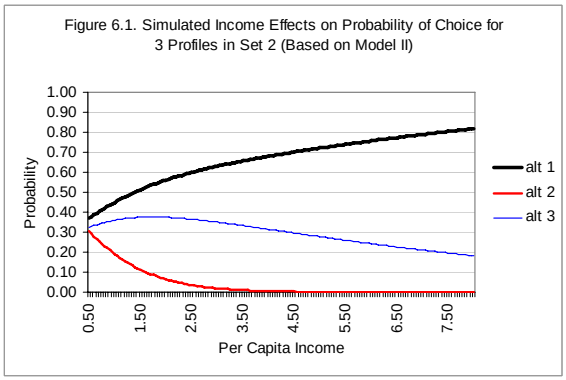


Figure 6.1. Simulated Income Effects on Probability of Choice for 3 Profiles in Set 2 (Based on Model II)
Probability
1.00
0.90
0.80
0.70
0.60
0.50
0.40
0.30
0.20
0.10
0.00
0.50
1.50
2.50
3.50
4.50
5.50
6.50
7.50
Per Capita Income
alt 1
alt 2
alt 3

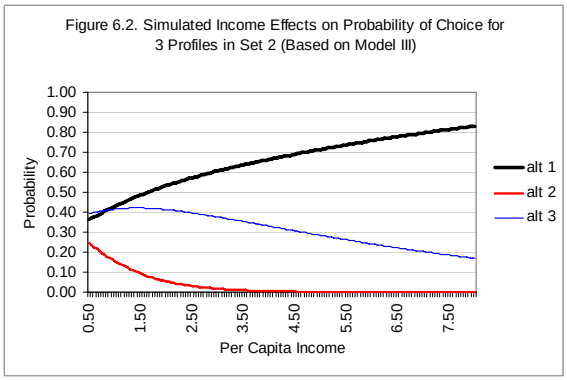


Figure 6.2. Simulated Income Effects on Probability of Choice for 3 Profiles in Set 2 (Based on Model III)
Probability
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0.90
0.80
0.70
0.60
0.50
0.40
0.30
0.20
0.10
0.00
0.50
1.50
2.50
3.50
4.50
5.50
6.50
7.50
Per Capita Income
alt 1
alt 2
alt 3

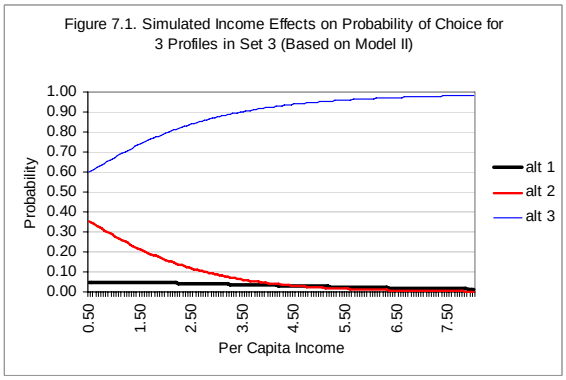


Figure 7.1. Simulated Income Effects on Probability of Choice for 3 Profiles in Set 3 (Based on Model II)
Probability
1.00
0.90
0.80
0.70
0.60
0.50
0.40
0.30
0.20
0.10
0.00
0.50
1.50
2.50
3.50
4.50
5.50
6.50
7.50
Per Capita Income
alt 1
alt 2
alt 3

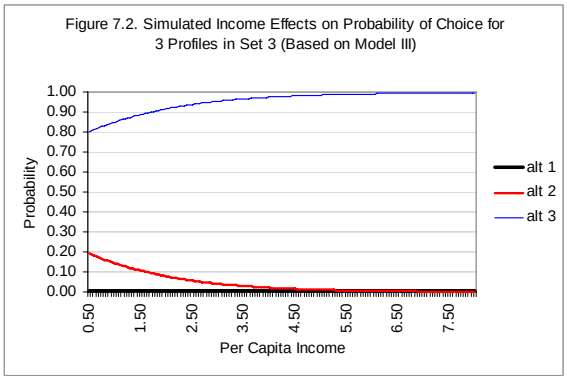


Figure 7.2. Simulated Income Effects on Probability of Choice for 3 Profiles in Set 3 (Based on Model III)
Probability
1.00
0.90
0.80
0.70
0.60
0.50
0.40
0.30
0.20
0.10
0.00
0.50
1.50
2.50
3.50
4.50
5.50
6.50
7.50
Per Capita Income
alt 1
alt 2
alt 3

Figure 8.1. Simulated Income Effects on Probability of Choice for 3 Profiles in Set 4 (Based on Model II)

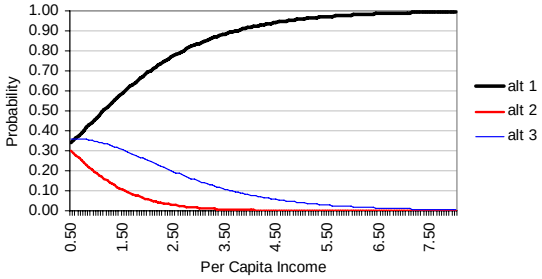


Figure 8.2. Simulated Income Effects on Probability of Choice for 3 Profiles in Set 4 (Based on Model III)

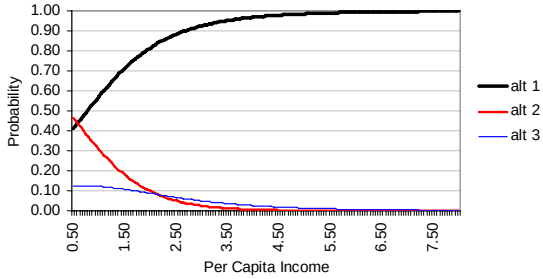


Figure 9.1. Simulated Income Effects on Probability of Choice for 3 Profiles in Set 5 (Based on Model II)

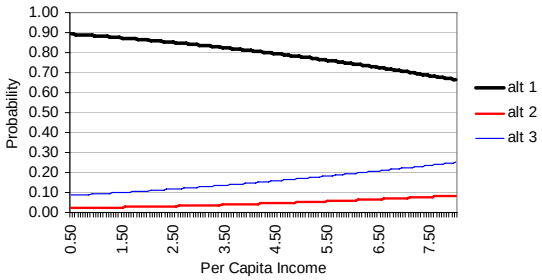


Figure 9.2. Simulated Income Effects on Probability of Choice for 3 Profiles in Set 5 (Based on Model III)

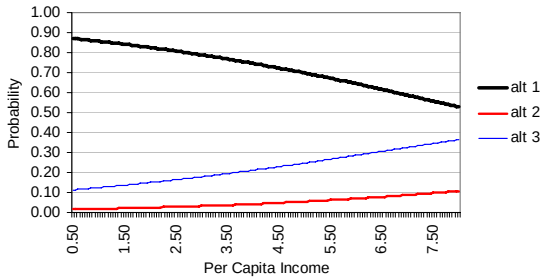


Figure 10.1. Simulated Income Effects on Probability of Choice for 3 Profiles in Set 6 (Based on Model II)

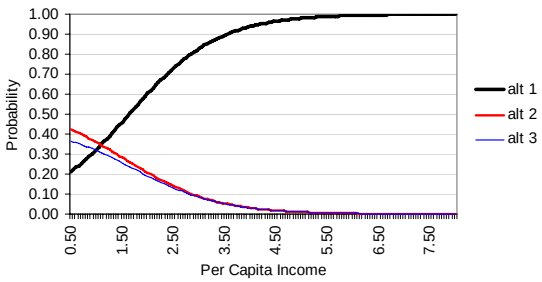
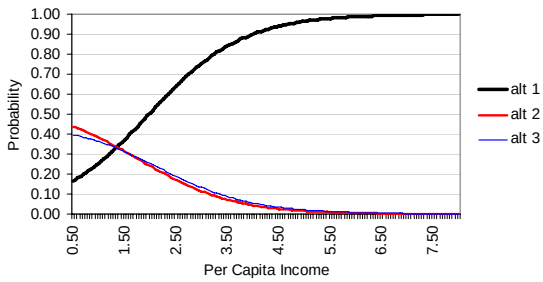


Figure 10.2. Simulated Income Effects on Probability of Choice for 3 Profiles in Set 6 (Based on Model III)



Appendix

Table A.1. Canonical Correlations Between the Factors

	Process	Fat	Taste	Price
36-Run Full Factorial Design				
Process	1	0	0	0
Fat	0	1	0	0
Taste	0	0	1	0
Price	0	0	0	1
18-Run Fractional Factorial Design				
Process	1	0	0.11	0
Fat	0	1	0	0
Taste	0.11	0	1	0
Price	0	0	0	1

Table A.2. Summary of Frequencies in 36-run and 18-run Designs

Main/Interaction		36-Run Full Factorial Design										18-Run Fractional Factorial Design								
Process		18	18									9	9							
Fat		12	12	12								6	6	6						
Taste		18	18									9	9							
Price		12	12	12								6	6	6						
Process	Fat	6	6	6	6	6	6					3	3	3	3	3	3			
Process	Taste	9	9	9	9						*	5	4	4	5					
Process	Price	6	6	6	6	6	6					3	3	3	3	3	3			
Fat	Taste	6	6	6	6	6	6					3	3	3	3	3	3			
Fat	Price	4	4	4	4	4	4	4	4	4		2	2	2	2	2	2	2	2	2
Taste	Price	6	6	6	6	6	6					3	3	3	3	3	3			
N-Way		1	1	1	1	1	1	1	1	1	*	1	1	1	1	1	1	2	1	1
		1	1	1	1	1	1	1	1	1		1	1	1	1	1	1	1	1	
		1	1	1	1	1	1	1	1	1										
		1	1	1	1	1	1	1	1	1										

* Indicates unequal frequencies.

Table A.3. Comparison of Efficiencies Between 36-run and 18-run Designs

	D-Efficiency	A-Efficiency	G-Efficiency	Average Prediction Standard Error
36-Run	100.00	100.00	100.00	0.4410
18-Run	99.82	99.64	98.26	0.6236