# Three Essays on Consumer Behavior and Health Outcomes: An Economic Analysis of the Influence of Nutrition Information and Knowledge on Food Purchasing Behavior and the Impacts of Primary Care Givers' Parenting on Childhood Obesity

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ABSTRACT

This dissertation is comprised of three essays that investigate consumer behavior and health outcomes. The first essay uses experimental economic techniques to explore consumers' preferences and willingness to pay (WTP) for nutritionally differentiated grass-fed beef. Our findings suggest that consumers' nutrition knowledge about the functions of Vitamin A, Vitamin E, CLA, and Omega 3 could positively affect their WTP for grass-fed beef while the knowledge about the main food sources of these nutrients negatively affects their WTP for grass-fed beef. Furthermore, a higher sensory evaluation score of grass-fed beef compared to conventional beef will lead to a higher probability for a consumer to choose grass-fed beef and a higher monetary value she/he is willing to pay for grass-fed beef.

Using the same experimental data collected in the first study, the second essay investigates the impacts of consumers' nutrition knowledge on their WTP by accommodating the potential endogeneity problem using an instrumental variable approach and a non-instrumental variable approach. Our results suggest the existence of the endogeneity of nutrition knowledge and indicate that ignoring the endogeneity problem in econometric modeling will downwardly bias the estimates of the true effects of nutrition knowledge. The estimates obtained from different estimation strategies in the study indicate the robustness of our findings about the effects of nutrition knowledge on consumers' food purchasing behavior.

The third essay investigates the impacts of primary care giver (PCG)'s time allocation patterns and household food expenditure choices on childhood obesity using the national panel study of income dynamics data. Our results do not suggest significant impacts of PCG's labor force participation, involvement in children's outdoor activity, and household food expenditures on children's Body Mass Index (BMI). However, the estimates from iterated seemingly unrelated regression (SUR) and semi-parametric polynomial estimation indicate that parents' BMI significantly influence children's BMI. Interestingly, physical activity appears to have weak correlation with children's BMI.

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# Introduction

Do nutrition information and nutrition knowledge influence food behaviors? It is a question without an affirmative answer. Under the rationality assumption of economics, a reasonable prediction would be that consumers with better information and knowledge about the nutritional attributes of the foods they consume will hold more favorable attitudes towards healthful foods and practice healthier food behaviors. However, controversies and mixed evidence about the influence of nutrition information and knowledge on food behaviors remain unsolved. Perceived health consequences, individual food goals, unobserved preferences, information search and processing patterns, and socioeconomic impacts may all play influential roles in consumers' complex dietary decision-making process.

The first essay is entitled "Consumer Preferences and Willingness to Pay (WTP) for Grass-Fed Beef: Empirical Evidence from In-Store Experiments". Using grass-fed beef as a vehicle, the first essay intends to offer empirical evidence of the influence of consumers' nutrition information and knowledge on their food behaviors. For the first time in literature, this study reveals that nutrition knowledge can significantly influence consumers' willingness to pay for beef products. Furthermore, different types of nutrition knowledge can express such influence in opposite ways. We find that consumers' knowledge about the functions of four nutrients (Vitamin A, Vitamin E, CLA, Omega 3) are positively related to consumers' willing to pay for nutritionally enhanced grass-fed beef, while consumers' knowledge on the main food sources for these nutrients appears to be negatively associated with their willingness to pay for grass-fed beef. Our analysis also suggests that the sensory characteristics of beef products' play a central role in determining consumers' preferences and willingness to pay in beef shopping. Moreover, the visual attributes and the palatability attributes do not exert their influence to the same extent. The ultimate actual eating satisfaction plays a key role in consumers' purchasing decisions.

The second essay is entitled "The Influence of Endogenous Nutrition Knowledge on Consumers' WTP for Grass-Fed Beef". As an econometric issue, endogenity of nutrition knowledge may arise in model estimation due to unobserved individual heterogeneity. Many existing studies have ignored this potential problem which may partially contribute to the mixed evidence about the relationship between nutrition knowledge and food behaviors in literature. By treating nutrition knowledge as endogenous variables explicitly, the second essay assesses the impacts of nutrition knowledge on consumers' willingness to pay for grass-fed beef using instrumental variable (IV) approach. This study investigates the legitimacy of two possible instrumental variables. The possibility of using a non-IV approach is also examined in the study. As a natural choice, we first use consumers' label use frequency as instruments for nutrition knowledge. However, Food label use seems to be only weakly correlated with nutrition knowledge as statistical tests indicated. To tackle the potential weak instrument problem, Fuller's limited information maximum likelihood (LIML) estimator is used. However, fuller' LIML could not fix the problem. Then, we refer to the use of Lewbel (1997) approach which constructs higher order moments as instruments. Under IV framework, the existence of the endogeneity of the two sets of nutrition knowledge is revealed and the direction of the bias of the estimates caused by endogenous nutrition knowledge is shown to be downward. In the two-stage estimation using Lewbel instruments, the opposite effects on consumers' willingness to pay on grass-fed beef are confirmed again. As an alternative, we investigate a non-IV approach by sub-grouping the full sample based on nutrition levels and estimate four separate Tobit models. This method enables us to exclude nutrition knowledge variables from willingness to pay equations but still be able to identify the effects of nutrition knowledge. Our results indicate that consumers in different nutrition groups did bid differently and the differences of willingness to pay between these groups are also significant, implying the influential role of nutrition knowledge on consumers' willingness to pay.

Third essay is entitled "Primary Care Giver's Time allocation, Household Food Expenditures, and Childhood Obesity". The rate of childhood obesity rate has been growing rapidly over the past three decades. Childhood obesity is a complex phenomenon which is affected by a broad spectrum of biological, genetic, sociological, and economic factors. What has caused the rapid increase of childhood obesity remains an open question. The third essay investigates the possible influences of primary care giver (PCG)'s time allocation and food expenditure choices on childhood obesity measured by Body Mass Index (BMI) using the national panel study of income dynamics (PSID) data. A simultaneous triangular system of equations is estimated in iterated Seemingly Unrelated regression (SUR) model to examine the determinants of children's energy intake and consumption patterns and their relations to childhood obesity epidemic. Furthermore, from the methodological point of view, we are aware that the validity of parametric model estimates relies heavily on the restrictive distributional assumptions and functional forms. To examine the robustness of the SUR estimates, for the first time in literature, this study introduces a semi-parametric approach to estimate a triangular simultaneous system of equations to investigate the influential factors on childhood obesity. Our estimates from iterated SUR and semi-parametric polynomial estimation indicate that obese parents tend to have obese children. In contrast to some previous studies, our results do not suggest significant impacts of labor force participation choices of PCG, usually the mothers in a household, on children's BMI. Furthermore, physical activity appears to have weak correlation with children's BMI. These results indicate the complexity of the causes of childhood obesity epidemic. The performances of the two modeling strategies are compared using predictive ability measures with the aid of bootstrap method. Although the predictive ability tests suggest better performance of the SUR model, comparison of the estimates from both parametric and semi-parametric models indicates no dramatic changes in the results, implying little influence of the model fitting choices on our findings.

# Essay 1: Consumer Preferences and Willingness to Pay for Grass-Fed Beef: Empirical Evidence from In-Store Experiments

**Abstract**

This essay uses experimental economic techniques to explore consumers' preferences and willingness to pay (WTP) for nutritionally differentiated grass-fed beef. The impacts of nutrition information and knowledge on consumers' WTP under the influence of uncertainty are examined using non-hypothetical Becker–DeGroot–Marschak (BDM) auction. Our findings suggest that consumers' nutrition knowledge about the functions of Vitamin A, Vitamin E, CLA, and Omega 3 could positively affect their WTP for grass-fed beef while the knowledge about the main food sources of these nutrients negatively affects their WTP for grass-fed beef. Interestingly, the results also suggest that if a consumer or any of her/his household members have ever been diagnosed with diabetes, heart disease, high blood pressure, high cholesterol, or obesity, she/he will be willing to pay more for grass-fed beef. Moreover, consumers who live with other household members or have higher beef consumption frequencies are shown to be willing to pay more for grass-fed beef as well, ceteris paribus. Furthermore, sensory characteristics of beef products play a central role in consumers' purchasing decisions. A higher sensory evaluation score of grass-fed beef compared to conventional beef will lead to a higher probability for a consumer to choose grass-fed beef and a higher monetary value she/he is willing to pay for grass-fed beef.

**Keywords**: Nutrition Knowledge, Sensory Characteristics, BDM Auction, Grass-Fed Beef, Willingness-To-Pay

## 1. Introduction

Consumer demand for beef is increasingly influenced by consumers' concerns about the healthfulness, quality, nutritional content, and safety of the foods they consume; and by growing demand for intangible attributes such as animal welfare and environmental impacts of production and marketing (Farm Foundation, 2006). As a product that responds to many of these demands, grass-fed beef has gained increasing attention.

The grass-fed marketing claim standards of the USDA require that grass-fed ruminants be fed solely with grass and forage during their lifetimes, and that, with the exception of milk consumed prior to weaning, grass-fed animals have continuous access to pasture during the growing season (USDA, 2007). We use this definition as the basis for our use of the term "grass-fed beef" in this paper. In contrast, "grain-fed beef" (also referred to as "conventional beef" in this paper) refers to beef produced from cattle fed in confinement on grain-based concentrate-only diets.

As a result of the feeding regime and physical activities of grass-fed cattle, the quality characteristics of grass-fed beef are different from conventional beef in terms of marbling, color, meat texture, tenderness, juiciness, and flavor. For example, carcasses from pasture-fed steers have darker longissimus color and yellower fat than animals finished on concentrate (Realini, Duckett, Brito, Dalla Rizza and De Mattos 2004). They also tend to have lower fat thickness (Realini, Duckett, Brito, Dalla Rizza and De Mattos 2004); Duckett,Neel, Sonon, Fontenot, Clapham, and Scaglia 2007). Grass-fed beef has lower Warner-Bratzler shear force values at 7 and 14 days post-mortem, meaning that it is tender than conventional beef (Realini, Duckett, Brito, Dalla Rizza and De Mattos 2004). Furthermore, the different feed regimes result in different nutritional attributes for grass-fed beef compared to conventional beef. Specifically, grass-fed beef has been found to have 2–4 times more natural vitamin E (Arnold et al., 1992), higher amounts of β-carotene (Descalzo et al., 2005), approximately 60% more Omega-3 fatty acids (Duckett et al., 1993); and 2–3 times more Conjugated linoleic acids (CLA) than grain-fed cattle (Duckett et al. 1993). Diet components can also affect meat flavor. The products of oxidation of linolenic acid and its derivates which derive substantially from grass feeding can cause a unique pastoral flavor of grass-fed beef (Priolo, Micol and Agabriel 2001).

Not much work has been done to assess the impacts of these unique attributes on consumers' preferences and willingness to pay for grass-fed beef and the few studies that exist have conflicting results. Notably, McCluskey et al. (2005) and Evans (2008) both showed that the majority of their sample consumers were willing to pay positive premiums ranging from $2.28 to $5.65 for grass-fed beef compared to conventional beef of similar cuts and quality. In contrast, Umberger (2002) found that only 23% of her study participants preferred grass-fed beef and they were only willing to pay an average premium of $1.36 per pound. These inconsistent findings in the literature may be attributed to various factors such as differences in experimental design, subjects' representativeness, and the environments in which the experiments were conducted. For example, McCluskey (2005) used a hypothetical conjoint analysis approach to elicit consumers' WTP, and it is known that subjects often overstate their preferences in hypothetical settings (List and Gallet, 2001). Likewise, the inconsistencies between Umberger's and Evans' results could be due to the use of laboratory versus field methods as Umberger relied on laboratory experiments while Evan used field research. It is also worth mentioning that Evans (2008) only had a subset of his subjects evaluate the taste of grass-fed beef which implies that many of his subjects stated their WTP with only limited knowledge of the product. Thus, on the merit of the few existing studies that exist on grass-fed beef demand and their inconsistent results, further analysis of the issue is warranted.

This study aims to contribute to the literature in several respects. First, we make a contribution to the literature by testing the effects of consumers' nutrition knowledge and the provision of information about the nutritional attributes of grass-fed beef on consumers' WTP for the product. According to Sapp (1991), although nutritional knowledge is not directly related to intentions, behavior, or attitudes, it significantly influences beef-eating intentions and behavior because consumers make tradeoffs between health benefits and eating pleasure when consuming foods. We hypothesize that consumers' nutrition knowledge could affect their WTP for grass-fed beef which contains elevated levels of some nutrients. Second, we hope to help resolve the contradictory findings of previous studies and to advance our understanding of consumers' preferences and willingness to pay for grass-fed beef. Third, instead of using hypothetical valuation methods, we conduct non-hypothetical in-store experiments not just in one location but in three cities to more comprehensively investigate consumers' behavior at the point of purchase. Our results generally show that palatability attributes play a central role in determining consumers' preferences and WTP for grass-fed beef. We also find that consumers' nutrition knowledge, beef consumption behavior, health status, living status and household size have significant impacts on their WTP for grass-fed beef.

The remainder of the article proceeds as follows. First, we introduce our conceptual framework. Next, we explain our study's experimental design. Then, summary statistics of the data are presented, followed by a section discussing the empirical model structure and estimation results. The paper concludes with summary and discussion of the results with a focus on marketing implications.

## 2. Conceptual Framework

Consumers obtain utility from a bundle of attributes of beef products, such as nutritional benefits and taste. The nutritional value is different from other attributes in the sense that, at the point of purchase, its effects can only be perceived under expectation. The difference in consumers' the expected utility of consuming grass-fed beef and the expected utility of consuming conventional beef determines their WTP for grass-fed beef. Based on this assumption, we derive consumers' WTP for grass-fed beef under Von Neumann and Morgenstern's (1944) random utility framework.

We assume a consumer's expected utility of consuming one pound of grass-fed beef is of the form:

(1) $$EU_1 = \pi^1 u_c(m, X, Z, S; 1) + (1 - \pi^1) u_{nc}(m, X, Z, S; 1)$$

Where $m$ denotes the consumer's income. $X$ is a vector of observable characteristics of the choice and $Z$ is a vector of the unobservable attributes of the choice. The socio-economic characteristics of the consumer are denoted by a vector S. The number 1 denotes that the consumer decides to purchase one pound of grass-fed beef. To factor the nutritional information effect into the model, we let this representative consumer face two states: the occurrence or nonoccurrence of the positive health outcome from purchasing grass-fed beef. $u_c, u_{nc}$ denote the state-dependent utility of occurrence and nonoccurrence respectively. The probabilities attached to the two states when the consumer chooses to purchase grass-fed beef are: $\pi^1$ for occurrence and $1 - \pi^1$ for nonoccurrence. These probabilities do not indicate the occurrence/ nonoccurrence of positive health outcomes from one-time grass-fed beef consumption; rather they reflect the cumulative outcomes from repeated consumption. Note the fact that consumers are offered numerous alternatives by the market and they can gain possible health benefits by choosing to consume other products, we therefore set the probabilities the consumer faces when he chooses not to purchase grass-fed beef as: $\pi^0$ for occurrence of a positive health outcome and $1-\pi^0$ for nonoccurrence. Similarly, the expected utility of choosing not to consume grass-fed beef is:

$$EU_0 = \pi^0 u_c(m, X, Z, S; 0) + (1-\pi^0) u_{nc}(m, X, Z, S; 0) \tag{2}$$

Incorporating the monetary cost of purchasing grass-fed beef, the consumer's expected utility of consuming one pound of grass-fed beef is

$$EU_1 = \pi^1 u_c(m - WTP, X, Z, S; 1) + (1-\pi^1) u_{nc}(m - WTP, X, Z, S; 1) \tag{3}$$

WTP is the consumer's willingness to pay for grass-fed beef. In our experiment, consumers' nutrition knowledge is categorized as the knowledge of nutrient function and the knowledge of the nutritious food sources, denoted as $k_f$ and $k_s$. We hypothesize that a consumer's knowledge of the nutrient functions assists the consumer to process the nutritional information of grass-fed beef more effectively and thus the consumer will hold more positive attitudes about consuming grass-fed beef; at the same time, if a consumer has good knowledge of the food sources of the nutrients emphasized in the nutrition information of grass-fed beef, he will be aware of the alternative food choices in the market and thus be less positive about consuming grass-fed beef. We thus assume that the consumer's nutrition knowledge k favorable to grass-fed beef is a function of both nutrient function knowledge and food source knowledge $k = \alpha k_f + \beta k_s$ and hypothesize that $\alpha > 0$ and $\beta < 0$. We assume that the knowledge k and new information I provided enter the model via probability, i.e. $\pi^0$ and $\pi^1$ are functions of $k(k_f, k_s)$ and I. Differentiating equation (3) with respect to WTP and information k, we have

$$\frac{dWTP}{dk} = \frac{\pi^{1\prime} u_c - \pi^{1\prime} u_{nc}}{\pi^1 u_c'} > 0 \tag{4}$$

The sign is deterministic because the utility of the occurrence of the desired state is assumed to be greater than the utility of the nonoccurrence state. If we disentangle the effects of the nutrient function knowledge and food source knowledge, under our hypothesis, equation (4) suggests that

(5) $$\frac{dWTP}{dk_f} = \frac{dWTP}{dk}\alpha > 0$$

(6) $$\frac{dWTP}{dk_s} = \frac{dWTP}{dk}\beta < 0$$

Hanemann (1984) shows a utility maximization based approach to obtain the utility-theoretical measure of the money value of a permit to the individual hunter. Using the similar method, we set the expected utility as

(7) $$EU_d = EV_d(m, X, Z, S, \pi^d; d) + \varepsilon_d$$

Where

(8) $$E[EU_1] = EV_1(m, X, Z, S, \pi^1; 1)$$

(9) $$E[EU_0] = EV_0(m, X, Z, S, \pi^0; 0)$$

d is a state variable: d = 1 if the individual chooses to purchase grass-fed beef; d = 0, otherwise. $\varepsilon_0, \varepsilon_1$ are iid random variables with zero means. A money value of the individual's maximum WTP for one pound of grass-fed beef should satisfy

(10) $$EV_1(m - WTP, X, Z, S, \pi^1; 1) + \varepsilon_1 = EV_0(m, X, Z, S, \pi^0; 0) + \varepsilon_0$$

we can set

(11) $$\Delta EV = EV_1(m - WTP, X, Z, S, \pi^1; 1) - EV_0(m, X, Z, S, \pi^0; 0)$$

Then

(12) $$\Pr\{\eta < \Delta EV(WTP)\} = F_\eta[\Delta EV(WTP)] = p$$

Where $\eta = \varepsilon_0 - \varepsilon_1$, $F(\cdot)$ denotes the CDF of $\eta$. p is the probability that we perceive the consumer will purchase grass-fed beef. Thus,

(13) $\Delta EV(WTP) = F_{\eta}^{-1}(p)$

If we postulate some functional form of the expected utility function EV and chose a specific form of $F_{\eta}$ which is ensured to have an inverse representation, we can solve equation (8) to get the individual's WTP for one pound of grass-fed beef

(14) $\text{WTP} = \Delta EV^{-1}(WTP \mid F_{\eta}^{-1}(p)) = w(m, X, k_f, k_s, I, S, Z)$

## 3. Materials and Methods

### *3.1 Participants*

Non-hypothetical in-store experiments (Nayga Jr., Woodward, and Aiew, 2006) were conducted in one supermarket in each of the three cities: Knoxville TN, Middlesboro KY, and Bluefield WV during September and October 2008. These experimental sites were chosen with reference to U.S. census data to maximize the heterogeneity of the potential sample pool. The experiments were conducted on both weekdays and weekends and throughout the morning, afternoon and early evening of each day in order to achieve a diverse and representative subject pool (Kahn and Schimittlein, 1989; East, Lomax, Willson, and Harris, 1994).

### *3.2 Product*

Grass-fed beef used in experiments were New York strip steaks which were fabricated from the strip loin primal (Institutional Meat Purchasing Specifications item number 180) of 20-month grass-fed cattle. Carcasses were hung for 48 hours prior to fabrication at 33ºF - 35ºF. Then they were fabricated and shipped overnight in the chilled state from a certified grass-fed farm in Georgia to the experimental sites as fresh, primal cuts vacuum packaged and were stored overnight in the meat department's refrigerators of the host supermarket. Conventional beef used were fresh supermarket New York strip steaks which were prepared from the same strip loin primal of fed-lot cattle aged from 18-22 month and stored in chilled state in the meat department's refrigerators. All grass-fed and conventional carcasses received USDA quality grades ranging between select$^{-}$ and select + . Beef samples were cut on the same day of experiments and were held about 40ºF in coolers until the tests started. Professional meat cutters in the supermarket prepared similar sizes, one pound portions of grass-fed and conventional beef samples and packaged them in identical, unlabeled polystyrene trays with shrink wrap covering. External fat was smoothly trimmed following the contour of the underlying muscle surface. The maximum fat thickness at any point was less than 0.1 inches. We changed beef samples for sensory valuation every one hour. Hence, consumers received random samples of steaks from different part of strip lions and from different steers. Although meat sensory attributes could differ within and among steers, our large sample ensures the experimental results to represent the population difference with respect to consumers' preferences for grass-fed beef and supermarket conventional beef to a meaningful extent.

*3.3 Experimental Protocol*

Consumers were recruited and screened for eligibility from among shoppers who passed by the experiment table which was set up in the shopping aisle near the meat department of each supermarket. To be eligible for the study, each participant had to be aged 18 or above, a beef consumer, and serve as the primary person responsible for either buying or preparing food for his or her household.

Compensation in the form of a $10 store gift card was offered to subjects as an incentive to participate. The number of participants varied depending on the store and time of day, but on average about 40 percent of those invited to participate completed the experiment.

The experimental protocol consisted of a written survey, blind visual and taste evaluations of grass-fed beef and conventional beef samples, and a WTP experiment for those consumers who preferred grass-fed beef. The experimental procedure usually took a total of twenty minutes with the written survey, taste and visual evaluations, and WTP experiments comprising seven minutes, six minutes and seven minutes respectively. The survey instrument is provided in Appendix A.

The written survey collected data on consumers' personal and household characteristics; beef consumption behavior; prior consumption experience with grass-fed beef and impressions of the effects of grass-fed beef on health, the environment and animal welfare; self-reported health status; and knowledge of the specific sources and functions of nutrients present in grass-fed beef. In the visual and palatability evaluations, participants were first presented with unlabeled samples of conventional and grass-fed beef, and asked to fill out two single-page surveys; one addressing their visual evaluations and one addressing their taste evaluations of the samples. Respondents reported their rankings of the lean meat color, fat color, and meat texture for each sample based on visual evaluation using a 7 point Likert scale, and also indicated which sample they preferred overall based on their visual evaluation. Respondents then tasted cooked samples of each product and after each tasting evaluated it on the basis of tenderness, flavor and juiciness (using the same 7 point Likert scale) and indicated which sample's taste they preferred. Finally, consumers were asked to indicate which beef sample they preferred overall.

At the conclusion of the visual and taste tests, subjects who either preferred the conventional beef or were indifferent between the two were given their gift cards as compensation for their participation, and their role in the study was concluded. Subjects who preferred the grass-fed beef after the visual and taste tests were given a one-pound package of conventional beef along with the store gift card, and were asked whether they would be willing to pay any amount to trade the conventional beef that they had been given for the grass-fed beef that they preferred. If the subject answered in the affirmative, a Becker-DeGroot-Marshak (BDM) auction was used to determine the consumers' WTP for the grass-fed beef. Under the BDM auction format, the subject states a monetary value that s/he would be willing to pay to exchange the conventional beef for the grass-fed beef. A monetary value, which represents the market price premium for the beef, is randomly drawn from a box and is the binding value. If the subject offers an amount equal to or greater than the binding value, then the exchange is made with the subject paying the binding value to make the exchange. If the subject offers less than the binding value then the exchange is not made. The procedure was explained prior to the auction being executed so that the subject was clear on the process and understood that the auction format removed any incentive to either understate or overstate his or her bid.

We also randomly introduced an information shock to participants in order to determine the effect that the provision of information about grass-fed beef's nutritional attributes had on consumers' preferences and WTP. Participants were randomly assigned to three treatment groups: Treatment Group A was the control group and received no nutritional information about grass-fed beef; Treatment Group B received information about the nutritional attributes of grass-fed beef before the visual and taste evaluations; and Treatment Group C received the nutrition information after completing the visual and taste evaluations. The nutrition information provided is presented in Appendix B.

Admittedly, our experimental design limits the examination of the impact of health benefit information of grass-fed beef on all participants' beef preferences. It is indeed possible that consumers who preferred conventional beef at first based on their sensory evaluations might find grass-fed beef more preferable once aware of the potential health benefits from grass-fed beef consumption. However, we are unable to investigate such possibility since we excluded the participants who preferred conventional beef from our information treatments. Future studies should examine this issue further.

*3.4 Data analysis*

All the data analyses were conducted using Stata 10. Preliminary data examination based on kernel smoothing indicates the likelihood of non-normal distribution of WTP measures. Therefore, a nonparametric Wilcoxon- Mann-Whiteney U test, which is robust to outliers and efficient when the underlying distributions are non-normal, was used to statistically compare the auction bids across experimental sites and between treatment groups (Hollander and Wolfe, 1999). A Probit model was estimated to examine the relationship between consumers' sensory evaluations and their beef preferences. Finally, a Tobit model was used in the WTP estimation in order to accommodate those cases where the subjects had zero WTP for the grass-fed beef. Marginal effects in Tobit estimates were decomposed based on McDonald and Moffitt (1980) approach. Using the McDonald and Moffitt (1980) approach, the formula for the expected value of the dependent variable for all cases is $Ey = X\beta \times F(z) + \Sigma \times f(z)$ ,where $F(z)$ is the normal CDF, f(z) is the normal density function and $\Sigma$ is the standard deviation of the error term. The marginal effect of an independent variable on $Ey$ is given by

$$\frac{\partial Ey}{\partial X_i} = F(z) \times \frac{\partial Ey^*}{\partial X_i} + Ey^* \times \frac{\partial F(z)}{\partial X_i}$$

Where $\frac{\partial Ey^*}{\partial X_i}$ measures the change in expected value above the censoring limit and $\frac{\partial F(z)}{\partial X_i}$ measures the possibility change of being above the limit. McDonald and Moffitt (1980) show that

$$\frac{\partial Ey^*}{\partial X_i} = \beta_i \times [1 - (z \times \frac{f(z)}{F(z)} - \frac{f(z)^2}{F(z)^2}]$$

$$\frac{\partial F(z)}{\partial X_i} = \beta_i \times \frac{f(z)}{\Sigma}$$

**4. Data**

Table 1 summarizes the socio-demographic characteristics of our sample. Table 2 provides comparative census data for the three cities. In general, the participants are predominately white, female, and middle aged. Most participants have some college education or above and are in the middle income category. The average household has three members while householders living alone represent only 17% of the sample. Relative to the population in each city, female consumers and non-single living consumers seem to be over-represented in our sample. However, this should not be treated as sampling bias but rather reflects the fact of disproportionate composition of primary food shoppers in terms of gender and living status, as supported by the American Time Use Survey's finding that women, on average, spend more time on grocery shopping than men (Bureau of Labor Statistics, 2008).

Table 3 reports the participants' preferences between the grass-fed and grain-fed beef samples in terms of their visual, palatability, and overall evaluations. Results show that the majority of the participants (54%) preferred grass-fed beef based on visual evaluation. However, when the participants considered palatability satisfaction, only 37% of the participants preferred grass-fed beef over conventional beef. Furthermore, only about 39% of the samples preferred grass-fed beef overall. These results indicate that consumers generally possess positive attitudes towards the visual appearance of grass-fed beef but not towards its taste and that ultimately they tend to prefer conventional beef over grass-fed beef, which then signifies the influential role of palatability in consumers' beef preferences. T–tests are performed to test whether there are significant differences in consumers' beef preferences across cities. The test results are reported in Table 4. The results suggest that consumers' beef preferences do not differ significantly between the three experimental cities. The only exception is the consumers' preferences based on visual evaluation between Knoxville and Middlesboro which are marginally significant at the significance level of 0.1 with more consumers preferring grass-fed beef in Knoxville.

Participants' auction bids by experimental location are presented in Table 5. Only those participants who preferred grass-fed beef participated in the auction resulting in a sample of 159 respondents. Table 6 shows the results of the Wilcoxon- Mann-Whiteney U test comparing the auction bids between participants by location. It is shown that the bids are not significantly different from each other in the three experimental sites implying that geographic variation does not seem to have an influence on participants' WTP.

Table 7 reports the auction results by treatment group. Participants in Treatment Groups B (which received information before the visual and taste evaluations) and C (which received information after the visual and taste evaluations) exhibit higher mean bids than participants in group A which was the control group though it is worth noting that Treatment Groups A and B have relatively close bids ($1.61 and $1.71 respectively) while Treatment Group C's bids are much larger at $2.20 per pound. As shown in Table 8, the Wilcoxon Mann Whiteney U test results indicate that the bids in treatment group A are significantly different from the bids in treatment group B and treatment group C. Bids from group B and group C are not significantly different as the test results suggest though the mean bid $2.20 of Treatment Group C seem to be evidently larger than the bid $1.71 of Treatment Group B. Dispersed distribution of the bids from group C may possibly be attributed to the insignificant difference in mean bids . These results argue for including these treatments as explanatory variables in the WTP regression.

## 5. Empirical Model and Estimation Results

We now turn to the discussion of the multivariate econometric analysis results. Estimates from Probit and Tobit models are reported and discussed to explain consumers' preferences and WTP for grass-fed beef respectively.

### *5.1 Sensory Evaluation and Consumer Choice*

The following Probit model is estimated to analyze the effect of these sensory characteristics on consumers' overall beef preference:

$$\begin{aligned} &Probability(consumer\ i\ chooses\ grass\text{-}fed\ beef) \\ &= f(Dlcolor, Dfcolor, Dtexture, Dtender, Djuicy, Dflavor, Gender, Age, \\ &\quad Single, Householdsize, Ethnicity, Edu, Income) \end{aligned}$$

Table 9 presents the associated variable descriptions and summary statistics. The explanatory variables include differences between the consumers' ratings of the visual and taste attributes of conventional and grass-fed beef as well as socio-economic characteristics. Previous studies suggested that color of lean muscle tissue, visible fat content, flavor, and tenderness are important cues for consumers' beef purchase decisions (e.g. Feldkamp, Schroeder, and Lusk 2003; Huffman et al. 1996; Lusk et al. 2001(b)). We include the differences in consumers' ratings of the lean meat color (Dlcolor), fat color (Dfcolor), meat texture (Dtexture), tenderness (Dtendrness), juiciness (Djuiciness), and flavor (Dflavor) between conventional beef and grass-fed beef samples (i.e. conventional beef sample score minus grass-fed beef sample score, since we are interested in the relative ratings to represent consumers visual and taste evaluations of the products. We include gender (Gender), age (Age), single and non-single living status (Single), household size (Householdsize), ethnicity (Ethnicity), education level (Edu), and household income level (Income) as socio-demographic variables.

Table 10 presents the results of the Probit model estimation which was run on a sample of 404 observations. After the estimation, we used the model to predict consumers' choices using the sample data. The high percentage of the correct predictions (89%) indicates that our model performs well in explaining the impact of sensory attributes on consumer purchasing choice.

The results suggest that four of the six attributes significantly influence consumers' preference. The more that a consumer rates the grass-fed beef sample favorably in terms of its meat texture, tenderness, juiciness, and flavor, the more likely she/he is to prefer grass-fed beef to conventional beef. Only one of these attributes, texture, is a visual cue; the other three are all palatability attributes and have a relatively greater impact on the consumers' choice. These results show that consumers are more likely to base their choices of beef products on eating satisfaction than appearance. Among the demographic variables, age is an influential factor when consumers making beef choices. The results suggest that older consumers are more likely to prefer grass-fed beef than younger consumers. Indeed, traditionally, all beef was grass-fed beef. Older consumers may consume grass-fed beef as regular meat when they were raised. Thus, the old-fashioned meat qualities of grass-fed beef may be preferable to them.

*5.2 Consumers' WTP for grass-fed beef Model*

Most existing studies suggest that consumers are willing to pay a premium for food perceived as natural, organic or environment friendly (e.g. Gil et al., 2000; Loureiro and Hine, 2002; Wandel and Bugge, 1996). Harper and Henson (2001) show that consumers also are concerned about farm animal welfare and use animal welfare as an indicator of product attributes such as food safety, quality and healthiness. However, their study does not identify the positive relationship between such concerns and the price that consumers actually are willing to pay. Our study intends to revisit this issue. According to Melton et al. (1996), appearance and taste are important predictors of consumer perceptions and WTP for fresh food. The effect of sensory attributes on consumer food behavior has been identified by numerous studies. For example, Alfnes et al. (2006) show that consumers are willing to pay significantly more for salmon fillets with normal or above-normal redness; and Lusk et al. (2001) show that consumer are willing to pay extra for more tender steaks. Health concerns and nutritional knowledge have also been shown to be influential factors in consumer WTP for food products with proven health benefits (Bower et al., 2003). With respect specifically to grass-fed beef, Evans (2008) indicates that the frequency of in-home steak preparation and income level have significant impacts on consumers' WTP for grass-fed beef steaks, and grass-fed beef purchasing experience and gender also significantly influence consumers' preference for grass-fed beef, which may lead to higher WTPs. Based on these findings, we include the following variables in our empirical model:1) nutrition information treatments (Tb, Tc); 2)frequency of beef consumption (Freq); 3) prior experience with grass-fed beef ( Experience); 4) expectations about grass-fed beef 's impact on human health (Exph), environment (Expe) and animal welfare (Expa); 5) consumers' perceptions of the sensory characteristics of grass-fed beef; and 6) consumers' knowledge of the sources(Ks) and functions of the nutrients found in FPB (Kf). While the main effects of the sensory characteristics on consumers' beef WTP are expected to be significant, participants who received nutrition information about grass-fed beef may tend to value these characteristics differently from those who did not receive the nutrition information. For this reason, we include twelve interaction terms (Tb*DLcolor, Tb*DFcolor,Tb*DTexture, Tb*DTenderness, Tb*DJuiciness, Tb*DFlavor, Tc*DLcolor, Tc *DFcolor,Tc*DTexture, Tc*DTenderness, Tc*DJuiciness, Tc*DFlavor) to assess the interaction effects between the provision of nutrition information and sensory evaluation.

We also hypothesize that the health status of consumers and their immediate families will influence consumers' WTP for food perceived healthy since it's more important for those with diet-related diseases to eat healthfully. Therefore, health status (Diseases) is included as an explanatory variable. To control for the effect of individual characteristics, the model also includes a set of socio-demographic variables.

Our investigation of the impact of consumers' nutrition knowledge on the WTP for grass-fed beef is a unique contribution to the literature and consequently deserves further explanation. We expect that consumers who are knowledgeable about nutrition will be more capable of processing nutrition information about the product and put more value on grass-fed beef's nutritional attributes. At the same time, consumers may be also aware of other food sources for the nutrients which have equal or better nutritional values than grass-fed beef. To disentangle these competing effects, we include two nutrition knowledge variables in the WTP equation. The first (Kf) measures consumers' knowledge about the functions of four nutrients (Vitamin A, Vitamin E, CLA, and Omega 3) that are found in higher concentrations on grass-fed beef than conventional beef. The second (Ks) measures consumers' knowledge of the main food sources of these nutrients. We hypothesize that consumers' nutrient functions knowledge has positive impact on consumers' WTP for grass-fed beef, while the knowledge about food sources negatively impacts consumers' WTP for grass-fed beef. In the meantime, we expect that consumers with different levels of nutrition knowledge may differ in their capabilities of processing nutrition information. Consequently, nutrition information may have different impacts on consumers WTP for grass-fed beef. Therefore, four interaction terms between the two sets of nutrition knowledge and treatments, Kf*Tb, Kf*Tc, Ks*Tb, Ks*Tc, are included in the WTP model to capture such effects.

Hence, our empirical WTP model is expressed as:

$$
\begin{aligned}
WTP = f(&Tb, Tc, Freq, Experience, Eeph, Eepe, Expa, Disease, Kf, Ks, DLColor, DFColor, DTexture,\\
&DTenderness, DJuiciness, DFlavor, Tb*DLColor, Tb*DFColor, Tb*DTexture, Tb*DTenderness\\
&Tb*DJuiciness, Tb*DFlavor, Tc*DLColor, Tc*DFColor, Tc*DTexture, Tc*DTenderness, Tc*DJuiciness,\\
&Tc*DFlavor, Kf*Tb,\ Kf*Tc,\ Ks*Tb,\ Ks*Tc, Gender, Age, Single, Householdsize, Ethnicity, Edu, Income)
\end{aligned}
$$

The description and the summary statistics of the variables in the model are reported in Table 11.

Tobit models rely heavily on the normality assumption, and the MLE will be inconsistent if the underlying distribution is not normal. Thus, the conditional moment test (Skeels and Vella 1999) using a bootstrap approach (Drukker, 2002) is used to test the null that the underlying distribution of the error term is normal[1]. There is no statistical evidence indicating the violation of the normality assumption.

Table 11 reports the Tobit coefficient estimates, the marginal effects on unconditional expected value, and the marginal effects conditional on being uncensored. As we are more interested in the behavior of those who preferred grass-fed beef in the experiments, the following discussion is restricted to the conditional results only.

As Table 11 shows, the coefficients of Treatment B and Treatment C are not significant even at $\alpha = 0.1$ level, indicating that the provision of nutrition information has no significant impacts on consumers' WTP. We find that there are interaction effects between the information

[1] The value of the conditional moment test statistic is 8.13, with the critical value of 18.50 and 18.00 at 10% level under the 500 and 1000 replications respectively.

and consumers' evaluation of sensory characteristics. The negative coefficients of the interactions between information treatment and visual inspection of the lean meat color and fat color suggest that consumer who are exposed to nutrition information are less concerned with the lean meat color and fat color of the grass-fed beef. This implies that nutrition information effects on consumers' WTP are expressed through consumers' sensory evaluation. Their main effects are not evident in the estimation.

Consumers' WTP for grass-fed are also significantly influenced by their knowledge of nutrient functions and nutrients' main food sources. Knowledge about the nutrient functions positively affects consumer's WTP. The marginal effect estimates suggest that each point increase in this knowledge score induced a $0.19 increase in WTP for participants who preferred grass-fed beef. In contrast, consumers with more knowledge about the main food sources of the four nutrients have lower WTP, supporting our hypothesis that consumers who are more aware of substitutes in the market will not value the nutritional attributes of grass-fed beef as much. Specifically, each point increase of the score of this set of knowledge reduced WTP by about $0.15 for those who preferred grass-fed beef. The relative magnitude of the combined effects of the nutrition knowledge variables suggests a positive overall influence of the nutrition knowledge on consumers' WTP for grass-fed beef. However, for the joint effect of the interaction effects between nutrition knowledge and the provision of nutrition information, the likelihood ratio test indicates that these interaction terms do not have significant influence on consumers WTP.

Sensory characteristics are also found to be important determinants of consumers' WTP for grass-fed beef. The differences in ratings of lean meat color, meat texture, tenderness, juiciness evaluation between grass-fed beef and conventional beef are significantly positive. On average, if a consumer perceives that grass-fed beef is less dark than conventional beef, each rank difference generates about $0.09 increase in her/his WTP for grass-fed beef; if a consumer perceives the texture of grass-fed beef to be finer than conventional beef , each rank difference increases her/his WTP for grass-fed beef by about $0.07; and if a consumer perceives that the grass-fed beef tastes more tender and juicier than conventional beef then each rank increase in this difference generates about $0.16 and $0.13 increase in her/his WTP for grass-fed beef, respectively. Among these sensory attributes, tenderness has the largest effect on consumers' WTP. This is in line with previous studies' results (e.g. Feldkamp, Schroeder, and Lusk, 2003; Lusk et al. 2001). However, our results suggest an insignificant impact of flavor differentials on consumers' WTP, which is inconsistent with the findings from Huffman et al. (1996) who found that flavor accounts for most of the variation in palatability of beef steaks in regression analysis (R-square =0 .67). Overall, we find that the impact of palatability attributes is much larger than the visual attributes, which indicates that consumers are more likely to base their value perception of beef products on the palatability than on the visual appearance, and that the actual eating satisfaction largely determines how much they are willing to pay for grass-fed beef.

Consumers' beef consumption behavior also has a significant effect on their WTP for grass-fed beef. Specifically, consumers who prepare and eat beef at home more frequently are willing to pay more for grass-fed beef. For example, if a consumer eats beef at home 3 or more times a week, she/he will be willing to pay about $0.15 more for grass-fed beef than consumers who eat beef at home only 1-2 times a week.

Another interesting finding is the importance of the health status of the consumer and/or consumers' household members in influencing WTP. If a consumer or any of her/his household members have ever been diagnosed with diabetes, heart disease, high blood pressure, high cholesterol, or obesity, she/he will be willing to pay about $0.3 more for one pound of grass-fed beef.

The estimation results lend little support to our hypotheses that consumers' impressions of grass-fed beef on human health, environment, and animal welfare have a significant impact on their WTP for grass-fed beef. As Table 10 shows, although approximately half of the consumers in our sample have positive impressions of grass-fed beef's impacts on human health, environment, and animal welfare (45%, 45%, 46% respectively), they do not necessarily translate into consumers' WTP. Table 11 shows that none of the coefficients corresponding to these variables are statistically significant. The likelihood ratio test suggests the insignificant joint effect of these factors as well (test statistic LR chi-square (3) = 0.57). This indicates that the grass-fed production system has no value to consumers beyond its effect on the physical attributes of the product. Various reasons could be attributed to this and other concerns may take precedence in the decision. These concerns could include a wide range of factors, such as the immediate consumption satisfaction and budget constraints. Further research is warranted to explore this issue.

Regarding the socio-demographic characteristics, living status and household size significantly influence consumers WTP for grass-fed beef. The results suggest that, in general, consumers who live with others (including spouse, partner, children, relatives and unrelated people) are willing to pay about $0.40 more for grass-fed beef than consumers who live alone. It is possible that consumers who do not live alone are more concerned with the heath of the household members and thus are willing to pay more for healthier food when the food is purchased for others to consume. However, there is a negative relationship between household size and WTP in non-single living households. The negative coefficient of household size in the

WTP equation suggests that consumers from larger household are less willing to pay for grass-fed beef than those from smaller household. This may reflect the fact that larger households usually face a tighter budget constraint than smaller households. In this case, economizing on food expenditure may dominate their food purchase decisions, reducing consumers' WTP for grass-fed beef as household size increases.

**6. Discussion and conclusion**

Our analysis offers several important results. First, it shows that the majority of consumers we surveyed do not prefer grass-fed beef over conventional beef. While the majority prefers it visually, mainstream consumers' responses to the taste and their overall evaluations are consistently in favor of conventional beef. This finding is in line with Umberger et al.'s (2002) study in which the authors found that only 23% of the study participants preferred grass-fed beef. In sharp contrast to our findings, Evans et al.'s (2008) study found that 74% and 82% of his study participants preferred grass-fed steaks and grass-fed ground beef respectively. The controversial findings could be due to the taste heterogeneity among participants across experimental samples. The differences between sampling strategies may be important factors contributing to the conflicting results. Second, our study shows that consumers are willing to pay a \$2 premium for one pound of grass-fed beef compared to conventional beef. Umberger et al.'s (2002) and Evans et al.'s (2008) studies found similar amounts of price premium (ranging from \$1.4 to \$2.6 for one pound). However, in McCluskey et al.'s (2005) study, the estimated WTP is as high as \$5.69, perhaps due to the hypothetical nature of their study. Third, our study suggests that sensory attributes play a central role in determining consumers' preferences and WTP, with eating satisfaction playing a more important role than visual satisfaction. Fourth, making a unique contribution to the literature, this study reveals that nutrition knowledge can significantly influence consumers' WTP. We found that consumers' knowledge about the functions of the nutrients has a positive effect on WTP for grass fed beef; while consumers' knowledge about the main food sources for these nutrients has a negative effect. These results support our hypotheses that 1) consumers who are more knowledgeable about nutrient functions are more capable of processing the nutrition information of grass-fed beef and thus put more value on the nutritional attributes of grass-fed beef; and 2) consumers with better food source knowledge are more knowledgeable about other and possibly better or less expensive sources of these nutrition, reducing their WTP for these nutrients in grass-fed beef. The influence of consumers' beef consumption frequency is confirmed by the results, suggesting that consumers who consume beef at home more frequently are willing to pay more for grass-fed beef. Another interesting finding is the importance of the health status of the consumer and/or consumers' household members in influencing WTP. With respect to consumers' socio-demographic characteristics, only consumers' living status and household size have significant impacts on consumers' WTP. Thus, it seems that socio-demographic variables play a relatively minor role.

These results have several important implications. First, it is important to note that palatability traits play a more important role than visual traits in determining consumers' preferences for grass-fed beef. Thus, promotion efforts that emphasize the palatability of grass fed beef will be more effective—for example providing cooked samples to consumers at point of sale could be an effective approach. Second, consumers who prepare and consume beef at home more frequently, as well as older consumers and those who live with others but in smaller households all tend to be willing to pay more for grass-fed beef. These consumers should thus be targeted in efforts to promote grass-fed beef. Finally, as consumers' WTP are influenced by their nutrition knowledge, promoting nutrition education can help increase consumers' acceptance and purchases for healthier food products

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### Table 1. Characteristics of Experiment Participants

| Variable | Definition | Knoxville (N =131) | | Middlesboro (N=156) | | Bluefield (N=117) | | Overall (N=404) | |
|---|---|---|---|---|---|---|---|---|---|
| | | Mean | S.D. | Mean | S.D. | Mean | S.D. | Mean | S.D. |
| GENDER | Male=1, 0 otherwise | 0.31 | 0.46 | 0.33 | 0.47 | 0.39 | 0.49 | 0.34 | 0.47 |
| AGE | Participant's age<br>1 if <=24<br>2 if >24 and <=34<br>3 if >34 and <=44<br>4 if >44 and <=54<br>5 if >54 and <=64<br>6 if >64 | 4.08 | 1.60 | 3.53 | 1.50 | 4.21 | 1.42 | 3.90 | 1.54 |
| HOUSEHOLDSIZE | Number of people in participant's household | 2.27 | 1.28 | 2.90 | 1.36 | 2.74 | 1.38 | 2.65 | 1.36 |
| ETHNICITY | White=1, Otherwise=0 | 0.92 | 0.27 | 0.98 | 0.18 | 0.97 | 0.16 | 0.96 | 0.21 |
| EDU | No high school diploma or equivalent =1<br>High school diploma or equivalent = 2<br>Some college/technical school = 3<br>Associate's degree = 4<br>Bachelor's degree = 5<br>Graduate or professional degree = 6 | 4.05 | 1.40 | 2.71 | 1.32 | 3.38 | 1.48 | 3.33 | 1.50 |
| INCOME | Less than $10,000 = 1<br>$10,000 - $19,999 = 2<br>$20,000 - $29,999 = 3 | 5.48 | 3.24 | 3.94 | 2.45 | 4.99 | 2.87 | 4.75 | 2.92 |

| Variable | Definition | Knoxville (N =131) | | Middlesboro (N=156) | | Bluefield (N=117) | | Overall (N=404) | |
|---|---|---|---|---|---|---|---|---|---|
| | | Mean | S.D. | Mean | S.D. | Mean | S.D. | Mean | S.D. |
| | $30,000 - $39,999 = 4 | | | | | | | | |
| | $40,000 - $49,000 = 5 | | | | | | | | |
| | $50,000 - $59,999 = 6 | | | | | | | | |
| | $60,000 - $69,999 = 7 | | | | | | | | |
| | $70,000 - $79,000 = 8 | | | | | | | | |
| | $80,000 - $89,999 = 9 | | | | | | | | |
| | $90,000 - $99,999 = 10 | | | | | | | | |
| | More than $100,000 = 11 | | | | | | | | |
| SINGLE | Live alone =1, Otherwise = 0 | 0.30 | 0.46 | 0.10 | 0.30 | 0.12 | 0.33 | 0.17 | 0.38 |

**Table 2. Population Socio-demographic Characteristics of Experimental Areas**

| Variable | Definition | Knoxville Mean(Median) | Middlesboro Mean(Median) | Bluefield Mean(Median) |
|---|---|---|---|---|
| GENDER | Male=1, 0 otherwise | 0.49 | 0.46 | 0.46 |
| AGE | Participant's age (year) | 33.9(median) | 38.6(median) | 42.2(median) |
| HOUSHOLDSIZE | Number of people in participant's household | 2.07 | 2.30 | 2.23 |
| ETHNICITY | White=1, Other=0 | 0.80 | 0.93 | 0.76 |
| EDU | No high school diploma or equivalent =1 | 3.12 | 2.21 | 2.88 |
| | High school diploma or equivalent = 2 | | | |
| | Some college/technical school = 3 | | | |
| | Associate's degree = 4 | | | |
| | Bachelor's degree = 5 | | | |
| | Graduate or professional degree = 6 | | | |
| INCOME | Dollars | 34185(median) | 19565(median) | 27672(median) |
| SINGLE | Live alone=1, Otherwise = 0 | 0.41 | 0.32 | 0.35 |

Source: American Community Survey, U.S. Census Bureau. Knoxville: 2005-2007 data. Middlesboro and Bluefield: 2000 data.

**Table 3. Consumer Preference for Grass-Fed Beef / Conventional Beef**

| | | Knoxville(N=131) | | Middlesboro(N=156) | | Bluefield (N=124) | | All Regions | |
|---|---|---|---|---|---|---|---|---|---|
| Preference | | Proportion | S.E. | Proportion | S.E. | Proportion | S.E. | Proportion | S.E. |
| Based on visual test | Grass-fed beef | 0.59 | 0.04 | 0.49 | 0.04 | 0.57 | 0.05 | 0.54 | 0.02 |
| | Conventional beef | 0.34 | 0.04 | 0.46 | 0.04 | 0.38 | 0.04 | 0.40 | 0.02 |
| | Indifferent | 0.07 | 0.02 | 0.05 | 0.02 | 0.05 | 0.02 | 0.06 | 0.01 |
| Based on palatability test | Grass-fed beef | 0.38 | 0.04 | 0.38 | 0.04 | 0.35 | 0.04 | 0.37 | 0.02 |
| | Conventional beef | 0.59 | 0.04 | 0.56 | 0.04 | 0.61 | 0.05 | 0.58 | 0.02 |
| | Indifferent | 0.03 | 0.02 | 0.05 | 0.02 | 0.04 | 0.02 | 0.04 | 0.01 |
| Over all | Grass-fed beef | 0.39 | 0.04 | 0.40 | 0.04 | 0.38 | 0.05 | 0.39 | 0.02 |
| | Conventional beef | 0.59 | 0.04 | 0.57 | 0.04 | 0.56 | 0.05 | 0.57 | 0.02 |
| | Indifferent | 0.02 | 0.01 | 0.03 | 0.01 | 0.05 | 0.02 | 0.03 | 0.01 |

## Table 4. T-test of Consumer Preference for Grass-Fed Beef

| | Knoxville (N=131) | Middlesboro (N=156) | Bluefield (N=124) |
|---|---|---|---|
| Knoxville | | 0.09<br>1.00<br>0.86 | 0.75<br>0.62<br>0.87 |
| Middlesboro | | | 0.18<br>0.60<br>0.73 |

Note: In each comparison, the first number is the p-value of the test under the null hypothesis that the proportion of the consumers who preferred grass-fed beef from the row location equals the proportion of the consumers who preferred grass-fed beef from the column location based on visual evaluation. The second number is the p-value of the test under the null hypothesis that the proportion of the consumers who preferred grass-fed beef from the row location equals the proportion of the consumers who preferred grass-fed beef from the column location based on palatability evaluation. The third number is the p-value of the test under the null hypothesis that the proportion of the consumers who preferred grass-fed beef from the row location equals the proportion of the consumers who preferred grass-fed beef from the column location based on both visual and palatability evaluation.

**Table 5. Grass-Fed Beef Auction Bids by Location**

| | Knoxville (obs=51) | | | | Middlesboro (obs=63) | | | | Bluefield (obs=45) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | S.D. | Min | Max | Mean | S.D. | Min | Max | Mean | S.D. | Min | Max |
| WTP | 2.01 | 1.85 | 0 | 10 | 1.70 | 1.64 | 0 | 6 | 1.70 | 1.44 | 0 | 6 |

**Table 6. Wilcoxon-Mann-Whitney Test of the Auction Bids for Grass-Fed Beef between Locations**

| | Knoxville (obs=51) | Middlesboro (obs=63) | Bluefield (obs=45) |
|---|---|---|---|
| Knoxville | | 0.19 | 0.43 |
| | | 0.57 | 0.55 |
| | | 0.43 | 0.45 |
| Middlesboro | | | 0.69 |
| | | | 0.48 |
| | | | 0.52 |

Note: In each comparison, the first number is the p-value of the test under the hypothesis that the mean bid from the row location equals the mean bid from the column location. The second number is the probability that a bid from the row location is greater than a from the column location. The third number is the probability that a bid from the row location is less than a bid from the column location.

**Table 7. Grass-Fed Beef Auction Bids by Treatment Group**

| | Treatment Group A (obs=59) (Control Group) | | | | Treatment Group B (obs=58) (Information before Visual and taste) | | | | Treatment Group C (obs=42) (Information after Visual and Taste) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | S.D. | Min | Max | Mean | S.D. | Min | Max | Mean | S.D. | Min | Max |
| WTP | 1.61 | 1.83 | 0 | 10 | 1.71 | 1.20 | 0 | 5 | 2.20 | 1.89 | 0 | 6 |

**Table 8. Wilcoxon-Mann-Whitney Test of the Auction Bids for Grass-Fed Beef between Treatments**

| | Treatment A(obs=59) | Treatment B(obs=58) | Treatment C (obs=42) |
|---|---|---|---|
| Treatment A | | 0.10 | 0.04 |
| | | 0.41 | 0.38 |
| | | 0.59 | 0.62 |
| Treatment B | | | 0.56 |
| | | | 0.47 |
| | | | 0.53 |

Note: In each comparison, the first number is the p-value of the test under the hypothesis that the mean bid from the row location equals the mean bid from the column location. The second number is the probability that a bid from the row location is greater than a from the column location. The third number is the probability that a bid from the row location is less than a bid from the column location.

## Table 9. Variable Description of Consumer Choice Equation

| Variable | Description | Scale | Mean | S.D. | N |
|---|---|---|---|---|---|
| Dependent | | | | | |
| Pr(grass-fed beef preference) | Beef sample preference | 1=grass-fed beef, 0=otherwise | 0.3936 | 0.4891 | 404 |
| Independent | | | | | |
| Dlcolor | Difference of lean meat color evaluation scores: conventional beef minus grass-fed beef | -6 to 6 | -0.8540 | 1.3718 | 404 |
| Dfcolor | Difference of fat color evaluation scores: conventional beef minus grass-fed beef | -6 to 6 | -0.3713 | 1.8307 | 404 |
| Dtexture | Difference of meat texture evaluation scores: conventional beef minus grass-fed beef | -6 to 6 | 0.0693 | 1.8112 | 404 |
| Dtender | Difference of tenderness evaluation scores: conventional beef minus grass-fed beef | -6 to 6 | -0.3366 | 2.0851 | 404 |
| Djuicy | Difference of juiciness evaluation scores: conventional beef minus grass-fed beef | -6 to 6 | 0 | 1.6921 | 404 |
| Dflavor | Difference of flavor evaluation scores: conventional beef minus grass-fed beef | -6 to 6 | -.2921 | 1.6904 | 404 |
| Age | Participant's age | | 3.9035 | 1.5396 | 404 |
| | | 1 if <=24 | | | 33 |
| | | 2 if >24 and <=34 | | | 53 |
| | | 3 if >34 and <=44 | | | 67 |
| | | 4 if >44 and <=54 | | | 93 |
| | | 5 if >54 and <=64 | | | 83 |
| | | 6 if >64 | | | 75 |

| Variable | Description | Scale | Mean | S.D. | N |
|---|---|---|---|---|---|
| Single | Marital status | 1=single, 0 otherwise | 0.1733 | 0.3790 | 404 |
| Householdsize | Household size | >=1, integers | 2.6485 | 1.3642 | 404 |
| Ethnicity | Participant's ethnicity | 1=White, 0=otherwise | 0.9554 | 0.2066 | 404 |
| Edu | Education level | | 3.3342 | 1.5026 | 404 |
| | | 1=No high school diploma or equivalent | | | 34 |
| | | 2= High school diploma or equivalent | | | 106 |
| | | 3=Some college/technical school | | | 113 |
| | | 4=Associate's degree | | | 37 |
| | | 5=Bachelor's degree | | | 70 |
| | | 6=Graduate or professional degree | | | 44 |
| Income | Household income level | | 4.7451 | 2.9151 | 404 |
| | | 1=Less than $10,000 | | | 33 |
| | | 2=$10,000 - $19,999 | | | 75 |
| | | 3=$20,000 - $29,999 | | | 68 |
| | | 4=$30,000 - $39,999 | | | 49 |
| | | 5=$40,000 - $49,000 | | | 42 |
| | | 6=$50,000 - $59,999 | | | 36 |
| | | 7=$60,000 - $69,999 | | | 30 |
| | | 8=$70,000 - $79,000 | | | 18 |
| | | 9=$80,000 - $89,999 | | | 10 |
| | | 10=$90,000 - $99,999 | | | 9 |
| | | 11=More than $100,000 | | | 34 |

## Table 10. Probit Estimates for Consumer Choice Equation (N=404)

| Variable | Coefficients | Std.Error | Marginal Effect | Std.Error |
|---|---|---|---|---|
| Constant | -0.6583 | 0.6220 | | |
| Dlcolor | -0.0177 | 0.0764 | -0.0062 | 0.0268 |
| Dfcolor | -0.0122 | 0.0690 | -0.0043 | 0.0242 |
| Dtexture | 0.2083*** | 0.0597 | 0.0732*** | 0.0206 |
| Dtender | 0.6565*** | 0.0901 | 0.2306*** | 0.0307 |
| Djuicy | 0.3569*** | 0.0868 | 0.1254*** | 0.0309 |
| Dflavor | 0.4467*** | 0.0862 | 0.1569*** | 0.0308 |
| Gender | -0.2436 | 0.2101 | -0.0837 | 0.0706 |
| Age | 0.1226* | 0.0699 | 0.0431* | 0.0247 |
| Single | -0.4635 | 0.3227 | -0.1483 | 0.0930 |
| Householdsize | 0.0676 | 0.0917 | 0.0238 | 0.0322 |
| Ethnicity | 0.2630 | 0.4097 | 0.0862 | 0.1242 |
| Edu | -0.0604 | 0.0735 | -0.0212 | 0.0258 |
| Income | -0.0155 | 0.0398 | -0.0054 | 0.0140 |
| Log likelihood | -109.1397 | | | |
| Likelihood-Ratio Test, $\chi^2$ | 323.34 | | | |
| Pseudo R-Square | 0.5970 | | | |
| Percentage of correct predictions | 89% | | | |

Notes: (*) denotes statistical significance at least at a=0.1. (**) denotes statistical significance at least at a=0.05. (***) denotes statistical significance at least at a=0.01.

**Table 11. Variable Description of WTP Equation**

| Variable | Description | Scale | Mean | S.D. | N |
|---|---|---|---|---|---|
| Dependent | | | | | |
| Wtp | Willingness-To-Pay | >=0, continuous | 0.7089 | 1.3607 | 404 |
| | | | | | |
| Independent | | | | | |
| TreatmentB | Treatment B | 1=Treatment B,0 otherwise | 0.3614 | 0.4810 | 404 |
| TreatmentC | Treatment C | 1=Treatment C,0 otherwise | 0.2599 | 0.4391 | 404 |
| Frequency | Beef consumption frequency per week | | 2.3515 | 0.6062 | 404 |
| | | 1=less than once | | | 28 |
| | | 2=1 or 2 times | | | 206 |
| | | 3=3 or more times | | | 170 |
| Experience | Consumption experience about grass-fed beef | 1=Yes, 0 otherwise | 0.5767 | 0.4947 | 404 |
| Exph | Impression of grass-fed beef's impact on human health | 1= positive, 0 otherwise | 0.4505 | 0.4982 | 404 |
| Expe | Impression of grass-fed beef's impact on environment | 1= positive, 0 otherwise | 0.4530 | 0.4984 | 404 |
| Expa | Impression of grass-fed beef's impact on animal welfare | 1= positive, 0 otherwise | 0.4604 | 0.4990 | 404 |
| Disease | If the participant and her/his household member has ever been diagnosed with any of the five food-related diseases | 1=Yes, 0 otherwise | 0.8663 | 0.3407 | 404 |

| Variable | Description | Scale | Mean | S.D. | N |
|---|---|---|---|---|---|
| KnowledgeF | Nutrient function knowledge | 0-4,(low to high) | 1.4827 | 1.1037 | 404 |
| | | 0 | | | 86 |
| | | 1 | | | 127 |
| | | 2 | | | 120 |
| | | 3 | | | 52 |
| | | 4 | | | 19 |
| KnowledgeS | Food source knowledge | 0-4(low to high) | 1.6609 | 1.2469 | 404 |
| | | 0 | | | 98 |
| | | 1 | | | 90 |
| | | 2 | | | 88 |
| | | 3 | | | 107 |
| | | 4 | | | 21 |
| Dlcolor | Difference of lean meat color evaluation scores: conventional beef minus grass-fed beef | -6 to 6 | -0.8540 | 1.3718 | 404 |
| Dfcolor | Difference of fat color evaluation scores: conventional beef minus grass-fed beef | -6 to 6 | -0.3713 | 1.8307 | 404 |
| Dtexture | Difference of meat texture evaluation scores: conventional beef minus grass-fed beef | -6 to 6 | 0.0693 | 1.8112 | 404 |
| Dtender | Difference of tenderness evaluation scores: conventional beef minus grass-fed beef | -6 to 6 | -0.3366 | 2.0851 | 404 |
| Djuicy | Difference of juiciness evaluation scores: conventional beef minus grass-fed beef | -6 to 6 | 0 | 1.6921 | 404 |
| Dflavor | Difference of flavor evaluation scores: conventional beef minus | -6 to 6 | -.2921 | 1.6904 | 404 |

| Variable | Description | Scale | Mean | S.D. | N |
|---|---|---|---|---|---|
| | grass-fed beef | | | | |
| Age | Participant's age | | 3.9035 | 1.5396 | 404 |
| | | 1 if <=24 | | | 33 |
| | | 2 if >24 and <=34 | | | 53 |
| | | 3 if >34 and <=44 | | | 67 |
| | | 4 if >44 and <=54 | | | 93 |
| | | 5 if >54 and <=64 | | | 83 |
| | | 6 if >64 | | | 75 |
| Single | Living status | 1=single, 0 otherwise | 0.1733 | 0.3790 | 404 |
| Householdsize | Household size | >=1, integers | 2.6485 | 1.3642 | 404 |
| Ethnicity | Participant's ethnicity | 1=White, 0=otherwise | 0.9554 | 0.2066 | 404 |
| Edu | Education level | | 3.3342 | 1.5026 | 404 |
| | | 1=No high school diploma or equivalent | | | 34 |
| | | 2= High school diploma or equivalent | | | 106 |
| | | 3=Some college/technical school | | | 113 |
| | | 4=Associate's degree | | | 37 |
| | | 5=Bachelor's degree | | | 70 |
| | | 6=Graduate or professional degree | | | 44 |
| Income | Household income level | | 4.7451 | 2.9151 | 404 |
| | | 1=Less than $10,000 | | | 33 |
| | | 2=$10,000 - $19,999 | | | 75 |

| Variable | Description | Scale | Mean | S.D. | N |
|---|---|---|---|---|---|
| | | 3=$20,000 - $29,999 | | | 68 |
| | | 4=$30,000 - $39,999 | | | 49 |
| | | 5=$40,000 - $49,000 | | | 42 |
| | | 6=$50,000 - $59,999 | | | 36 |
| | | 7=$60,000 - $69,999 | | | 30 |
| | | 8=$70,000 - $79,000 | | | 18 |
| | | 9=$80,000 - $89,999 | | | 10 |
| | | 10=$90,000 - $99,999 | | | 9 |
| | | 11=More than $100,000 | | | 34 |

**Table 12. Tobit Estimates of WTP Equation (N=404)**

| | | | Marginal Effects | |
|---|---|---|---|---|
| Variable | Coefficient | S.E. | Unconditional Expected Value | Conditional on being uncensored |
| Constant | -2.8750 | 1.3319 | | |
| TreatmentB | -0.2173 | 0.7141 | -0.0710 | -0.0602 |
| TreatmentC | -0.4031 | 0.7970 | -0.1317 | -0.1116 |
| Frequency | 0.5460** | 0.2718 | 0.1784** | 0.1512** |
| Experience | -0.0575 | 0.3166 | -0.0188 | -0.0159 |
| Exph | -0.1454 | 0.4834 | -0.0475 | -0.0403 |
| Expe | 0.3637 | 0.4930 | 0.1188 | 0.1007 |
| Expa | -0.1125 | 0.4304 | -0.0367 | -0.0311 |
| Disease | 1.2210** | 0.5356 | 0.3989** | 0.3381** |
| KnowledgeF | 0.7038** | 0.3126 | 0.2300** | 0.1949** |
| KnowledgeS | -0.5241** | 0.2445 | -0.1712** | -0.1451** |
| Dlcolor | 0.3082* | 0.1823 | 0.1007* | 0.0853* |
| Dfcolor | 0.0843 | 0.1451 | 0.0275 | 0.0233 |
| Dtexture | 0.2600* | 0.1383 | 0.0850* | 0.0720* |
| Dtender | 0.5950*** | 0.1661 | 0.1944*** | 0.1648*** |
| Djuicy | 0.4734** | 0.2201 | 0.1547** | 0.1311** |
| Dflavor | -0.0989 | 0.1798 | -0.0323 | -0.0274 |
| Tb*Dlcolor | -0.5455** | 0.2681 | -0.1782** | -0.1511** |
| Tb*Dfcolor | -0.4642* | 0.2476 | -0.1517* | -0.1285* |

| | | | Marginal Effects | |
|---|---|---|---|---|
| Variable | Coefficient | S.E. | Unconditional Expected Value | Conditional on being uncensored |
| Tb*Dtexture | 0.0341 | 0.2009 | 0.0111 | 0.0094 |
| Tb*Dtender | 0.1421 | 0.2758 | 0.0464 | 0.0394 |
| Tb*Djuicy | -0.1606 | 0.3253 | -0.0525 | -0.0445 |
| Tb*Dflavor | 0.3139 | 0.2854 | 0.1026 | 0.0869 |
| Tc*Dlcolor | -0.6722** | 0.3304 | -0.2196** | -0.1861** |
| Tc*Dfcolor | -0.3814 | 0.3321 | -0.1246 | -0.1056 |
| Tc*Dtexture | 0.1192 | 0.2364 | 0.0390 | 0.0330 |
| Tc*Dtender | -0.4028 | 0.2746 | -0.1316 | -0.1115 |
| Tc*Djuicy | 0.0741 | 0.3236 | 0.0242 | 0.0205 |
| Tc*Dflavor | 0.9263*** | 0.3020 | 0.3026*** | 0.2565*** |
| Kf*Tb | -0.3020 | 0.3904 | -0.0987 | -0.0836 |
| Kf*Tc | -0.2906 | 0.4691 | -0.0950 | -0.0805 |
| Ks*Tb | 0.2789 | 0.3405 | 0.0911 | 0.0772 |
| Ks*Tc | 0.0716 | 0.4192 | 0.0234 | 0.0198 |
| Gender | -0.3243 | 0.3335 | -0.1060 | -0.0898 |
| Age | -0.0393 | 0.1072 | -0.0128 | -0.0109 |
| Single | -1.5050*** | 0.5195 | -0.4917*** | -0.4168*** |
| Householdsize | -0.2646* | 0.1395 | -0.0865* | -0.0733* |
| Ethnicity | 0.2493 | 0.7447 | 0.0815 | 0.0690 |
| Edu | 0.1187 | 0.1206 | 0.0388 | 0.0329 |
| Income | -0.0365 | 0.0603 | -0.0119 | -0.0101 |

| | | | Marginal Effects | |
|---|---|---|---|---|
| Variable | Coefficient | S.E. | Unconditional Expected Value | Conditional on being uncensored |
| Log likelihood | -366.79 | | | |
| Likelihood-Ratio Test, $\chi^2$ | 230.94 | | | |
| Pseudo R-Square | 0.24 | | | |

Notes: (*) denotes statistical significance at least at a=0.1. (**) denotes statistical significance at least at a=0.05. (***) denotes statistical significance at least at a=0.01.

# Essay 2: The Influence of Endogenous Nutrition Knowledge on Consumers' Willingness-To-Pay for Grass-Fed Beef


### Abstract

The relationship between nutrition knowledge and consumers' food behavior has been debated for years. This may be partially attributed to the difficulty introduce by endogeneity of nutrition knowledge in econometric modeling. Using grass-fed beef as a vehicle, this essay investigates the impacts of consumers' nutrition knowledge on their willingness to pay by accommodating the endogeneity problem using an instrumental variable approach and a non-instrumental variable approach. Our results suggest the existence of the endogeneity of nutrition knowledge. Ignoring the endogeneity problem in econometric modeling is shown to downwardly bias the estimates. Furthermore, the estimates obtained from different estimation strategies we use all suggest the significant impacts of consumers' nutrition knowledge on their willingness to pay for grass-fed beef, implying the robustness of our findings about the influences of nutrition knowledge on consumer food behavior.



**Keywords**: Food Behavior, Nutrition Knowledge, Endogeneity, Instrumental Variables

## 1. Introduction

Nutritional value is an important attribute of food whose benefits can only be experienced by repetitive consumption in long run. Consumers' knowledge about the importance and usefulness of specific nutrients in a food product may influence their expectation of the product's health benefits which, in turn, affects their food consumption behavior. Previous studies have identified the correlation between consumers' nutrition knowledge and food consumption and purchasing practices (e.g., Chern et al. 1995; Elbon et al. 1996; Harnack et al. 1997; Wardle et al. 2000; Kim, Nayga, and Capps 2001; Baker and Wardle 2003; Drichoutis, Lazaridis, and Nayga 2005). These studies found that knowledge is significantly associated with the consumption of particular food and nutrients. Nevertheless, in contrast, many existing studies suggest only weak relevance of nutrition knowledge on food consumption as well (e.g. Axelson et al 1985; Stafleu et al. 1996; Nayga 2000; Rolls et al. 2002; Reinehr et al. 2003; O'Dea and Wilson 2006). Flawed measures of nutrition knowledge and the potential endogeneity in econometric modeling may contribute to the controversies in literature (e.g. Guthire and Fulton, 1995; Kim and Chern 1997; Variyam et al. 1999; Kaabia and Angulo 2001).

Given mixed evidence about the influences of nutrition knowledge on food behavior, this study intends to further the understanding of the impacts of nutrition knowledge on food consumption by assessing the influence of nutrition knowledge on consumers' willingness to pay (WTP) for a nutritionally differentiated beef product - grass-fed beef. The Nutrition Labeling and Education Act (NLEA) of 1990 does not require mandatory food labeling on packaged fresh meats, hence, personal nutrition knowledge should play a crucial role in consumers' beef purchasing decision concerning diet quality and health benefits. Potential nutrition knowledge effects are twofold: (1) facilitating nutrition information processing, such as the nutrient facts about meat products; and (2) assisting more informed food choice decision making, such as selecting nutritious food to meet dietary needs while obeying budget constraints. Since consumers' nutrition knowledge cannot be directly observed, we have to use indirect measures to indicate their knowledge. We thus developed two sets of nutrition knowledge questions assessing different aspects of consumers' knowledge concerning Vitamin A, Vitamin E, Omega 3 and CLA. One set of the questions measures consumers' familiarity with the functions of these four nutrients. The other set probes consumer knowledge of the main food sources of these nutrients. Each set consists of four questions. Answers to each question are scaled only as "Yes", "No" and "Don't Know".

This study features an improved econometric model specification by treating nutrition knowledge as endogenous explicitly. Increased nutrition knowledge is likely to influence consumers' WTP for nutritionally enhanced food products. There is possibility that consumers who offer higher WTP differ inherently from those who offer lower WTP. However, as investigators, we are unable to fully observe the factors that are relevant to explain the differences in consumers' WTP. If some of these unobservables are correlated with consumers' nutrition knowledge levels, endogeneity bias will arise in estimation and the magnitude of the true effects of nutrition knowledge on consumers' WTP will be distorted. In an instrumental variable (IV) framework, this study assesses the impact of nutrition knowledge on consumers' WTP for grass-fed beef by tackling the endogeneity issue caused by the presence of correlated unobservables in the econometric model. The legitimacy of two sets of possible instrumental variables is investigated. The possibility of using a non-IV approach is also examined.

The remainder of the article proceeds as follows: in the subsequent section, we discuss the conceptual framework; next, we present the results from benchmark models examining the influences of nutrition knowledge on consumers' WTP for grass-fed beef; then we investigate the relevance and validity of food label use as the instrumental variable candidate followed by a section examining the use of the Lewbel (1997) instruments; after the IV estimation sections, we explore the possibility of using non-IV approach; the last section concludes the essay.

## 2. The conceptual framework

Following Grossman's (1972) health demand model, we define health as a consumption goods which directly produces utility and an investment goods which influences productivity. We assume that a typical consumer's preference for health can be characterized by a utility function. In random utility framework, this utility is known to the consumer, but is measured with error by the researcher. It thus can be expressed as the sum of a deterministic portion (V) and a random component:

(1) $U = V(H, Y, Z; S) + \varepsilon$

Where *H* is the health of the consumer, *Y* is a vector of health related consumption goods, *Z* is the vector of other consumption goods, *S* is a vector of shifters, such as demographic factors, and $\varepsilon$ follows a normal distribution. The consumer derives the utility of *Y* from direct consumption through its effects of improving health. Let the production of health by the consumer be described by the production function

(2) $H = H(Y, E; S)$

where *E* is the consumer's stock of nutrition knowledge. Substitute equation (2) into (1) we have the random utility function

(3) $U = V(Y, Z, E; S) + \varepsilon$

It's highly possible that the consumer's nutrition knowledge is correlated with the error term due to unobservable individual characteristics, such as some of the attitudinal and situational factors (for example, attitude toward nutrition, diet-health awareness, food choice motivation, etc), which are influential factors on the consumer's WTP, and that they also affect the consumer's motivation to search for nutrition information. In this sense, we treat *E* as endogenous,

(4) $E = E(N; S)$

where *N* is a vector of instrumental variables.

A practical assumption would be that the consumer experiences illness when *H* is below a certain unknown threshold of the stock level and that illness decreases utility. The consumer thus tends to consume healthier foods to produce higher *H*. However, he also faces a budget constraint and the possible sacrifice of eating pleasure. Therefore, the choice of a new healthier food input, say *y*, occurs if and only if

(5) $U_y(y, Y_{-y}, Z, E, m - p_y; S) \geq U_0(Y, Z, E, m; S)$

Where $U_0$ is the reference state utility, $U_y$ is the utility resulted from the new input y, m is income, and $p_y$ is the price of input y. Due to uncertainty, such comparisons are made with probability. Following Hanemann (1984), we define $\Delta U = U_y - U_0$, which follows CDF F(.). Let *p* be the minimum probability that the consumer would decide to consume *y*, the decision rule is then

(8) $\Pr(\Delta U > 0) = P$

Therefore, the maximum WTP of the input y can be derived as

(9) $WTP = \Delta^{-1}U(WTP \mid F^{-1}(P)) = w(Y, Z, E, m; S)$

A linear form of equation (9) is estimated in the empirical estimation.

### 3. Nutrition Knowledge and Consumers' WTP

Since consumers' nutrition knowledge cannot be directly observed, the nutrition knowledge indexes are constructed based on two sets of indicator questions as listed in Table 1. One set measures consumers' familiarity with the functions of four specific nutrients - Vitamin A, Vitamin E, Omega 3 and CLA; the other set probes consumers' knowledge of the main food sources of these nutrients. The scores for knowledge about the nutrient functions and knowledge about the main food sources are obtained by adding up binary 0/1 scores assigned to the responses in each set. Incorrect answers and "don't know" answers were assigned 0 score. The correlation between the two set of nutrition knowledge may have some impact on consumers' WTP as well. For example, consumers with high level knowledge about the functions of the four nutrients and low level knowledge about the food sources of these nutrients could possibly offer his WTP for grass-fed beef differently from consumers with high level knowledge about the functions of the four nutrients and high level knowledge about the food sources of these nutrients. Such correlation effects of nutrition knowledge will be examined in our sub-group estimation.

We first estimate an OLS model and a Tobit model to provide benchmarks for the analysis. OLS estimation ignores the censoring problem in the WTP data and the potential endogeneity of nutrition knowledge, while the Tobit estimation takes the censoring issue into account but still does not control for endogeneity. In these benchmark models, two sets of nutrition knowledge are included as two explanatory variables. The sensory attributes of a food product are also included since they immediately affect consumers' actual consumption experience. Previous studies have found, for example, the impact of appearance and taste experience on consumers' WTP of fresh food (Melton et al. 1996), the influence of color on consumers' WTP for salmon fillets ( Alfnes et al. 2006), and the impact of tenderness on consumers' WTP for steaks ( Lusk et al. 2001). Therefore, six sensory evaluation indexes with respect to visual and palatability attributes are included as explanatory variables to measure their impacts on consumers' WTP for grass-fed beef. We hypothesize that a consumer and his family members' health status could influence their food consumption pattern because enhanced nutrition attributes may be more desirable for those who are experiencing diet-related diseases. We thus include a dummy variable to indicate consumers' and their immediate family members' health condition in WTP equation to capture the motivational impact. Evans (2008) finds that the frequency of in-home steak preparation significant impacts on consumers' WTP for grass-fed beef steaks, and grass-fed beef purchasing experience significantly influence consumers' preference for grass-fed beef. Hence we include consumers' beef consumption frequency at home and grass-fed beef consumption experience as two additional explanatory variables. Two experimental group dummies are also included to capture the effect of nutrition information on consumers' WTP. Gender, age, living status, household size, education level, and household income are controlled for individual difference. Table 2 presents the summary of the variables in the model.

The marginal effects of Tobit estimates are decomposed into unconditional and unconditional marginal effects using the McDonald and Moffitt (1980) approach. The formula for the expected value of the dependent variable for all cases is $Ey = X\beta \times F(z) + \Sigma \times f(z)$, where $F(z)$ is the normal CDF, f(z) is the normal density function and $\Sigma$ is the standard deviation of the error term. The marginal effect of an independent variable on $Ey$ is given by

$$(10)\quad \frac{\partial Ey}{\partial X_i} = F(z) \times \frac{\partial Ey^*}{\partial X_i} + Ey^* \times \frac{\partial F(z)}{\partial X_i}$$

Where $\frac{\partial Ey^*}{\partial X_i}$ measures the change in expected value above the censoring limit and $\frac{\partial F(z)}{\partial X_i}$ measures the possibility change of being above the limit. McDonald and Moffitt (1980) show that

(11) $$\frac{\partial Ey^*}{\partial X_i} = \beta_i \times [1-(z \times \frac{f(z)}{F(z)} - \frac{f(z)^2}{F(z)^2}]$$

(12) $$\frac{\partial F(z)}{\partial X_i} = \beta_i \times \frac{f(z)}{\Sigma}$$

Table 3 reports the OLS and Tobit estimates. As the results suggest, the significant role of the two sets of nutrition knowledge are evident in both models: consumers who are more knowledgeable about the functions of Vitamin A, Vitamin E, CLA, and Omega 3 are willing to pay more for one pound of grass-fed beef – one point increase of the knowledge could cause about \$0.2 increase in consumers' WTP for one pound of grass-fed beef ; while consumers' knowledge about the main food sources of the nutrients negatively affects consumers' WTP - one point increase of the knowledge will decrease consumers' WTP for one pound of grass-fed beef about \$0.1. The results also suggest that meat texture, tenderness, juiciness, and flavor are influential factors of consumers' value perception of beef products. The most influential attributes are the tenderness and juiciness. One point increase of consumers' sensory evaluation scores of these two attributes will lead to about \$0.2 and \$0.15 increase in consumers WTP for one pound of grass-fed beef. Nevertheless, although the two models indicate similar pattern of the influential factors on consumers WTP for grass-fed beef, it's possible that the results are biased because of the potential endogeneity with respect to nutrition knowledge in the model. The endogeneity arises when consumers inherently differ in their information processing and food behavior which we do not observe within our model. Lack of controls for endogeneity is common in literature and may have contributed to the mixed conclusions about the relationship between consumers' food behavior and nutrition knowledge.

The major goal of this study is to examine the existence of endogeneity problem and to provide practical solutions. Instrumental variable (IV) approach is a popular choice to handle the endogeneity issue. The difficulty of using IV approach lies in the hardship of finding suitable instrument variables. The requirement of strong correlation between instrumental variables and the instrumented endogenous variables and the requirement of non-correlation between the structural equation disturbance and the instruments are hard to meet simultaneously. Researchers thus have to use theories, experiences, and even intuition to guide the choice of instrumental variables or refer to mathematical tools to seek suitable instruments. In the following discussion, we investigate two sets of possible instruments.

## 4. IV Estimation Using Food Label Use as Instruments

### *4.1 Food Label Use and Nutrition Knowledge*

The Nutrition Labeling and Education Act (NLEA) signed in 1990 mandates nutrition labeling on most of processed food. Food labels are used as a tool for nutrition education. A consumer who reads labels more often is exposed to more nutrition information which should improve his nutrition knowledge. Furthermore, reading labels requires time and efforts to process the nutrition information provided. Thus the level of a consumer's food label use also reflects his motivation and attitude towards nutrition information seeking. Active information seeking behavior would possibly result in high nutrition knowledge. Furthermore, reading food labels would be an exogenous source of variation for identifying the influence of nutrition knowledge on consumers' WTP for grass-fed beef because the Nutrition Labeling and Education Act

(NLEA) of 1990 does not require mandatory food labeling on packaged fresh meats, hence, consumers' food label use should have no independent effect on their WTP for grass-fed beef. This assumption is related to the validity of the instrumental variables and will be examined later in the discussion.

Food label use status is represented by five indictor variables which categorize the frequency of consumers' label use as "Always," "Most of the time," "Sometimes," "Rarely," and "Never". The data on food label use are based on respondents' self-reported food label use frequency. Figure 1 and Figure 2 present the relationship between the nutrition knowledge scores and food label use. There is a clear pattern that consumers' nutrition knowledge is being positively correlated with their food label use frequency. The positive correlations shown in Figure 1 and Figure 2 suggest that consumers who read nutrition labels more often when making purchasing decisions tend to have higher nutrition knowledge. The explanation is intuitive: consumers who read nutrition labels more could obtain more nutrition information contained in food labels; furthermore, consumers' food label use serves as the indicator of the intensity of their nutrition information search and it is likely that these consumers who read food label more often are active nutrition knowledge learners who may refer to more information sources to acquire nutrition knowledge.

We first examine the relevance of the food label use as instruments in regression framework. To illustrate the idea, we write the equation to be estimated in a general form:

(13) $y = X\beta + u$

Where X is a $n \times K$ matrix, $n$ is the number of observation. Suppose $X = [X_1, X_2]$ with $X_1$ is assumed endogenous and $X_2$ is assumed exogenous. The set of instrumental variables is a $n \times L$ matrix $Z = [Z_1, Z_2]$ with $Z_1$ and $Z_2$ being excluded and included instruments respectively.

For the equation to be identified, the order condition $L \geq K$ and the rank condition should be satisfied. The rank condition implies that $E[X_i' Z_i]$ is of full rank. The rank condition can be tested in the first stage IV estimation by examining the relevance between the endogenous variables and the instrumental variables. Bound et al. (1995) recommend the use of squared partial correlation ( $R^2$ ) between instruments and the endogenous variables,

(14) $R^2 = \frac{RSS_{z_2} - RSS_z}{TSS}$,

where $RSS_{z_2}$ is the residual sum of the squares of the reduced form regression on $Z_2$, $RSS_z$ is the residual sum of the squares of the reduced form regression on Z. A short coming of this method as mentioned by Baum (2007) is the compound effect among instrumental variables, i.e. irrelevant instrumental variables may not be detected by using squared partial correlation $R^2$. Hence Shea's (1997) partial $R^2$ measure is suggested to be used along with the squared partial correlation. A rule of thumb is that a large value of the squared partial correlation and a small value of Shea's partial $R^2$ may suggest a lack of sufficient relevance (Baum 2007). One caveat is that there is no clear cutoff lines to define "large" and "small". Practitioners' experience should play a role in the judgment.

Table 4 report the first stage estimates from two-stage least squares (2SLS) IV estimation. Label 2-Label5 are category indicators of "Most of the time," "Sometimes," "Rarely," and "Never" respectively. The omitted label use frequency category is the "Always read nutrition labels when purchasing" category, hence the estimated effects of other food label use status are relative to this highest label use frequency category. Squared partial correlation $R^2$, Shea's partial $R^2$, and F-test all suggest the relevance between food label use and nutrition knowledge ( $\alpha$ =0.05). The impact of label use on consumers' knowledge of nutrient functions and food sources are significant and carry the expected signs. Results indicate that a consumer who never reads nutrition labels when purchasing food products would have one point lower nutrition knowledge score than a consumer who always reads nutrition labels when purchasing food products. The other two indicators of the category “read nutrition labels sometimes” and the category “read nutrition labels rarely” show the same direction of the impact of label use on consumers’ nutrition knowledge. The seemingly troublesome estimates are the effects of the “read nutrition label most of time” indicator. A plausible explanation is that respondents in the experiments may not be able to clearly distinguish the “always” label use frequency and the “most of the time” food label use frequency, since the difference between these two concepts may be vague to respondents. Consequently, the difference of the impact between these two categories on nutrition knowledge is not discernable.

Although our first stage screening statistics indicate the relevance of food label use as instruments for nutrition knowledge, however, Bound et al. (1995), and Staiger and Stock (1997) have shown that the weak instrument problem can arise even when the correlations between X and Z are significant. We thus conduct the Anderson (1984) canonical correlations and the Cragg-Donald (1993) Wald tests to check the relevance issue of instruments. The Anderson (1984) test is a version of LM test. The test statistic is based on the smallest canonical correlation between the endogenous regressors and the excluded instruments. Specifically, the Anderson test statistic is the sample size (N) times the square of the smallest canonical correlation (SCC) between the endogenous regressors and the excluded instruments. Under the null that the equation is under-identified., the statistic follows a Chi-square distribution with degrees of freedom= (L1-K1+1), where L1 is the number of excluded instruments and K1 is the number of endogenous variables. The Cragg-Donald (1993) test statistic is just $N \times \frac{SCC^2}{1-SCC^2}$ which also follows a Chi-square distribution with degrees of freedom= (L1-K1+1) under the null that that the equation is under-identified. We rejected the null that the model is under-identified in the Anderson test. However, in Cragg-Donald test, we fail to reject the null, indicating the potential weak relevance between food label use and nutrition knowledge.

Validity is another concern of the instrumental variable choice, i.e. if the instrumental variables can be validly excluded from the original equation. Since error terms are unobservable in practice, there is still no ideal method available in literature to statistically test the validity of instrumental variables. A naïve way to test this condition is to include the instrumental variables in the original equation and test if the coefficients of the instrumental variable candidates are significantly different from zero. As Murray (2006) points out, the problem of this approach is that the endogenous explanatory variables would worsen the estimates and lead to misleading statistical inferences. Another test we can apply is the Sargan test (1958). However, Sargan test assumes that there are at least enough instrumental variables are valid to identify the equation exactly besides the doubtful instrument variables. Based on this assumption, the test examines if the model is over-identified. As we can imagine, the validity of the assumption is difficult to test as well. Practitioners have to rely on theories to justify the applicability of the Sargan test. Hence, following Levitt (1996), we adopt a simpler way to check the validity of food label use by estimating a regression of WTP only on food label use along with a set of exogenous covariates. The estimates are presented in Table 5. If the food label frequencies are valid exogenous instrumental variables, we should not observe significant impact of food label use status on consumers' WTP. As Table 5 shows, the insignificant coefficients of the food label use indicators support our hypothesis. Their joint effect is also not significant as F test suggest ($\alpha$ = 0.05). The explanation should be straightforward: since there is no compulsory labeling on meat products, hence food label use seems not to be directly correlated with consumers' WTP for grass-fed beef.

*4.2 IV Estimation Using Food Label use as Instruments*

As discussed in the previous section, the first stage regression tests suggest the weak relevance between food label use and nutrition knowledge. A well known way to tackle the weak instrumental problem is to use the Fuller's (1977) limited information maximum likelihood (LIML) estimator. Simulation studies have found it robust to potentially weak instruments (Andrews et al.2005). We thus employ Fuller's LIML to estimate the WTP equation. Table 6 reports the Fuller LIML estimates of the first stage regression. The coefficients of the instrumental variables are significantly different from zero in both nutrition knowledge functions. Furthermore, a consumer's education level appears to affect his knowledge about the functions of Vitamin A, Vitamin E, CLA, and Omega 3 while consumers' gender seems to be an influential factor on their knowledge about the main food sources about these nutrients. However, the estimates of the second stage WTP equation suggest low precision of IV estimates, i.e., the estimated standard errors of the parameters are larger than those of OLS estimates. This may be an indication of the loss of efficiency due to weak instruments, which cause the effects of most variables insignificant and thus weaken the statistical inferences.

The results indicate that Fuller LIML seems not to be able to fix the weak instrumental variable problem. We need to search for stronger instruments if we want to tackle the endogeneity problem using IV approach. However, due to the limitation of our cross-sectional data, it is hard to find both relevant and valid instrumental variables. This motivates us to consult to the Lewbel (1997) method that provides legitimate instruments constructed from the data set available.

## 5. Lewbel Instrumental Variable Estimation

### *5.1 Lewbel Instrumental Variables*

The use of higher-order moments as instruments has a long history in econometrics (e.g., Kendall and Stuart 1979; Aigner et al.1983; Ahn and Schmidt 1995; Dagenais and Dagenais 1997). The basic idea is to instrument endogenous variables using their higher-order moments because the higher-order moments satisfy the relevance and validity conditions even though the associated first moment is correlated with error term in the structural model. As the extension of previous studies, Lewbel (1997) proposes the method to construct higher-order terms as instruments from functions of the independent variable and endogenous variables. The Lewbel instruments used in this study are of the form:

(15) $Lewbel1 = (WTP - \overline{WTP})^2$

(16) $Lewbel2 = (KnowledgeF - \overline{KnowledgeF})^2$

(17) $Lewbel3 = (KnowledgeS - \overline{KnowledgeF})^2$

(18) $Lewbel4 = (WTP - \overline{WTP})(KnowledgeF - \overline{KnowledgeF})$

(19) $Lewbel5 = (WTP - \overline{WTP})(KnowledgeS - \overline{KnowledgeS})$

Lewbel (1997) mathematically proved the legitimacy of these instruments and showed 2SLS estimation using these instruments yields consistent estimates.

### *5.2 Estimation Strategies*

In this section, we discuss our estimation strategy taking into account the censoring issue. Under the IV framework, we intend to estimate a structural WTP function and two reduced-form nutrition knowledge functions $E_1$ and $E_2$

$$
\begin{aligned}
(20)\ & WTP = X\beta_1 + \alpha_1 E_1 + \alpha_2 E_2 + S\gamma_1 + u_1 \\
& E_1 = E(N;S) = X\beta_2 + N\delta_{21} + S\gamma_{21} + u_2 \\
& E_2 = E(N;S) = X\beta_3 + N\delta_{31} + S\gamma_{31} + u_3
\end{aligned}
$$

Where $X$ is a vector of variables that describe the consumer's consumption characteristics, $N$ is the instrument vector. S is a vector of exogenous variables including consumers' health status, sensory evaluation scores, and the socio-demographic characteristics. Error terms, $u_1, u_2, u_3$, are assumed jointly normal with zero means and independent of instruments $N$. Due to unobservable variables in the main WTP equation, nutrition knowledge about the nutrient's functions $E_1$, and nutrition knowledge about the food sources, $E_2$, are endogenous and modeled as the non-zero correlation between $u_1$ and $u_2, u_3$. In the reduced form functions of $E_1$ and $E_2$, N is the instrumental variable vector which includes five Lewbel instruments. Table 2 provides summary statistics of these variables.

What makes the WTP estimation complicated is the censoring problem in the empirical WTP data. Since negative WTP is not allowed in the auction, the distribution of WTP is censored at zero from below. It is evident that the censored conditional means are no longer linear in the covariates even when the underlying DGP actually generates a linear population mean. Smith and Blundell (1986) proposed a two-stage estimation approach for Tobit model with endogenous regressors. We can extend this method to our model. Following Smith and Blundell (1986), we express

(11) $u_1 = \theta_1 u_2 + \theta_2 u_3 + e_1$

We assume $e_1$ is normal and independent of $u_2, u_3$. Under the joint normality assumption,

$\theta_1 = \frac{\text{cov}(u_1, u_2)}{\text{var}(u_2)}$, and $\theta_2 = \frac{\text{cov}(u_1, u_3)}{\text{var}(u_3)}$. Plugging equation 11 into WTP equation, we have

(12) $WTP = X\delta_1 + \alpha_1 E_1 + \alpha_2 E + S\gamma_1 + \theta_1 u_2 + \theta_2 u_3 + e_1$

Since $u_1, u_2, u_3$ are independent of the N, $e_1$ is independent of N. In this framework, if we know $u_2, u_3$, the coefficients can be consistently estimated using normal Tobit model. However, $u_2, u_3$ cannot be observed. So, in the first step, we estimate the reduced form nutrition knowledge functions using OLS and by fitting the model, we obtain the estimates of $u_2, u_3$, the residuals, $\hat{u}_2, \hat{u}_3$. In the second step, we simply estimate a Tobit of WTP on X, $E_1, E_2, S, u_2, u_3$. Smith and Blundell (1986) have proven that this approach generates consistent estimators of the parameters and covariance matrix.

In the first stage regression in Table 8, the squared partial correlation $R^2$ (0.12 in nutrient function equation and 0.02 in food source knowledge equation) and the Shea Partial $R^2$ (0.15 in nutrient function equation and 0.03 in food source knowledge equation) suggest the relevance between the Lewbel instrumental variables and nutrition knowledge. The first stage F-test statistically indicates such correlation at the significance level of 0.01 and 0.1 respectively for the two nutrition knowledge functions. Furthermore, Anderson (1985) canonical correlations statistics reject the null that the model is under-identified ($\alpha$ =0.05), implying the strong relevance of the instruments. However, the results of the Cragg–Donald (1993) F test and Sargan's (1958) test indicate potential under-identification problem as well. Should we conclude that Lewbel instruments are not proper to use? The answer lies in two facts. First, the small sample size may weaken the tests and cause the results to be misleading. Indeed, the power of these tests heavily relies on asymptotic properties. Only in large samples that the test statistics can be calculated consistently with a small relative bias (Bound et al., 1995; Stock et al, 2002). 404 observations of our sample may not be able to be guaranteed as large enough. In addition, over 50% of our WTP observations are censored. This could possibly impact the accuracy and distributions of test statistics, which may require the adjustments in the tests. Indeed, IV identification tests accounting for the small sample size and censoring issues are still not available in literature. Second, the way that the Lewbel instruments are constructed was specifically designed to ensure strong and valid instruments. Therefore, when there is possibility that the identification tests may be invalid, it may be more appropriate to treat the contradicting results as an indication of the data issue.

*5.3. IV Estimates using Lewbel Instrumental Variables*

As Table 8 shows, in the first stage reduced-form equation estimation, the coefficients of gender are significant and negative in both nutrition knowledge equations, implying that females tend to have higher nutrition knowledge. This finding may actually reflect the fact that women, on average, spend more time on grocery shopping than men (Bureau of Labor Statistics, 2008), which may drive variation in the nutrition knowledge acquiring behavior between women and men. Our results support the findings from previous studies about the difference of search behavior between males and females for certain nutrients (e.g. Drichoutis et al. 2005). The effect of education on consumers' nutrient function knowledge is positive and statistically significant ($\alpha = 0.01$) in both nutrition knowledge equations as well. The result is in line with the findings from previous studies with respect to the effect of education on consumers' nutrition knowledge (e.g., Wang et al. 1995; Nayga 1996; Kim et al. 2001; Drichoutis et al. 2005).

Table 9 presents the two-stage Tobit estimates using Lewbel instruments. Most importantly, the significant coefficients of the residuals obtained from the first-stage estimation strongly indicate the existence of endogeneity of nutrition knowledge ($\alpha = 0.01$) in the structural model. Furthermore, the Tobit estimates suggest significant effects of nutrition knowledge and sensory evaluation on consumers' WTP as the benchmark models. The two sets of the nutrition knowledge exhibit opposite influences on consumers' WTP for grass-fed beef: knowledge about nutrient functions positively affect consumers' WTP, while the impact of knowledge about the nutritious food sources on consumers' WTP for grass-fed beef is negative. In contrast with the benchmark models, the magnitudes of the effects of the nutrition knowledge are greater with a marginal effect about $0.5 of the knowledge about nutrient functions and about $1.00 of knowledge about the nutritious food sources on consumers' WTP for grass-fed beef. The results indicate that the endogeneity of nutrition knowledge in the WTP equation could downwardly bias the OLS and the Tobit estimates. The policy implication of this finding is that if nutrition educators use models without taking into account the potential endogeneity problem to estimate the impacts of nutrition knowledge on consumers' food purchasing behavior, the impact will be under-estimated. Consequently, the influential role of nutrition education in motivating healthier diets could be hidden.

The effects of the provision of nutrition information on consumers' WTP are shown to be not significant after controlling for the endogeneity of nutrition knowledge. This result is in line with the estimates from models without controlling for the endogeneity, implying that the insignificant impacts of nutrition information may not be due to the model choices and estimation issues.

There is still downside of using Lewbel instruments. Previous studies have shown that higher-moment based estimators can be erratic in small samples (Aigner et al.1984; Hausman, Newy, and Powell 1995). Potentially, our IV estimates could be subject to the small sample size problem. Hence, a non-IV approach may be an alternative worth investigating.

## 6. Estimation Based on Sub-grouping

The difficulty of implementing IV method as discussed in the previous sections have made it necessary to find an alternative approach which does not reply on the strong instrumental variables but handles the potential endogeneity of nutrition knowledge as well. In this section, we examine a sub-grouping method instead of the IV approach.

The econometric model can be written as $WTP_{ig} = X_{ig}\beta_g + u_i$, where *i* indexes consumers and *g* indexes subgroups. Our estimation strategy is as follows. First, we control for the potential effects of nutrition knowledge by grouping the full sample into four subgroups: (1) consumers with low knowledge about the nutrient functions and low knowledge about the food sources for the nutrients (LKF-LKS group); (2) consumers with low knowledge about the nutrient functions and high knowledge about the food sources for the nutrients (LKF-HKS group); (3) consumers with high knowledge about the nutrient functions and low knowledge about the food sources for the nutrients (HKF-LKS group); (4) consumers with high knowledge about the nutrient functions and high knowledge about the food sources for the nutrients (HKF-HKS group). The random experimental design allows us to make such division since consumers' bidding behavior is independent from each other. This way, we should be able to exclude the endogenous nutrition knowledge from the model. We then estimate four Tobit models separately and compare the coefficient estimates across groups. The cost of using this method is the potential efficiency loss since we are using smaller samples. Intuitively, we are making use of less information in the estimation.

Table 10 presents the Tobit estimates for the four groups, while Table 11 presents the decomposed results of the conditional and unconditional marginal effects of the independent variables in the Tobit model. As the results suggest, sensory attributes play an important role in determining consumers' value perception of grass-fed beef. Meat texture, tenderness, juiciness, and flavor have significant impact on consumers' willingness to pay for grass-fed beef. These results are similar to the estimates of benchmark models in which the two sets of nutrition knowledge are treated as exogenous. However, the coefficients of these attributes have relatively smaller value if the two sets of nutrition knowledge are treated as exogenous. Among the four significant sensory attributes, tenderness consistently influences consumers' WTP across the four nutrition knowledge groups. Its unconditional effect ranges from \$0.1 to \$0.4. The estimates also suggest that consumers with low knowledge about nutrient functions tend to rely more on sensory evaluation in their value perception of grass-fed beef since more sensory attributes are significant in LKF groups (consumers with low knowledge about nutrient functions).

Examining the results in Table 10 and Table 11, we can find that consumers with low knowledge about the nutrient functions (LKF) behave differently with consumers with high knowledge about the nutrient functions (HKF). The sensory attributes, meat texture, tenderness, and juiciness, all significantly impact consumers' WTP in the LKF –LKS and LKF-HKS groups, while only tenderness affects consumers' WTP in both HKF –LKS and HKF-HKF groups. The different patterns of the impact of sensory attributes suggest the potential effects of nutrition knowledge on consumers' WTP. As a further exercise to investigate the influence of nutrition knowledge, we can statistically test if the coefficients across groups are different. The rejection of the null that the coefficients from different sub-group estimations are equal will provide evidence of the impacts of nutrition knowledge on consumers' WTP for grass-fed beef. Hence, we test if the coefficients from subgroup estimations are jointly significantly different from each other. The null hypotheses we test are

H1: $\beta_{LKF-LKS} = \beta_{LKF-HKS}$

H2: $\beta_{LKF-LKS} = \beta_{HKF-LKS}$

H3: $\beta_{LKF-LKS} = \beta_{HKF-HKS}$

H4: $\beta_{LKF-HKS} = \beta_{HKF-LKS}$

H5: $\beta_{LKF-HKS} = \beta_{HKF-HKS}$

H6: $\beta_{HKF-LKS} = \beta_{HKF-HKS}$

Table 12 reports the Chi-square test results. Hypothesis H1, H2, H4, and H5 are rejected.

The rejection of H1 suggests that the impact of the knowledge about the nutritious food sources is significant among consumers with low knowledge about the nutrient functions, while the rejection of H2 suggests that the impact of the knowledge about the nutrient functions is significant among consumers with low knowledge about the nutritious food sources. Similarly, the rejection of H5 indicates that impact of the knowledge about the nutritious food sources is significant among consumers with high knowledge about the nutrient functions. The rejection of the null of H4 suggests that the change of the levels of the two sets of the nutrition knowledge in the opposite direction would also have impact on consumers' WTP. The null of H6 could be marginally rejected at $\alpha = 0.1$ level, which may imply the influence of the knowledge about nutritious food sources among consumers with high knowledge about the food functions. An interesting finding is that there seems to be no sizeable difference of the impact of nutrition knowledge on consumers' WTP between LKF-LKS group and HKF-HKS group. One plausible explanation is that the two sets of nutrition knowledge exert their effects in opposite directions. Consequently, increasing the two sets of nutrition knowledge in the same direction would cause the effects to offset each other. The rejection of H4 lends additional support to this judgment.

The significant effects of nutrition knowledge support the findings of Guthrie et al. (1995) who found that nutritionally knowledgeable consumers translate their knowledge to behavior. The implication of our results is that effective nutrition education could promote healthy diets. In line with previous studies (e.g. Evans 2008), the estimates suggest that the beef consumption frequency significantly influences consumers' WTP in for consumers with low knowledge about nutrient functions. Consumers who consume beef more often are willing to pay more for grass-fed beef than those who consume beef less often. We categorized consumers' beef consumption frequency as "Less than once a week," "1 - 2 times a week," and "more than 3 times a week." The difference in the premium that the consumers are willing to pay for grass-fed beef caused by each category difference is up to $0.46. An explanation could be that consumers who consume beef more often are more concerned about the cumulative health effects from beef consumption and thus are willing to pay more for healthy beef products.

The effects of demographic variables are not consistent across groups. The results suggest that living status, family size have significant impact on consumers' WTP for consumers with low knowledge about nutrient functions. In LKF groups, consumers living with other household memebers are willing to pay more for grass-fed beef than those who live alone. The impact of household size on consumers' WTP for grass-fed beef is significant and negative. A possible explanation is that the influences of budget constraint may dominate the decision. Such influences reduce consumers' WTP for healthy food as the household size increases.

The estimated effect of education level is only significant in LKF-HKS group. No priori hypothesis of the sign of the effect of education is made as it could be positive or negative. Misra et al. (1991) suggest that education negatively impacts consumers' WTP for pesticide-free fresh produce. Bernard and Mathios (2005) find that higher education levels of consumers are associated with lower sales of rBST-free and organic milk. However, our results do not indicate such trend. Also, age and ethnicity exhibit no significant impact on consumers' WTP except in LKF-HKS group.

To quantify the effects of nutrition knowledge, we first fit the models and then calculate the expected mean WTP changes in different nutrition knowledge groups. The change in the WTP across groups would infer the effects of the nutrition knowledge. These effects can be referred as conditional effects as they are conditional on a set of characteristics of consumers, including consumption habit, health status, sensory evaluation scores, and demographic characteristics. Since the models are fitted by nutrition knowledge groups, the effects are also conditional on consumers' nutrition knowledge. Table 12 reports the conditional effects of the two sets of nutrition knowledge. Results indicate that an increase of the level of knowledge about the nutritious food sources would lead to an increase of $0.8 on consumers' WTP for grass-fed beef when the knowledge about the nutrient functions of these consumers is low ( $\alpha = 0.01$ ) (LKF-LKS group vs. LKF-HKS group). In contrast, a change of the knowledge about the nutrient functions for consumers with high knowledge about the nutritious food sources would negatively change consumers' WTP for grass-fed beef about $0.75 (LKF-HKS group vs. HKF-HKS group). These significant differences are suggested by the test results of H1 and H5 since the coefficient estimates significantly differ between these subgroup models. Nevertheless, according to previous findings, we should expect WTP to positively correlate with the level of nutrition knowledge about the nutrient functions and negatively correlate with nutrition knowledge about nutritious food sources. If we compare HKF-LKS group to HKF-HKS group, and LKF-LKS group to HKF-LKS group, we could observe the positive impact of nutrition knowledge about the nutrient functions and negative impact of nutrition knowledge about nutritious food on consumers' WTP for grass-fed beef. Although the differences in mean WTP are not significantly different from zero, the rejection of the null of H2 and H6 suggests that consumers in these groups did bid differently. Overall, the results indicate that the two sets of nutrition knowledge significantly impact consumers' WTP for grass-fed beef. The direction of the impact, however, is still inconclusive for each set of nutrition knowledge. Its effects in HKF groups and LKS groups are worth further investigating.

## 7. Conclusion

This paper investigates the impacts of potentially endogenous nutrition knowledge on consumers' WTP for grass-fed beef. The common solution to endogeneity issue is to use instrumental variables which are highly correlated with endogenous regressors and can be validly excluded from main equation. Finding legitimate instruments has always been a challenge in applied research especially when using cross-sectional data. We first use consumers' nutrition label use frequency as instruments for nutrition knowledge. However, Food label use seems to be weakly correlated with nutrition knowledge and Fuller's LIML estimation is not able to fix the weak relevance problem. Hence, we consult to the use of Lewbel (1997) approach which constructs higher order moments as instruments. Under IV framework using Lewbel instruments, the existence of the endogeneity of the two sets of nutrition knowledge is identified. In the IV estimation, the effects of nutrition knowledge on consumers' WTP for grass-fed beef are confirmed again. Moreover, the estimates of the effects of nutrition knowledge are greater than that of benchmark models, indicating the downward bias caused by the endogeneity of nutrition knowledge. One potential risk of using IV method is that the nutrition knowledge may be measured with errors. In that case, to instrument poorly measured variables could possibly worsen the estimation. As an alternative, we investigate a non-IV approach by sub-grouping the full sample based on nutrition levels and estimate four separate Tobit models. This method enables us to exclude nutrition knowledge variables from the WTP equations but still be able to identify their. Our results indicate that consumers in different nutrition groups do bid differently and the differences of WTP between these groups are also significant, implying the influential role of nutrition knowledge on consumers' WTP.

In summary, the estimates from different estimation approaches all indicate the significant impacts of nutrition knowledge on consumers' value perception of food products, implying the robustness of our findings about the influences of nutrition knowledge on food behaviors. Educating consumers with the benefits of healthy food products could increase their WTP for healthier diets though consumers' awareness about the better or equivalent alternative choices available in the market may offset such effect. Furthermore, our results suggest the endogeneity of nutrition knowledge. Ignoring the endogeneity problem in econometric modeling could downwardly bias the estimates. This could partially contribute to the controversies about the relationship between nutrition knowledge and food behaviors in previous studies.

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**Figure 1. Nutrient Function Knowledge and Food Label Use**

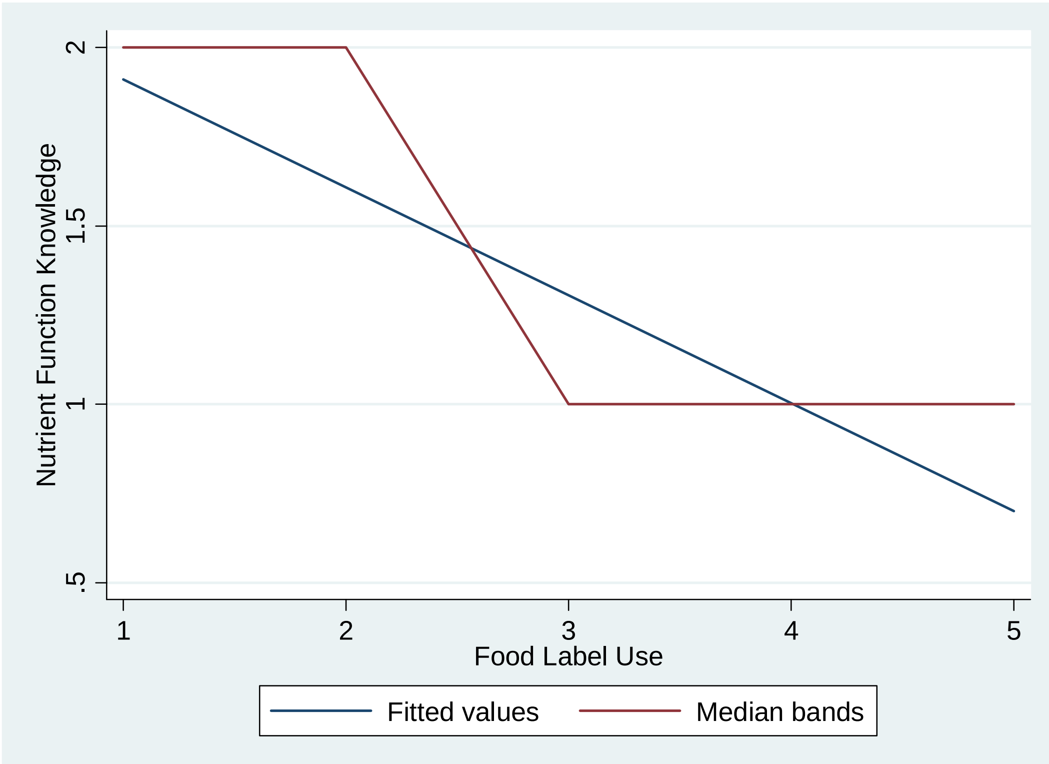
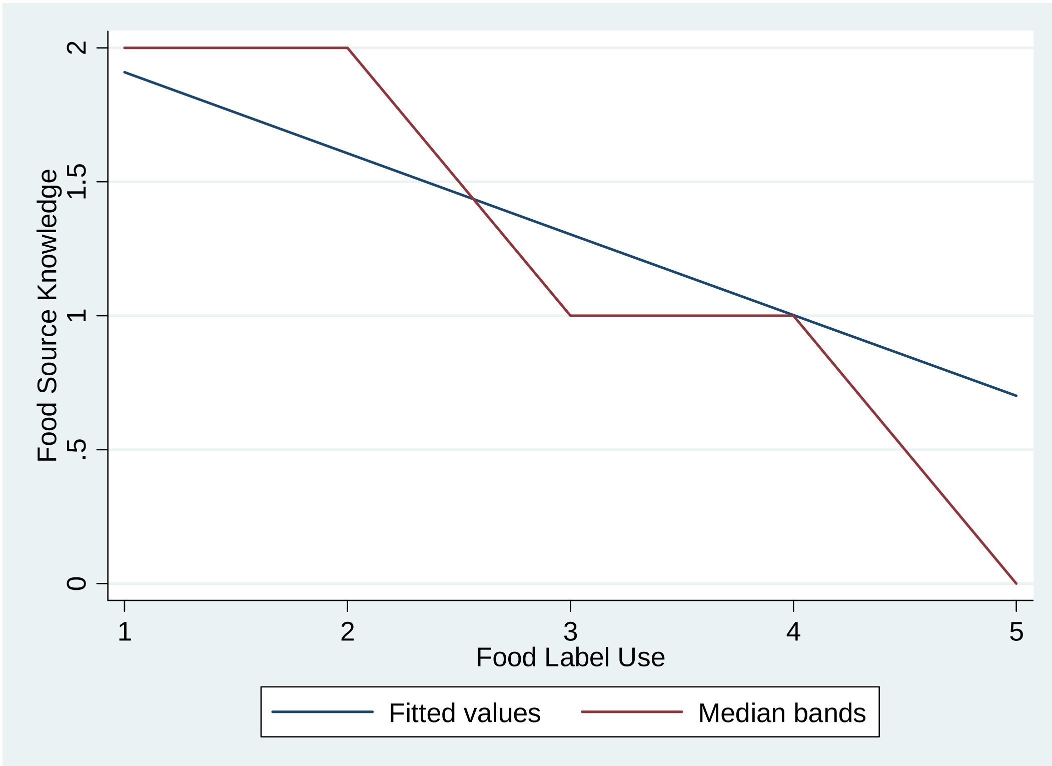


**Figure 2. Food Source Knowledge and Food Label Use**



## Table 1: Nutrition Knowledge Indicator Questions

| Nutrient function knowledge | Correct | Incorrect |
|---|---|---|
| (1) High levels of vitamin A in the body are toxic. | 22% | 78% |
| (2) Vitamin E can help protect against the development of cardiovascular disease and cancer. | 53% | 47% |
| (3) Omega 3 fatty acids can help reduce the risk of heart attacks. | 62% | 38% |
| (4) CLA (conjugated linoleic acid) has an anti-cancer effect. | 12% | 88% |
| **Food source knowledge** | | |
| (1) Beta-carotene is a safe dietary source for vitamin A. | 48% | 52% |
| (2) Nuts and green leafy vegetables are good sources of Vitamin E. | 58% | 42% |
| (3) Canola and soybean oils are good sources of Omega 3 fatty acids. | 49% | 51% |
| (4) Butterfat and meat are good food sources of CLA. | 12% | 88% |

## Table 2: Variable Description

| Variable | Description | Scale | Mean | S.D. | N |
|---|---|---|---|---|---|
| **Dependent** | | | | | |
| WTP | Willingness-To-Pay | >=0, continuous | 0.7089 | 1.3607 | 404 |
| **Independent** | | | | | |
| KnowledgeF | Nutrient function knowledge | 0-4,(low to high) | 1.4827 | 1.1037 | 404 |
| | | 0 | | | 86 |
| | | 1 | | | 127 |
| | | 2 | | | 120 |
| | | 3 | | | 52 |
| | | 4 | | | 19 |
| KnowledgeS | Food source knowledge | 0-4(low to high) | 1.6609 | 1.2469 | 404 |
| | | 0 | | | 98 |
| | | 1 | | | 90 |
| | | 2 | | | 88 |
| | | 3 | | | 107 |
| | | 4 | | | 21 |
| TreatmentB | Treatment B | 1=Treatment B,0 otherwise | 0.3614 | 0.4810 | 404 |
| TreatmentC | Treatment C | 1=Treatment C,0 otherwise | 0.2599 | 0.4391 | 404 |
| Frequency | Beef consumption frequency per week | | 2.3515 | 0.6062 | 404 |
| | | 1=Less than once | | | 28 |
| | | 2=1 or 2 times | | | 206 |
| | | 3=3 or more times | | | 170 |
| Experience | Consumption experience about grass-fed beef | 1=Yes, 0 otherwise | 0.5767 | 0.4947 | 404 |
| Disease | If the participant or any household member has ever been diagnosed with any of the | 1=Yes, 0 otherwise | 0.5507 | 0.4970 | 404 |

| Variable | Description | Scale | Mean | S.D. | N |
|---|---|---|---|---|---|
| | five food-related diseases | | | | |
| Dlcolor | Difference of lean meat color evaluation scores: conventional beef minus pasture-fed beef | -6 to 6 | -0.8540 | 1.3718 | 404 |
| Dfcolor | Difference of fat color evaluation scores: conventional beef minus pasture-fed beef | -6 to 6 | -0.3713 | 1.8307 | 404 |
| Dtexture | Difference of meat texture evaluation scores: conventional beef minus pasture-fed beef | -6 to 6 | 0.0693 | 1.8112 | 404 |
| Dtender | Difference of tenderness evaluation scores: conventional beef minus pasture-fed beef | -6 to 6 | -0.3366 | 2.0851 | 404 |
| Djuicy | Difference of juiciness evaluation scores: conventional beef minus pasture-fed beef | -6 to 6 | 0 | 1.6921 | 404 |
| Dflavor | Difference of flavor evaluation scores: conventional beef minus pasture-fed beef | -6 to 6 | -.2921 | 1.6904 | 404 |
| Gender | Respondent’s gender | 1=male; 0, otherwise | 0.3358 | 0.6642 | 404 |
| Age | Participant’s age | | 3.9035 | 1.5396 | 404 |
| | | 1 if <=24 | | | 33 |
| | | 2 if >24 and <=34 | | | 53 |
| | | 3 if >34 and <=44 | | | 67 |
| | | 4 if >44 and <=54 | | | 93 |
| | | 5 if >54 and <=64 | | | 83 |
| | | 6 if >64 | | | 75 |
| Single | Marital status | 1=single, 0 otherwise | 0.1733 | 0.3790 | 404 |
| Householdsize | Household size | >=1, integers | 2.6485 | 1.3642 | 404 |
| Edu | Education level | | 3.3342 | 1.5026 | 404 |
| | | 1=No high school diploma | | | 34 |

| Variable | Description | Scale | Mean | S.D. | N |
|---|---|---|---|---|---|
| | | or equivalent | | | |
| | | 2= High school diploma or equivalent | | | 106 |
| | | 3=Some college/technical school | | | 113 |
| | | 4=Associate's degree | | | 37 |
| | | 5=Bachelor's degree | | | 70 |
| | | 6=Graduate or professional degree | | | 44 |
| Income | Household income level | | 4.7451 | 2.9151 | 404 |
| | | 1=Less than $10,000 | | | 33 |
| | | 2=$10,000 - $19,999 | | | 75 |
| | | 3=$20,000 - $29,999 | | | 68 |
| | | 4=$30,000 - $39,999 | | | 49 |
| | | 5=$40,000 - $49,000 | | | 42 |
| | | 6=$50,000 - $59,999 | | | 36 |
| | | 7=$60,000 - $69,999 | | | 30 |
| | | 8=$70,000 - $79,000 | | | 18 |
| | | 9=$80,000 - $89,999 | | | 10 |
| | | 10=$90,000 - $99,999 | | | 9 |
| | | 11=More than $100,000 | | | 34 |

**Table 3: WTP equation estimates from OLS and Tobit Models**

| | OLS model | | Tobit model | | | |
|---|---|---|---|---|---|---|
| | Coefficients | S.E | Coefficients | S.E | Uncond. | Cond. |
| Constant | 0.58 | 0.51 | -2.74 | 1.33 | | |
| TreatmentB | 0.04 | 0.14 | 0.42 | 0.37 | 0.14 | 0.12 |
| TreatmentC | 0.10 | 0.15 | 0.26 | 0.40 | 0.08 | 0.07 |
| Frequency | 0.17* | 0.10 | 0.43 | 0.27 | 0.14 | 0.12 |
| Experience | 0.00 | 0.12 | -0.16 | 0.32 | -0.05 | -0.04 |
| Disease | 0.03 | 0.18 | 0.89* | 0.53 | 0.29* | 0.25* |
| KnowledgeF | 0.18*** | 0.07 | 0.54*** | 0.18 | 0.18*** | 0.15*** |
| KnowledgeS | -0.10* | 0.06 | -0.34** | 0.16 | -0.11** | -0.09** |
| Dlcolor | -0.02 | 0.04 | -0.02 | 0.12 | -0.01 | -0.01 |
| Dfcolor | 0.00 | 0.04 | -0.05 | 0.11 | -0.02 | -0.01 |
| Dtexture | 0.07** | 0.03 | 0.25*** | 0.09 | 0.08*** | 0.07*** |
| Dtender | 0.13*** | 0.04 | 0.55*** | 0.12 | 0.18*** | 0.15*** |
| Djuicy | 0.15*** | 0.05 | 0.42*** | 0.14 | 0.14*** | 0.12*** |
| Dflavor | 0.11** | 0.05 | 0.25** | 0.12 | 0.08** | 0.07** |
| Gender | -0.18 | 0.13 | -0.30 | 0.34 | -0.10 | -0.08 |
| Age | -0.08* | 0.04 | -0.07 | 0.11 | -0.02 | -0.02 |
| Single | -0.50*** | 0.19 | -1.25** | 0.52 | -0.41** | -0.35** |
| Famsize | -0.13** | 0.05 | -0.25* | 0.14 | -0.08* | -0.07* |
| Ethnicity | 0.40 | 0.28 | 0.37 | 0.76 | 0.12 | 0.10 |
| Edu | 0.03 | 0.05 | 0.09 | 0.12 | 0.03 | 0.02 |
| Income | -0.02 | 0.02 | -0.02 | 0.06 | -0.01 | 0.00 |

Notes: (*) denotes statistical significance at least at a=0.1. (**) denotes statistical significance at least at a=0.05. (***) denotes statistical significance at least at a=0.01.

## Table 4: OLS Estimates of Reduced-Form Nutrition Knowledge Equations

| | Nutrition knowledge of nutrient functions | | Nutrition knowledge of nutritious food sources | |
|---|---|---|---|---|
| | Coefficient | Std. Error | Coefficient | Std. Error |
| constant | 1.09 | 0.46 | 2.04 | 0.53 |
| Label2 | -0.03 | 0.14 | 0.22 | 0.16 |
| Label3 | -0.61*** | 0.15 | -0.64*** | 0.17 |
| Label4 | -0.45*** | 0.18 | -0.54*** | 0.21 |
| Label5 | -0.87*** | 0.25 | -1.22*** | 0.29 |
| TreatmentB | 0.13 | 0.12 | -0.08 | 0.14 |
| TreatmentC | 0.00 | 0.13 | -0.04 | 0.15 |
| Frequency | 0.13 | 0.09 | 0.18* | 0.11 |
| Experience | 0.14 | 0.11 | 0.17 | 0.12 |
| Disease | -0.15 | 0.16 | -0.17 | 0.18 |
| Dlcolor | 0.04 | 0.04 | 0.06 | 0.04 |
| Dfcolor | 0.01 | 0.04 | -0.08* | 0.04 |
| Dtexture | 0.01 | 0.03 | -0.01 | 0.03 |
| Dtender | 0.00 | 0.04 | -0.04 | 0.04 |
| Djuicy | 0.07 | 0.04 | -0.02 | 0.05 |
| Dflavor | 0.01 | 0.04 | 0.06 | 0.05 |
| Gender | -0.15 | 0.11 | -0.31** | 0.13 |
| Age | 0.03 | 0.04 | 0.00 | 0.04 |
| Single | 0.24 | 0.17 | 0.08 | 0.19 |
| Famsize | 0.01 | 0.05 | -0.05 | 0.06 |
| Ethnicity | -0.18 | 0.25 | -0.37 | 0.29 |
| Edu | 0.17*** | 0.04 | 0.08 | 0.05 |
| Income | -0.02 | 0.02 | -0.03 | 0.02 |
| | | | | |
| Partial R2 | 0.07 | | 0.11 | |
| Shea Partial R2 | 0.01 | | 0.01 | |
| F( 4, 379) | 7.3 | | 11.17 | |

Notes: (*) denotes statistical significance at least at a=0.1. (**) denotes statistical significance at least at a=0.05. (***) denotes statistical significance at least at a=0.01.

## Table 5: Impact of Label Use on Consumers' WTP for Grass-Fed Beef

| | Coefficient | Std.Error | t | P>t |
|---|---|---|---|---|
| constant | 0.51 | 0.53 | 0.95 | 0.34 |
| Label2 | -0.05 | 0.16 | -0.29 | 0.78 |
| Label3 | -0.13 | 0.17 | -0.76 | 0.45 |
| Label4 | -0.01 | 0.21 | -0.06 | 0.95 |
| Label5 | 0.33 | 0.29 | 1.13 | 0.26 |
| TreatmentB | 0.09 | 0.14 | 0.62 | 0.54 |
| TreatmentC | 0.12 | 0.15 | 0.76 | 0.45 |
| Frequency | 0.17 | 0.11 | 1.57 | 0.12 |
| Experience | 0.02 | 0.12 | 0.20 | 0.84 |
| Disease | 0.00 | 0.18 | -0.01 | 0.99 |
| Dlcolor | -0.01 | 0.04 | -0.33 | 0.75 |
| Dfcolor | 0.02 | 0.04 | 0.39 | 0.70 |
| Dtexture | 0.08 | 0.03 | 2.19 | 0.03 |
| Dtender | 0.14 | 0.04 | 3.36 | 0.00 |
| Djuicy | 0.17 | 0.05 | 3.40 | 0.00 |
| Dflavor | 0.10 | 0.05 | 1.97 | 0.05 |
| Gender | -0.19 | 0.13 | -1.48 | 0.14 |
| Age | -0.07 | 0.04 | -1.48 | 0.14 |
| Single | -0.46 | 0.19 | -2.39 | 0.02 |
| Famsize | -0.12 | 0.06 | -2.13 | 0.03 |
| Ethnicity | 0.47 | 0.29 | 1.60 | 0.11 |
| Edu | 0.06 | 0.05 | 1.27 | 0.21 |
| Income | -0.02 | 0.02 | -0.90 | 0.37 |

Notes: (*) denotes statistical significance at least at a=0.1. (**) denotes statistical significance at least at a=0.05. (***) denotes statistical significance at least at a=0.01.

## Table 6: Fuller's LIML Estimates of the First Stage Reduced-Form Nutrition Knowledge Equations

| | Nutrition knowledge of nutrient functions | | Nutrition knowledge of nutritious food sources | |
|---|---|---|---|---|
| | Coefficient | Std. Error | Coefficient | Std. Error |
| Label2 | -0.03 | 0.14 | 0.22 | 0.16 |
| Label3 | -0.61*** | 0.15 | -0.64*** | 0.17 |
| Label4 | -0.45** | 0.18 | -0.54*** | 0.21 |
| Label5 | -0.87*** | 0.25 | -1.22*** | 0.29 |
| TreatmentB | 0.13 | 0.12 | -0.08 | 0.14 |
| TreatmentC | 0.00 | 0.13 | -0.04 | 0.15 |
| Frequency | 0.13 | 0.09 | 0.18* | 0.11 |
| Experience | 0.14 | 0.11 | 0.17 | 0.12 |
| Disease | -0.15 | 0.16 | -0.17 | 0.18 |
| Dlcolor | 0.04 | 0.04 | 0.06 | 0.04 |
| Dfcolor | 0.01 | 0.04 | -0.08* | 0.04 |
| Dtexture | 0.01 | 0.03 | -0.01 | 0.03 |
| Dtender | 0.00 | 0.04 | -0.04 | 0.04 |
| Djuicy | 0.07 | 0.04 | -0.02 | 0.05 |
| Dflavor | 0.01 | 0.04 | 0.06 | 0.05 |
| Gender | -0.15 | 0.11 | -0.31** | 0.13 |
| Age | 0.03 | 0.04 | 0.00 | 0.04 |
| Single | -0.18 | 0.25 | -0.37 | 0.29 |
| Famsize | 0.24 | 0.17 | 0.08 | 0.19 |
| Ethnicity | 0.01 | 0.05 | -0.05 | 0.06 |
| Edu | 0.17 | 0.04 | 0.08 | 0.05 |
| Income | -0.02 | 0.02 | -0.03 | 0.02 |
| F( 4, 379) | 7.3 | | 11.17 | |

Notes: (*) denotes statistical significance at least at a=0.1. (**) denotes statistical significance at least at a=0.05. (***) denotes statistical significance at least at a=0.01.

## Table 7: Fuller's LIML Estimates of the Second Stage WTP Equation

| | Coefficient | Std.Error | t | P>t |
|---|---|---|---|---|
| _cons | 1.08 | 0.90 | 1.20 | 0.23 |
| KnowledgeF | 1.26 | 1.47 | 0.86 | 0.39 |
| KnowledgeS | -0.91 | 1.03 | -0.89 | 0.38 |
| TreatmentB | -0.15 | 0.31 | -0.47 | 0.64 |
| TreatmentC | 0.08 | 0.20 | 0.38 | 0.70 |
| Frequency | 0.17 | 0.14 | 1.22 | 0.22 |
| Experience | -0.01 | 0.17 | -0.03 | 0.98 |
| Disease | 0.04 | 0.24 | 0.17 | 0.86 |
| Dlcolor | -0.01 | 0.06 | -0.20 | 0.84 |
| Dfcolor | -0.07 | 0.11 | -0.66 | 0.51 |
| Dtexture | 0.05 | 0.05 | 1.04 | 0.30 |
| Dtender | 0.10 | 0.07 | 1.45 | 0.15 |
| Djuicy | 0.07 | 0.13 | 0.56 | 0.57 |
| Dflavor | 0.14* | 0.07 | 1.91 | 0.06 |
| Gender | -0.28 | 0.20 | -1.36 | 0.18 |
| Age | -0.10 | 0.07 | -1.47 | 0.14 |
| Single | 0.33 | 0.38 | 0.87 | 0.39 |
| Famsize | -0.69* | 0.37 | -1.87 | 0.06 |
| Ethnicity | -0.17* | 0.09 | -1.86 | 0.06 |
| Edu | -0.08 | 0.17 | -0.43 | 0.67 |
| Income | -0.02 | 0.03 | -0.54 | 0.59 |
| F( 20, 381) | 4.64 | | | |

Notes: (*) denotes statistical significance at least at a=0.1. (**) denotes statistical significance at least at a=0.05. (***) denotes statistical significance at least at a=0.01.

**Table 8: First-Stage Estimates of Reduced Form Equations of Nutrition Knowledge Using Lewbel Instrument**

| | Nutrition knowledge of nutrient functions | | Nutrition knowledge of nutritious food sources | |
|---|---|---|---|---|
| | Coefficient | Std. Error | Coefficient | Std. Error |
| constant | 0.26 | 0.44 | 1.00 | 0.54 |
| Lewbel1 | 0.01 | 0.01 | -0.01 | 0.01 |
| Lewbel2 | 0.25*** | 0.04 | 0.04 | 0.04 |
| Lewbel3 | -0.09*** | 0.04 | 0.07 | 0.05 |
| Lewbel4 | -0.02 | 0.04 | 0.05 | 0.05 |
| Lewbel5 | -0.05 | 0.04 | -0.12** | 0.05 |
| TreatmentB | 0.12 | 0.12 | 0.01 | 0.14 |
| TreatmentC | 0.00 | 0.13 | 0.08 | 0.16 |
| Frequency | 0.08 | 0.09 | 0.15 | 0.11 |
| Dxperience | 0.22** | 0.10 | 0.31** | 0.13 |
| Disease | -0.02 | 0.16 | -0.04 | 0.19 |
| Dlcolor | 0.03 | 0.04 | 0.06 | 0.05 |
| Dfcolor | -0.02 | 0.04 | -0.10** | 0.04 |
| Dtexture | 0.01 | 0.03 | 0.00 | 0.04 |
| Dtender | 0.02 | 0.03 | -0.02 | 0.04 |
| Djuicy | 0.09** | 0.04 | 0.02 | 0.05 |
| Dflavor | 0.00 | 0.04 | 0.04 | 0.05 |
| Gender | -0.21* | 0.11 | -0.40*** | 0.13 |
| Age | 0.03 | 0.04 | 0.01 | 0.05 |
| Single | 0.23 | 0.16 | 0.09 | 0.20 |
| Famsize | 0.00 | 0.05 | -0.06 | 0.06 |
| Ethnicity | 0.06 | 0.24 | -0.17 | 0.30 |
| Edu | 0.20*** | 0.04 | 0.16*** | 0.05 |
| Income | -0.02 | 0.02 | -0.02 | 0.03 |
| | | | | |
| Partial R2 | 0.12 | | 0.02 | |
| Shea Partial R2 | 0.15 | | 0.03 | |
| F( 5, 378) | 10.71 | | 1.89 | |

Notes: (*) denotes statistical significance at least at a=0.1. (**) denotes statistical significance at least at a=0.05. (***) denotes statistical significance at least at a=0.01.

**Table 9: Second-Stage Tobit Estimates Using Lewbel Instruments**

| Variable | Coefficient | S.E. | Unconditional expected value | Conditional on being uncensored |
|---|---|---|---|---|
| constant | -0.21 | 1.54 | | |
| TreatmentB | 0.17 | 0.36 | 0.06 | 0.05 |
| TreatmentC | 0.25 | 0.38 | 0.08 | 0.07 |
| Frequency | 0.66** | 0.29 | 0.22** | 0.18** |
| Experience | 0.38 | 0.37 | 0.12 | 0.11 |
| Disease | 0.78 | 0.52 | 0.26 | 0.22 |
| KnowledgeF | 1.96*** | 0.41 | 0.64*** | 0.54*** |
| KnowledgeS | -3.09*** | 0.88 | -1.02*** | -0.86*** |
| Dlcolor | 0.13 | 0.13 | 0.04 | 0.04 |
| Dfcolor | -0.29** | 0.13 | -0.10** | -0.08** |
| Dtexture | 0.22*** | 0.09 | 0.07*** | 0.06*** |
| Dtender | 0.44*** | 0.12 | 0.14*** | 0.12*** |
| Djuicy | 0.37*** | 0.13 | 0.12*** | 0.10*** |
| Dflavor | 0.35*** | 0.12 | 0.12*** | 0.10*** |
| Gender | -1.04** | 0.44 | -0.34** | -0.29** |
| Age | -0.07 | 0.11 | -0.02 | -0.02 |
| Single | -1.31*** | 0.51 | -0.43*** | -0.36*** |
| Famsize | -0.40*** | 0.14 | -0.13*** | -0.11*** |
| Ethnicity | 0.16 | 0.75 | 0.05 | 0.04 |
| Edu | 0.20 | 0.16 | 0.06 | 0.05 |
| Income | -0.05 | 0.06 | -0.02 | -0.01 |
| resid1 | -1.64*** | 0.45 | -0.54*** | -0.46*** |
| resid2 | 2.73*** | 0.83 | 0.90*** | 0.76*** |
| | | | | |
| Log likelihood | -372.15 | | | |
| LR chi2(22) | 218.6 | | | |
| Pseudo R2 | 0.23 | | | |

Notes: (*) denotes statistical significance at least at a=0.1. (**) denotes statistical significance at least at a=0.05. (***) denotes statistical significance at least at a=0.01.

**Table 10: Sub-grouping Tobit Estimates of WTP Equation**

| | LKF-LKS (N=138) | | LKS-HKS (N=74) | | HKF-LKS (N=48) | | HKF-HKS (N=142) | |
|---|---|---|---|---|---|---|---|---|
| | Coefficient | S.E. | Coefficient | S. E. | Coefficient | S.E. | Coefficient | S.E. |
| Constant | -3.68 | 2.48 | -12.25 | 4.85 | -2.93 | 3.59 | -4.41 | 2.45 |
| Treatmentb | 0.30 | 0.69 | -0.17 | 0.74 | 0.26 | 0.75 | 0.55 | 0.61 |
| TreatmentC | 0.25 | 0.74 | 3.29*** | 1.14 | -2.81* | 1.11 | 0.53 | 0.64 |
| Frequency | 1.12** | 0.51 | 1.79*** | 0.67 | 0.31 | 0.65 | 0.02 | 0.47 |
| Experience | -0.83 | 0.59 | 4.10*** | 1.13 | -0.26 | 0.76 | -0.01 | 0.54 |
| Disease | 0.36 | 1.02 | 2.75 | 2.03 | 1.22 | 2.45 | 0.96 | 0.77 |
| Dlcolor | -0.10 | 0.21 | 0.31 | 0.38 | 0.48* | 0.28 | -0.33 | 0.23 |
| Dfcolor | 0.15 | 0.20 | -0.66** | 0.30 | -0.07 | 0.28 | 0.09 | 0.18 |
| Dtexture | 0.34* | 0.19 | 0.85** | 0.33 | 0.36** | 0.16 | -0.03 | 0.15 |
| Dtender | 0.41* | 0.21 | 0.78*** | 0.30 | 0.83* | 0.46 | 0.49*** | 0.19 |
| Djuicy | 0.47* | 0.26 | 1.68*** | 0.61 | 0.65 | 0.43 | 0.21 | 0.21 |
| Dflavor | 0.58* | 0.23 | 0.44 | 0.38 | -0.34 | 0.22 | 0.46** | 0.23 |
| Gender | 0.01 | 0.61 | -1.11 | 0.83 | -1.77* | 0.93 | 0.36 | 0.58 |
| Age | 0.18 | 0.21 | -0.89*** | 0.34 | 0.09 | 0.29 | -0.02 | 0.19 |
| Single | -2.22* | 1.25 | -11.30*** | 2.83 | 0.14 | 1.06 | -0.70 | 0.79 |
| Famsize | -0.45* | 0.26 | -1.74*** | 0.48 | -0.21 | 0.28 | 0.16 | 0.24 |
| Ethnicity | 0.12 | 1.22 | 4.35* | 2.40 | 0.95 | 1.54 | 0.71 | 1.53 |
| Edu | 0.09 | 0.25 | 1.49*** | 0.51 | 0.47 | 0.29 | 0.19 | 0.20 |
| Income | -0.02 | 0.13 | 0.03 | 0.16 | -0.15 | 0.13 | 0.08 | 0.10 |

Notes: (*) denotes statistical significance at least at a=0.1. (**) denotes statistical significance at least at a=0.05. (***) denotes statistical significance at least at a=0.01.

## Table 11: Decomposed Marginal Effects of Tobit Estimates

| | LKF-LKS | | LKF-HKS | | HKF-LKS | | HKF-HKS | |
|---|---|---|---|---|---|---|---|---|
| | Uncond. | Cond. | Uncond. | Cond. | Uncond. | Cond. | Uncond. | Cond. |
| Treatmentb | 0.08 | 0.07 | -0.04 | -0.04 | 0.14 | 0.10 | 0.20 | 0.16 |
| TreatmentC | 0.06 | 0.06 | 0.84 | 0.80 | -1.46 | -1.05 | 0.19 | 0.16 |
| Frequency | 0.29 | 0.28 | 0.46 | 0.44 | 0.16 | 0.12 | 0.01 | 0.01 |
| Experience | -0.22 | -0.21 | 1.00 | 1.09 | -0.10 | -0.06 | 0.00 | 0.00 |
| Disease | 0.09 | 0.09 | 0.71 | 0.67 | 0.64 | 0.46 | 0.35 | 0.28 |
| Dlcolor | -0.02 | -0.02 | 0.08 | 0.08 | 0.25 | 0.18 | -0.12 | -0.10 |
| Dfcolor | 0.04 | 0.04 | -0.17 | -0.16 | -0.04 | -0.03 | 0.03 | 0.03 |
| Dtexture | 0.09 | 0.08 | 0.22 | 0.21 | 0.19 | 0.13 | -0.01 | -0.01 |
| Dtender | 0.11 | 0.10 | 0.20 | 0.19 | 0.43 | 0.31 | 0.18 | 0.15 |
| Djuicy | 0.12 | 0.12 | 0.43 | 0.41 | 0.34 | 0.25 | 0.08 | 0.06 |
| Dflavor | 0.15 | 0.14 | 0.11 | 0.11 | -0.18 | -0.13 | 0.17 | 0.14 |
| Gender | 0.00 | 0.00 | -0.29 | -0.27 | -0.92 | -0.66 | 0.13 | 0.11 |
| Age | 0.05 | 0.04 | -0.23 | -0.22 | 0.05 | 0.03 | -0.01 | -0.01 |
| Single | -0.58 | -0.55 | -2.90 | -2.77 | 0.07 | 0.05 | -0.26 | -0.21 |
| Famsize | -0.12 | -0.11 | -0.45 | -0.43 | -0.11 | -0.08 | 0.06 | 0.05 |
| Ethnicity | 0.03 | 0.03 | 1.12 | 1.06 | 0.50 | 0.36 | 0.26 | 0.21 |
| Edu | 0.02 | 0.02 | 0.38 | 0.36 | 0.25 | 0.18 | 0.07 | 0.06 |
| Income | 0.00 | 0.00 | 0.01 | 0.01 | -0.08 | -0.06 | 0.03 | 0.02 |

Notes: (*) denotes statistical significance at least at a=0.1. (**) denotes statistical significance at least at a=0.05. (***) denotes statistical significance at least at a=0.01.

## Table 12: Coefficient Comparison across Sub-group Estimations

| Hypothesis | $\chi^2$ (df =18) | P-value |
|---|---|---|
| H1: $\beta_{LKF-LKS} = \beta_{LKF-HKS}$ | 52.85 | 0.0000 |
| H2: $\beta_{LKF-LKS} = \beta_{HKF-LKS}$ | 28.36 | 0.0567 |
| H3: $\beta_{LKF-LKS} = \beta_{HKF-HKS}$ | 22.43 | 0.2134 |
| H4: $\beta_{LKF-HKS} = \beta_{HKF-LKS}$ | 63.62 | 0.0000 |
| H5: $\beta_{LKF-HKS} = \beta_{HKF-HKS}$ | 46.38 | 0.0003 |
| H6: $\beta_{HKF-LKS} = \beta_{HKF-HKS}$ | 25.05 | 0.1236 |

## Table 13: Nutrition Knowledge Impact on Consumers' WTP for Grass-Fed Beef

| | LKF-LKS Mean | S.E. | LKF-HKS Mean | S.E. | HKF-LKS Mean | S.E. | HKF-HKS Mean | S.E. |
|---|---|---|---|---|---|---|---|---|
| Predicted average WTP | 0.66 | 0.06 | 1.45 | 0.16 | 0.71 | 0.06 | 0.70 | 0.04 |
| **Difference** | | | | | | | | |
| LKF-LKS | | | -0.79 | 0.13 | -0.05 | 0.05 | -0.04 | 0.03 |
| LKF-HKS | | | | | 0.74 | 0.14 | 0.75 | 0.13 |
| HKF-LKS | | | | | | | 0.01 | 0.05 |

**Note:** Differences reported are row groups minus column groups: (LKF-LKS)-( LKF-HKS), (LKF-LKS)-( HKF-LKS), (LKF-LKS)-( HKF-HKS), (LKF-HKS)-( HKF-LKS), (LKF-HKS)-( HKF-HKS), and (HKF-LKS)-(HKF-HKS)

# Essay 3: Primary Care Giver's Time allocation, Household Food Expenditures, and Childhood Obesity


### Abstract

This essay investigates the impacts of primary care giver's (PCG) time allocation and food expenditure choices on childhood obesity using national panel study of income dynamic (PSID) data. A triangular system of equations is derived and estimated under parametric and semi-parametric model settings. The performances of the two modeling strategies are compared using predictive ability measures with the aid of bootstrap method. Test results suggest relatively better performance of the semi-parametric model than parametric model. Nevertheless, the comparison of the estimates from both parametric and semi-parametric estimation indicates no dramatic changes in our findings. Our results do not suggest significant impacts of PCG's labor force participation choices, involvement in children's outdoor activity, and household food expenditures on children's Body Mass Index (BMI). However, the estimates from both iterated seemingly unrelated regression (SUR) and semi-parametric polynomial estimation indicate that parents' BMI significantly influence children's BMI. Obese parents tend to have obese children. Furthermore, physical activity appears to have weak correlation with children's BMI. More physical activity time does not necessarily lead to lower BMI of children.



**Keywords**: Time Allocation, Childhood Obesity, Triangular System of Equations, Seemingly Unrelated Regression, Two-Stage Polynomial Regression

## 1. Introduction

The rate of childhood obesity has been growing rapidly over the past three decades. The prevalence of obesity among children aged 6 to 11 years and adolescents aged 12 to 19 years increased from 6.5% to 19.6% and from 5.0% to 18.1% respectively from 1980 to 2008 (National Center for Health Statistics 2004; Ogden et al. 2010). Childhood obesity is a complex phenomenon affected by a broad spectrum of biological, sociological, and economic factors. Some studies have suggested that certain factors are direct causes of childhood obesity while some studies indicate otherwise. For example, increased consumption of soft drinks (Ludwig et al. 2001; Troiano et al. 2004), snacking (Nielsen and Popkin; Cutler et al. 2003), and fast food (Paeratuku et al. 2003; Chou et al. 2004; Thompson et al. 2004) have been argued as causes of childhood obesity. However, the study of Rajeshwari et al. (2005) suggests that there is no significant positive relationship between sweetened beverage and children's Body Mass Index (BMI); Bandini et al. (2005) suggest that snacking does not appear to have impact on childhood overweigh; Ebbeling et al. (2004) indicate that children consuming more fast food are not more likely to be overweight and obese. Lack of physical activities is another issue that most studies have been arguing responsible for childhood obesity. Television watching is a good example of being blamed for causing less physical activities. However, Nielsen data indicate that viewing time of both younger children and teens had been falling between 1982 to1999 (Nielsen Media Research 2000). Indeed, the evidence is still mixed as beneficial effects of physical activities on health outcomes are unclear given that optimal intensities, volumes, and modalities are still inconclusive (Goran et al. 1999). What has caused the rapid increase of childhood obesity remains an open question, and given the mixed empirical evidence of the driven forces behind the epidemic in literature, further investigation in a well-defined theoretical framework is warranted to better explain the cross-country, cross-time, and cross-population evidences on childhood obesity.

Childhood obesity at its roots is a function of energy intake and energy expended. The more the former exceeds the latter, the more weight a child will gain. Parents play a central role in children's energy intake and energy expenditure process since they influence children's diet composition, eating habits, physical activity patterns, and psychological and emotional status which affect metabolic rates. The primary care giver (PCG) who takes care of the children most of the time in a family and supervises children's activities is especially influential as she/he largely decides what the children eat, how much the children eat, the levels and intensity of physical activities, and the time of sedative activities. From the production point of view, the PCG purchases foods on the market and combines them with time in a health production function to produce "commodities"- the health outcomes of the children. Children's health outcomes enter the PCG's utility function as arguments. Time is a source of PCG's market income as well as an input of the health commodity. As a new area of the interest, PCG's influences on childhood obesity have been gaining increasing attention. Some studies have been conducted to examine these influences in a household production framework which helps shade light on the impacts of intra-household factors on childhood obesity (e.g., You and Davis 2010). However, there has been a lack of empirical studies using nationally representative data to investigate the role of PCG influencing childhood obesity risk. This paper intends to fill this gap by assessing the impacts of PCG's time allocation and food spending choices on children's Body Mass Index (BMI) using national panel study of income dynamics (PSID) data. Furthermore, we are aware that the validity of parametric model estimates relies heavily on the restrictive distributional assumptions and functional forms. For the first time in literature, this paper introduces a semi-parametric approach to estimate a triangular simultaneous system of equations to investigate the influential factors on childhood obesity. The performances of the two modeling strategies are compared using predictive ability measures with the aid of bootstrap method.

The remainder of the paper proceeds as follows. First, we explain our theoretical framework. Next, empirical model and related econometric issues are discussed. Then we introduce the survey data used in the analysis, followed by a section discussing parametric and semi-parametric estimation results. After the result discussion, we compare the performance of the two different econometric models. The paper concludes with discussion focusing on the influential factors on childhood obesity and the application of proper econometric models.

## 2. Theoretical Framework

We define a child's health production function in terms of BMI as:

(1) $\text{BMI} = H(X^c, T_E^c, T_E^j; T_F, k^p, k^h, k^c, E)$

Where $X^c$ is the amount of food consumed by the child, $T_E^c$ is the physical activity time of the child, and $T_E^j$ is the joint physical activity time of the PCG and the child. The separation of the physical activity time of the child captures the difference of the child's energy intake and consumption patterns with and without the presence of the PCG. The difference could be brought by the activity goals, beliefs, and habits of the PCG which influence the types and intensity of the child's activity. $T_F$ is the PCG's food preparation time which could affect the food quality offered to the child. $h$ represents the household head who is usually the husband in a traditional household, $p$ represents the PCG. In this study, a PCG is defined as the wife who provides primary care to the children in a household. $c$ represents the child. $k^h, k^p, k^c$ describe the types of the head, the PCG and the child respectively. The type variables describe a set of biological, genetic, and socio-demographic characteristics of the parents and child which affect the energy-to-weight conversion process of the child. $E$ denotes the influential environmental factors on the child's BMI production.

Then the child's utility function is defined as:

(2) $v^c = v^c(X^c, X_0^c, BMI, T_E^c, T_E^j; k^c)$

Where $X_0^c$ is the child's consumption of other goods.

The PCG's utility function which can be expressed as:

(3) $v^p = v^p(X^p, X_o^p, BMI, T_w^p, T_F, T_L, T_E^j, T_O; k^p, v^c)$

Where $X^p$ is the amount of food consumed by the PCG, $X_0^p$ is the PCG's consumption of other goods, $T_W^p$ is the working time of PCG, $T_L$ is the leisure time for the PCG, and $T_O$ is the residual time of the PCG for other activities. The PCG's utility is conditional on the child's utility, implying that the PCG cares about the child's utility.

The budget constraints the PCG faces:

(4) $X^p + X^c + X^h + X_0^p + X_0^c + X_0^h = \sum w^i T_W^i + I$, $i = h, p$

Where $X^h$ is the amount of food consumed by the head, $X_0^h$ is the amount of other market goods consumed by the head, $T_W^i$ are the working hours of the head and PCG, $w^i$ are the wage rates of the head and PCG, and $I$ is the other non-labor income of the household.

The time constraint that the PCG faces is:

(5) $T_W^p + T_F + T_L + T_E^j + T_O = T$

Hence, from the PCG's perspective, the maximization problem is:

$$\underset{\begin{pmatrix} X^p, X_o^p, T_W, T_F \\ T_E^j, T_L^w \end{pmatrix}}{Max} \quad v = v^p(X^p, X_o^p, BMI, T_w^p, T_F, T_L, T_E^j, T_O; k^p, v^c)$$

$$s.t. \begin{cases} X^p + X^c + X^h + X_0^p + X_0^c + X_0^h = \sum w^i T_W^i + I, i = h, p \\ T_W^p + T_F + T_L + T_E^j + T_O = T \end{cases}$$

Maximizing PCG's utility function subject to income and time constraints, we can derive a system of equations:

$$(6) \quad \begin{cases} T_W^P = T_W^P(w^p, w^h, T_W^h, I, k^h, k^p, k^c, E) \\ T_E^j = T_E^j(w^p, w^h, T_W^h, I, k^h, k^p, k^c, E) \\ X^c = X^c(w^p, w^h, T_W^h, I, k^h, k^p, k^c, E) \\ BMI = H(X^c, T_W^P, T_E^j, k^h, k^p, k^c, E) \end{cases}$$

The system consists of three reduced form equations and one structural equation to define the PCG's optimal time allocation and food expenditure choices. There are four variables, $w^p, w^h, T_W^h, I$, are in reduced form equations but not in the structural equation. Therefore the number of the excluded exogenous variables from the structural equation is larger than the number of the included right-hand-side endogenous variables in the structural equation. The order condition is thus satisfied, which is necessary for the structural equation to be identified.

## 3. Empirical Model

### *3.1 Model specification*

Based on our theoretical model, a system of equations is specified assuming linear functional forms:

（1）$PCGWKHR = f_1(PCGWage, HDWKHR\ , HDWage, NlabIncome, HDBMI,$
$HDHealth, PCGBMI, PCGHealth,\ EmpMom, PCGage,$
$PCGedu\ PCGwhite, Lunchpro, ActiveTime, ChildWhite,$
$Childgender,\ Childage,\ \ Loved, NumChildren)$

（2）$PCGChildOutdoor = f_2(PCGWage, HDWKHR\ , HDWage, NlabIncome, HDBMI,$
$HDHealth, PCGBMI, PCGHealth,\ EmpMom, PCGage,$
$PCGedu\ PCGwhite, Lunchpro, ActiveTime, ChildWhite,$
$Childgender,\ Childage,\ \ Loved, NumChildren)$

（3）$FoodExp = f_3(PCGWage, HDWKHR\ , HDWage, NlabIncome, HDBMI,$
$HDHealth, PCGBMI, PCGHealth,\ EmpMom, PCGage,$
$PCGedu\ PCGwhite, Lunchpro, ActiveTime, ChildWhite,$
$Childgender,\ Childage,\ \ Loved, NumChildren)$

（4）$ChildBMI = f_4(\ PCGWKHR, PCGChildOutdoor, FoodExp, HDBMI,$
$HDHealth, PCGBMI, PCGage,\ PCGedu,\ PCGwhite, Lunchpro,$
$ActiveTime,\ ChildWhite, Childgender,\ Childage,\ Loved, NumChildren)$

The definitions of the dependent variables and the independent variables in the system are presented in Table 1. The head's weekly working hours ( $HDWKHR$ ), the head's wage rate ( $HDWage$ ), the PCG's wage rate ( $PCGWage$ ), and the family's non-labor income ( $NlabIncome$ ) are the excluded variables in the system. The weekly working hours of the PCG (PCGWKHR) is used to measure the PCG's working time. The PCG's participation in market could result in less food preparation time at home and increase the consumption of food away from home. According to the Bureau of Labor Statistics, from early 1970s to early 2000s, female labor force participation rate increased from 40% to 60%. In the meaning time, USDA's food intake surveys suggest that the share of people's daily caloric intake from food away from home increased from 18 percent to 32 percent between late 1970s' and middle 1990s. Food away from home tends to contain higher calories more calories per eating occasion than food prepared at home (Lin et al., 1999, 2001; Guthrie et al., 2002). We thus hypothesize that an increase of

PCG's working time will cause an increase of children's BMI. The second reduced form equation estimates the function of joint physical activity time the PCG spends with the child using child's outdoor activity frequency with PCG (PCGChildOutdoor) as the dependent variable. Given the mixed evidence of the impacts of physical activity on children's BMI (Goran et al. 1999;Nielson Media Research 2000), we have no priori expectation about the significance and the sign of this variable in the child's BMI function. Due to the data limitation, detailed information about the amount of food consumed by individuals is not available. Hence the third reduced form equation estimates the function of the household food expenditures (FoodExp) instead of the child's food expenditures. This substitution will not prevent us from examining the impacts of food expenditure on children's BMI. A reasonable assumption we can make is that an increase in the household food expenditure will cause an increase in the child's food expenditure. As higher amounts of food consumed may imply higher energy intakes, we hypothesize a positive casual relationship between household food expenditures and children's BMI. The head's health condition (HDHealth), the head's BMI (HDBMI), the PCG's health condition (PCGHealth), and the PCG's BMI (PCGBMI) along with a set of demographic variables are included in the system as type variables *k* defined in the theoretical model to assess the impacts of biological, genetic, and socio-demographic factors on PCG's choices and children's BMI. There is a growing body of research that addresses the influence of environmental factors related to children's psychological and emotional well-being on their BMI outcomes (e.g., Puhl and Brownell 2003; Friedlander, et al., 2003; Schwimmer et al., 2003; Zametkin et al. 2004). To explore such effects, a variable *Loved* which measures the child's perception of being loved or accepted by his/her parents and peers is included. Another environmental factor included is the number of children in the household (*NumChildren*). The variable *Lunchpro* intends to examine the effects of the National School Lunch Program (NSLP) on childhood obesity prevention. The NSLP is a federally assisted meal program that provides nutritionally balanced lunches to children each school day. We expect that the participation in the NSLP would help reduce children's BMI. Another important variable in the child's BMI function is *ActiveTime* which measures the weekly physical activity time of the child. The estimate of the effect of this variable will help advance our understanding of the relationship between physical activity and childhood obesity. The demographic variables *ChildWhite* , *Childgender* , and *Childage* describe the child's race, gender, and age.

*3.2 Econometric Issues*

We can express the above model in a more general form:

(7) $YB + X\Gamma = U$

Where $Y$ is a $N \times G$ matrix of dependent variables, $X$ is a $N \times K$ matrix of explanatory variables, and $U$ is a $N \times G$ matrix of disturbances. $N$ is the number of observations, and $G$ is the number of equations. We assume i.i.d. disturbances across observations. Further, we assume zero mean matrix of $U$ and a nonsingular covariance matrix $\Sigma \otimes I_N$ . $B$ is upper triangular. So we call it a triangular system of equations. As well known, if $\Sigma$ is diagonal, which implies the special case when unobserved individual effects are not correlated across equations, the model is the recursive specification of Wold (Hausman 2003). The system can be simply estimated using OLS equation by equation. However, in real world, the disturbances across equations are usually correlated. In our case, the PCG's time allocation, food expenditures and child's BMI functions cannot be assumed independent with each other. Therefore, we may turn to SUR model (Zellner 1962). SUR allows for the correlations of error terms across equations. In such context, we can rewrite the system of equation for each observation as

(8) $y_i = X_i\beta_i + u_i$

Where $y_i = [y_{1i}, y_{2i}, ..., y_{Gi}]'$, $u_i = [u_{1i}, u_{2i}, ..., u_{Gi}]'$, and

$$X_i = \begin{bmatrix} X_{1i} & 0 & 0 & \dots & 0 \\ 0 & X_{2i} & 0 & \dots & 0 \\ 0 & 0 & & & \vdots \\ \vdots & & & & 0 \\ 0 & 0 & & & X_{Gi} \end{bmatrix}, \qquad \beta = \begin{bmatrix} \beta_{1i} \\ \beta_{2i} \\ \vdots \\ \beta_{Gi} \end{bmatrix}$$

So $X_i$ is $G \times [K_1, K_2, ..., K_G]$ , and $K = [K_1, K_2, ..., K_G]$. We assume the orthogonality condition $E[X_i \otimes u_i] = 0$. We define $\Omega = E[u_i u_i^{'}]$ and further assume $\Omega$ is positive definite and $E[X_i^{'}\Omega X_i]$ is nonsingular. In practice, $\Omega$ is usually not available, we need to find a consistent estimator $\widehat{\Omega}$ for $\Omega$, i.e. plim $\widehat{\Omega} = \Omega$. We can have the general form of general least square (GLS) estimator or the feasible GLS estimator of $\beta$ in the following form (Woodbridge 2002):

(9) $\widehat{\beta} = (\sum_{i=1}^{N} X_i^{'}\widehat{\Omega}^{-1} X_i)^{-1}(\sum_{i=1}^{N} X_i^{'}\widehat{\Omega}^{-1} y_i), \quad \widehat{\Omega} = N^{-1}\sum_{i=1}^{N}\hat{u}_i\widehat{u}_i^{'}$

However, the performance of this estimator crucially depends on the assumption that $\widehat{\Omega}$ is a consistent estimator of $\Omega$, which requires a good priori knowledge on $\Omega$. The estimates from SUR regression can be iterated. For each iteration, new residuals will be generated which are used to construct a new weight matrix. Iteration may gain efficiency for the estimator, but again, we have to assume that the structure of $\Omega$ is correctly understood and specified. As suggested by Lahiri and Schmidt (1978), we will estimate an iterated SUR model in the analysis.

Another option we can turn to is the nonparametric approaches which are more robust to the deviation of underlying distributional assumptions and does not depend on tight functional form specifications. Based on the work of Roehrig (1988), Newey and Powell (1989), and Newey et al. (1999) regarding the estimation of triangular system of equations, Pinkse (2000) proposes a nonparametric polynomial estimator. Consider a structural model of the following form:

(10) $y_i = g_0(x_i) + \varepsilon_i$,

Where $x_i$ is a vector of endogenous variables. Then the reduced form equations of $x_i$ is

(11) $x_i = \Pi_0(Z_i) + \eta_i$

Where $Z_i$ is a vector of exogenous variables. The errors terms across equations are mutually correlated but are independent of $Z_i$. This setting exactly captures the structure of our model which consists of one structural equation and three reduced form equation with a non-diagonal variance matrix. Pinkse' nonparametric estimator does not impose distributional assumptions on error terms but only requires the existence of their second order moments. Furthermore, the functional forms of $g_0$ and $\Pi_0$ need not to be specified when using the Pinkse estimator. Hence, the estimates may be more robust to misspecification problems.

To apply Pinkse estimator, the first step is to estimate the vector $\Pi_0$ using nonparametric series regression to generate the residuals $\hat{\eta}$. The function $g_0$ is then estimated using nonparametric series regression of $y_i$ on ( $x_i, \hat{\eta}_i$). The series expansion of the focal *x* in a neighborhood will provide more information to smooth the observations in a local window, which ensures a better fit globally. Following Pinkse (2000), we use the commonly used Legendre polynomials for the first and second stage expansion, i.e. the j$^{th}$ term of the expansion around an endogenous variable *x* is constructed from the following recursion

(12) $(j+1)e_{X_{j+1}}(x) = (2j+1)\cdot x \cdot e_{X_j}(x) - j \cdot e_{X_{j-1}}(x)$

with $e_{X_0}(x) = 1/\sqrt{2}$ and $e_{X_1}(x) = 1/\sqrt{2/3}$.

Figure 1 shows the graph of Legendre Polynomials with the degree of 1 to 4.

**4. Data**

The data used in this study is the survey data from the national panel study of income dynamics (PSID) 2007. Since 1968, PSID has been providing longitudinal data on a wide variety of information about families' and individuals' economic and demographic characteristics, with substantial detail on income sources and amounts, employment, family composition changes, and residential location. In 1997, Child Development Supplement (CDS) data started to supplement PSID core data collection with additional information focusing on the human capital development of children in PSID families, including extensive measures of the children's home environment, children's time diaries in home and at school, school and day care environment, and measures of their cognitive, emotional and physical functioning. There have been three waves of CDS data since 1997: CDS-I 1997, CDS-II 2003, and CDS III 2007. This study uses CDS III 2007 data considering that the completed interview are more successful as the older children's have better ability to provide self-reported information in CDS III, as compared with CDS-I and CDS-II when the children were younger and a completed interview from the primary caregiver has to be considered a completed interview. After deleting missing values, our sample data resulted in 221 observations. Approximately 76% of the sampled PCG are white, and 20% are African-American with about 4% are Hispanic, Native Hawaiian or Pacific Islander, and Asian. The children in the sample are 12-19 years of age. Boys and girls account for half of the sample respectively. More importantly, the CDS collects time diaries from the sample children. These diaries provides information on how children across populations engage in a range of activities, which opens the possibility for us to examine the relationship between time spent in physical activities and childhood obesity. In our data, children's average weekly physical activity time is about 1664 seconds. The detailed summary statistics are presented in Table 1.

## 5. Results

### *5.1 Parametric ISUR Estimation*

Iterated seemingly unrelated regression (ISUR) estimates of the reduced form equations are reported in Table 2. In Column 2 of Table 2, the coefficient estimates suggest that the amount of time that a PCG inputs into market production to earn wage is influenced by her wage rate. As the wage rate increases, she works shorter hours. Although discussion of the reasons behind the reduction of working hours due to wage increase is beyond the scope of this paper, existing studies do suggest that wage increases could reduce working mothers' hours worked (e.g. Sabia 2007). The reduction could be both voluntary and involuntary. For example, Villa (1993) suggests that negative relationship between weekly hours worked and the gross hourly wage rate is due to the provision of fringe benefits. Further labor research needs to be done to examine the phenomenon. The household head's wage rate is negatively correlated with the PCG's working hours. The significant and negative coefficient of the household head's wage rate suggests that higher wage rate of the household head would influence the PCG to decrease her working hours. This may be attributed to the effects of higher income brought by the head which reduces the needs for the PCG to earn extra income for the household. An interesting finding is that if a PCG believes that an employed mother can establish as warm and secure a relationship with her children as a mother who is not employed, she will put more hours in market instead of in family. This results is indicated by the significant ($\alpha = 0.01$) and positive coefficient of the variable EmpMom which is a dichotomous variable indicating if a PCG holds that belief. Moreover, the number of children in a family is another influential factor that determines a

PCG's working hour input. The more children that a family has, the less hours a PCG will work for wages. This is an expected result, as more children requires the PCG to spend more time on parenting at home and thus indicates a need for less market participation.

The estimates of PCG's outdoor activity involvement function are reported in Colum 4 Table 2. As the estimates suggest, a PCG's health condition affects the frequency that she participates in her children's outdoor activities. Better health status could lead to higher participation frequency. Furthermore, higher BMI of a PCG is shown to lower the frequency of her involvement in children's outdoor activities. The outdoor activities include a broad range of physical activities, such as gymnastics, sports, cheerleading, art and crafts, dance, family groups, religious services, and etc. These findings are not surprising as physical conditions or functional impairments would affect people' capability and willingness to engage in outdoor activities. A PCG with less healthy status would face more physical challenges and limitations in outdoor activities which in turn cause her to choose to participate in these activities less frequently. The estimates also suggest the influence of a PCG's wage rate on her outdoor activity involvement with children. An increase of wage rate would increase the cost for a PCG to spend time with children in outdoor activities and thus may reduce the PCG-child outdoor activity involvement frequency. The negative coefficient of the PCG's wage rate in outdoor activity involvement function indicates this trend. Moreover, the results suggest the impact of a head's working hours on a PCG's participation in children's outdoor activities. The more time the head works, the less frequently that the PCG will play in outdoor activities with the children. This finding reflects the time constraint that a PCG faces in parenting when the head is out for work.

The obstacle posed by data limitation prevents us from analyzing detailed diet composition to investigate household energy intake patterns. For this reason, we use household food expenditures to estimate energy intake. One caveat of this proxy is that energy-dense nutrient-poor foods may be cheaper than less energy-dense foods, which allows for a higher energy intake at a lower cost. Consequently, it is possible that high food expenditures may not necessarily reflect high energy consumption but otherwise instead. Drewnowski and Specter's (2004) study shows a positive relationship between a household's energy intake and its diet costs in typical American diets. Hence, household food expenditures may still be able to serve as reasonable estimates for household energy intake. The food expenditure function estimates in column 5 Table 2 suggest that economic factors play a major role in determining how much a household would spend on food since the head's wage rate is the determinant of the amount of the food expenditures of a household.

Table 3 presents the estimates of the Child's BMI production function. A PCG's working time and participation in children's outdoor activities seem to have no significant impacts on children's BMI. These results do not support You and Davis's (2010) finding that PCG's time allocation choices would affect children's BMI. Regarding food expenditure, the confounding effects of energy cost may have caused the impact of food expenditure on children's BMI to be undetectable. Less energy-dense food, such as fruits and vegetables, usually carry higher price tags. Therefore, an increase in food expenditure may possibly reflect an energy intake decrease resulted from healthier food purchasing instead of an energy intake increase. Without information to document the detailed diet composition, we are unable to distinguish these effects. An interesting and notable finding is that parents' BMI significantly affect their children's BMI. Although biological factors may not be able to explain the rapid increase of obesity, parents' BMI do influence their children's BMI through their dietary behaviors and family environment. PCG's education also impacts children's BMI. It appears that more education of a PCG is associated with lower child BMI. It's possible that a PCG with more education will be able to make healthier food choices which would help lower children's BMI. Interestingly, the estimates do not suggest the significant impact of children's active leisure time on their BMI. It was hypothesized that more active leisure time would cause more energy expended. Therefore we expect to observe a significant and negative impact of active leisure time on children's BMI. However, the estimates do not suggest this trend.

*5.2 Semi-parametric Estimation*

Considering the system of equations includes a large number of explanatory variables, if we use fully nonparametric specification, the curse of dimensionality (i.e. the problem caused by the exponential increase in the number of extra dimensions added into the function space) would cause estimation difficulty and generate unacceptably large variances of estimates. Hence we take a semi-parametric specification which consists of an unknown nonparametric function of endogenous variables and additive parametric components:

$$\begin{aligned} ChildBMI = {} & \Pi_0(PCGWKHR, PCGChildOutdoor, FoodExp) \\ & + f_0(, HDBMI, HDHealth, PCGBMI, PCGage,\ PCGedu,\ PCGwhite, \\ & Lunchpro, ActiveTime,\ ChildWhite, Childgender,\ Childage,\ Loved, \\ & NumChildren) \end{aligned}$$

$$\begin{aligned} PCGWKHR = {} & \Pi_1(PCGWage, HDWKHR\ , HDWage, NlabIncome) \\ & + f_1(\ HDBMI, HDHealth, PCGBMI, PCGHealth,\ EmpMom, PCGage, \\ & PCGedu\ PCGwhite, Lunchpro, ActiveTime, ChildWhite, Childgender, \\ & Childage,\ \ Loved, NumChildren) \end{aligned}$$

$$
\begin{aligned}
PCGChildOutdoor = \Pi_2(&PCGWage, HDWKHR\ , HDWage, NlabIncome) \\
&+ f_2(\ HDBMI, HDHealth, PCGBMI, PCGHealth,\ EmpMom, PCGage, \\
&\quad PCGedu\ PCGwhite, Lunchpro, ActiveTime, ChildWhite, Childgender, \\
&\quad Childage,\ \ Loved, NumChildren)
\end{aligned}
$$

$$
\begin{aligned}
FoodExp = \Pi_3(&PCGWage, HDWKHR\ , HDWage, NlabIncome) \\
&+ f_3(\ HDBMI, HDHealth, PCGBMI, PCGHealth,\ EmpMom, PCGage, \\
&\quad PCGedu\ PCGwhite, Lunchpro, ActiveTime, ChildWhite, Childgender, \\
&\quad Childage,\ \ Loved, NumChildren)
\end{aligned}
$$

Where $\Pi_1, \Pi_2, \Pi_3$ are unknown functions which are expanded using Legendre polynomials series, while $f_1, f_2, f_3$ are additive linear functions. Another concern in the estimation is the orders of the polynomial in the first stage and in the second stage. The orders in the stage one and the stage two estimations can be different. It is not necessarily true that higher order smoothing will perform better than lower order smoothing. Systematic method for deciding optimal length of polynomials in the first stage and the second stage is not available in existing literature. Monte Carlo simulation results (Pinkse 2000) suggest that choosing 2 and 4 in the first and second regression stage separately would be good choices in terms of minimizing the mean squared errors. We therefore use the length of 2 and 4 for our first stage and second stage Legendre polynomial regressions respectively.

Table 4 and Table 5 report the results from the Pinkse (2000) semi-parametric estimation. In contrast with the ISUR estimates, the effects of PCG’s wage rate and the head’s wage rate on PCG’s working hour choice become insignificant. The consistent findings are the impacts of a PCG’s belief about the role of working mom and the number of children in a household on the PCG’s working time decision. The results suggest that if the PCG believes that an employed mother can establish as warm and secure a relationship with her children as a mother who is not employed, she will increase about 2 hours in a working week. Moreover, one more child increase in a family may cause the PCG to reduce about 2 hours working time per week ($\alpha = 0.01$). It can be reasoned that the need of child care plays an important role when the PCG decides how much time to work in market.

The estimates of PCG's outdoor activity involvement function in column 4 Table 4 also imply that a PCG's health condition can significantly influence the frequency that she participates in children's outdoor activities. This finding is consistent with the result from ISUR estimation, which suggests the robust effect of the health status of a PCG on her participation decision.

Household food expenditures are more associated with economic factors. The estimates in column 6 Table 4 suggest that a head's wage rate is the most influential factor of a household's food expenditures. Higher wage rate of the head would lead to higher spending on food. Ceteris paribus, on average, a dollar increase in a head's hourly wage rate may lead to 11 dollar increase in the household's monthly food expenditures ($\alpha = 0.01$). In line with the results of ISUR estimation, this finding suggests the impacts of income on food expenditures because the head is the primary income earner of a household and his wage rate largely determines the household income.

Table 5 reports the semi-parametric estimates from the child's BMI function. As in the ISUR estimation, the semi-parametric estimates do not suggest significant impacts of a PCG's working hours, the frequency of the child's outdoor activity with PCG, and household food expenditures on the child's BMI. The loose relations between these PCG choices and the child's BMI reflects the complexity of parenting impacts as they are related to children's dietary intake and energy expenditure. Notably, the semi-parametric estimates support the findings from ISUR estimation that parents' BMI significantly impact children's BMI. High BMI of parents could cause high BMI of their children, indicating that obese parents tend to have obese children. A plausible explanation behind this finding is that parents' energy intake and energy expense patterns which determine their own BMI may also indirectly affect their children's BMI, such as food and beverage preferences, exercise habits, and etc. Hence, the causes for adult obesity increase could also contribute to the rapid increase in childhood obesity. Furthermore, parents with higher BMI may be lack of efficient means for their own weight control, which in turn may lead to less effective control over children's weight gain.  In line with the findings from ISUR, the results indicate that the number of children in a household could also influence children's BMI. One more child increase in a family may lead to about a 0.8 increase in children's BMI. Quality of parenting and dietary intakes related to the family size may be a possible cause for such relation. As in ISUR estimation, the semi-parametric estimates suggest the insignificant impacts of physical activity time on children's BMI. Causal relationship between physical activity and childhood obesity cannot be established. Our findings add to the growing body of controversies about the relation between physical activity and body weight in literature (Robinson et al. 1993; DeLany et al. 1995; Treuth et al.1998; Goran et al.1999; Sallis 2003; Vandewate et al. 2004).

**6. Semi-parametric and Parametric Model Comparison**

How to choose an econometric model over others has always been a difficult task in applied research. There is a wealth of criteria that can be used to measure the model performance and adequacy, such as the variance explained by the model, error behaviors, robustness to the assumption deviations and misspefications, and other visual diagnostics. However, within-sample exploration of these attributes may not be as informative as researchers usually think for testing the model performance. White (2000) points out that the observed good performance of a model could only be due to luck instead of superior fit.

There is a trend in recent literature that advocates the using out-of-sample predictive ability to guide model choices (Corradi and Swanson 2007). Although such methods have become common in time-series research, cross-sectional applications are still rare. Racin and Parmeter (2009) propose an approach using sample-splitting for out-of sample prediction tests in cross-sectional studies. Their approach overcomes limitations of the popular predictive ability time-series tests, such as the reliance on only one split of the data and the need to have a sufficiently large hold-out sample to possess adequate test power, and provides practical metric for model choice based on predictive performance on independent and identically-distributed data. Suppose we have two models, Model A and Model B. Following Racin and Parmeter (2009), we could apply the proposed measure as:

(1). Use Bootstrap without replacement to resample original data set S times to form S resamples and index these resamples as $\left\{X_i^s, Y_i^s\right\}_{i=1}^n$;

(2). For each resample, we equally split the sample. Then we use the first half to form a training sample, $z_s^1 = \left\{X_i^s, Y_i^s\right\}_{i=1}^{n_1}$ and the second half to form the evaluation sample $z_s^2 = \left\{X_i^s, Y_i^s\right\}_{i=1}^{n_2}$

(3). Fit Model A and Model B on $z_s^1$ to obtain the regression models $\hat{g}_{z_s^1}^A$ and $\hat{g}_{z_s^1}^B$ for Model A and Model B respectively.

(4). Obtain predicted values using $z_s^2$ and compute the Average Squared Prediction Error (ASPE) for each model as: $ASPE_s^A = \frac{2}{n}\sum_{i=n/2+1}^{n}(y_i^s - \hat{g}_{z_s^1}^A(X_i^s))^2$, $ASPE_s^B = \frac{2}{n}\sum_{i=n/2+1}^{n}(y_i^s - \hat{g}_{z_s^1}^B(X_i^s))^2$

(5). Use the S draws to construct the empirical cumulative distributions of $\left\{ASPE_s^A\right\}_{s=1}^S$ and $\left\{ASPE_s^A\right\}_{s=1}^S$ respectively which can be used for statistical inferences.

Based on this algorithm, we test the performance of the semi-parametric model and iterated SUR model in terms of their ASPE using S=5000, S=10000, and S=50000 to avoid the random consequences of too few splits. Table 7 reports the P-value in each scenario. The test result suggests that the semi-parametric model is preferred to parametric model at α = 0.01 level when S = 5000. As we increase the number of splits, this trend does not alter, indicating the stochastic dominance of the semi-parametric model over the iterated SUR model. Figure 2 presents the empirical distribution functions of ASPE for each model. It presents a visual demonstration of the performance of different model specifications based on ASPE. There is a trend in Figure 2 that the gap between the empirical CDF of the two models tends to narrow when the number of splits increases from 5000 to 10000. The tendency continues when we increase the number of splits from 10000 to 50000. This trend suggests the asymptotic equivalency of the two estimators.

However, ASPE based tests are just indicators for relative predictive ability among alternative specifications. These tests are not about finding a “true” model which describes the true underlying data generating process but only provides a means to discriminate among models. Although the comparison indicates relatively better performance of the semi-parametric model, estimates from both parametric and semi-parametric approaches should be used jointly to examine the robustness of the results to model variations and to make more informative conclusions. Indeed, there is no large gap between the results from iterated SUR and the results from the semi-parametric polynomial estimation.

## 7. Conclusion

The main objective of this study is to examine the impacts of PCG's time allocation and food expenditure choices on children's BMI using nationally representative survey data. In contrast to previous studies, our results do not suggest the significant impacts of PCG's labor force participation choices, involvement in children's outdoor activity, and household food expenditures on children's BMI. Interestingly, the estimates from both iterated SUR and semi-parametric polynomial estimations indicate that parents' BMI significantly influence children's BMI. Obese parents tend to have obese children. This result cannot be solely attributed to the genetic influences as gene alone cannot explain the abrupt increase in childhood obesity. Furthermore, physical activity appears to have weak correlation with children's BMI. More physical activity time does not necessarily lead to lower BMI of children. These results reflect the complexity of the causes of childhood obesity. The second objective of this study is to investigate the applicability of parametric and semi-parametric approaches to estimate a simultaneous triangular system of equations, as the latter do not depend on restrictive distributional assumptions and tight functional forms. We compare the performance of the semi-parametric model and the iterated SUR model in terms of their ASPE. The ASPE tests indicate relatively better performance of the semi-parametric model. However, we do not observe dramatic changes in the results between the two models. The estimates from parametric and semi-parametric estimations are quite consistent, implying the robustness of our findings. In Summary, our results suggest that improving parent's behavior related to adult BMI reduction may also help lower their children's BMI. Although this paper does not reveal concrete evidences of what may have caused the rapid increase of childhood obesity, it does show that parents play a central role in fighting the epidemic.

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**Figure 1: Legendre Polynomial**

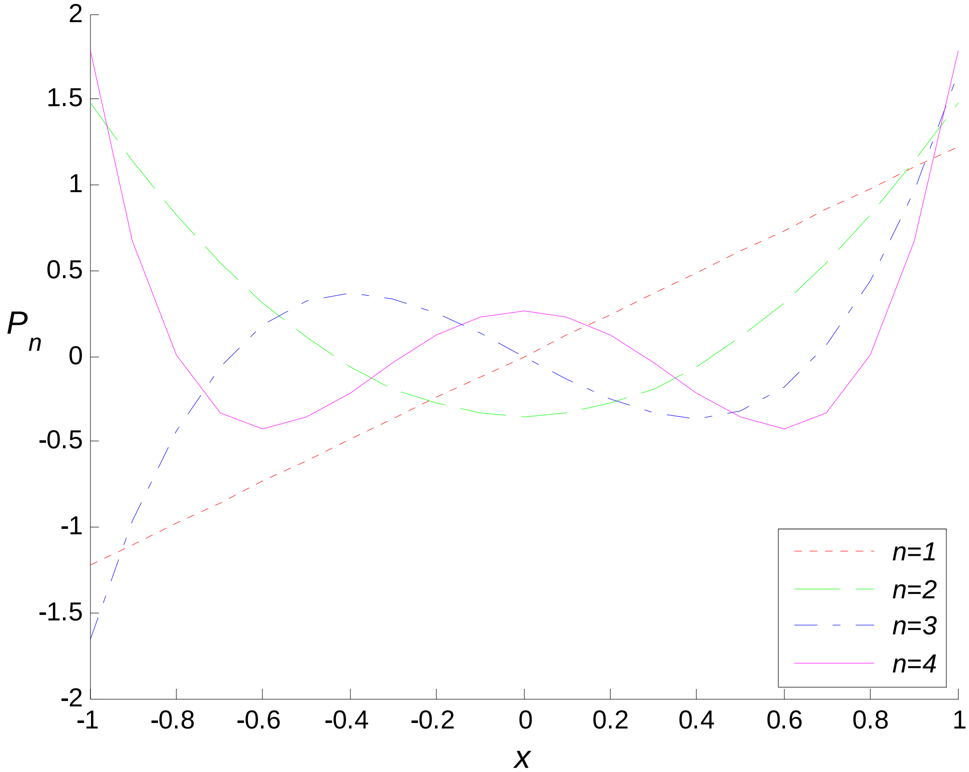
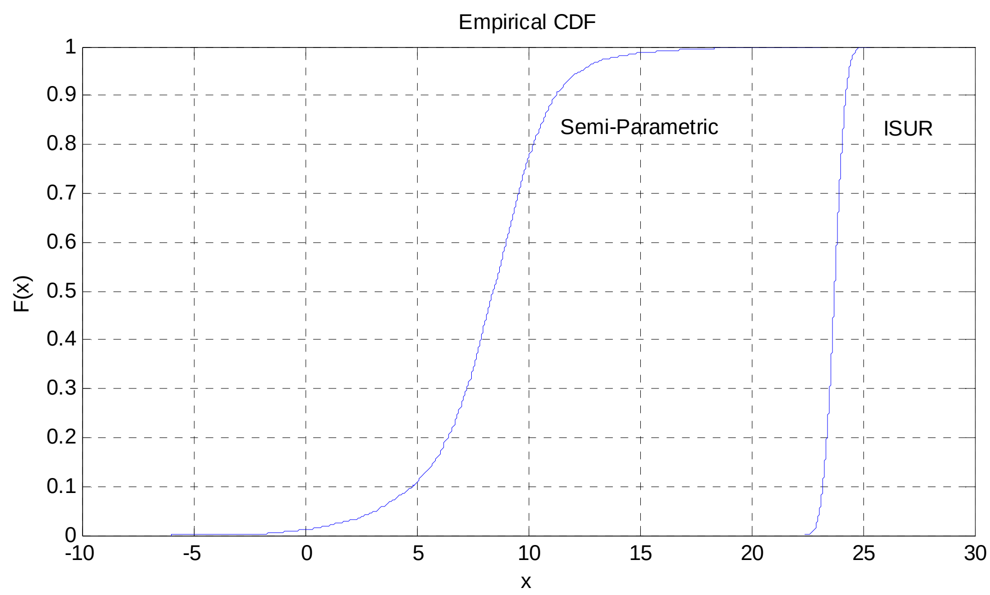
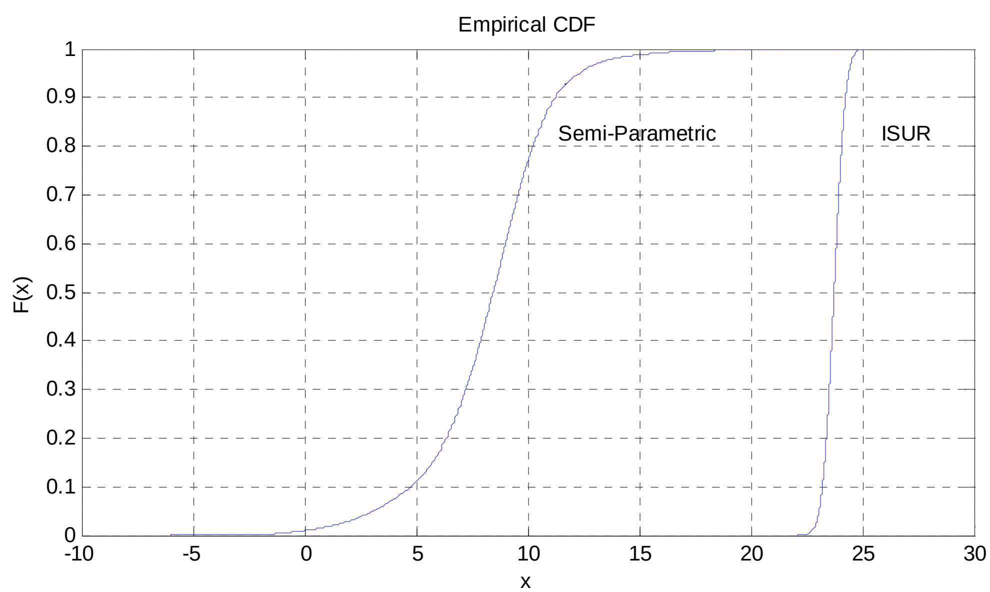


**Figure 2: Empirical Cumulative Distributions of ASPE (S = 5000, 10000, and 50000)**

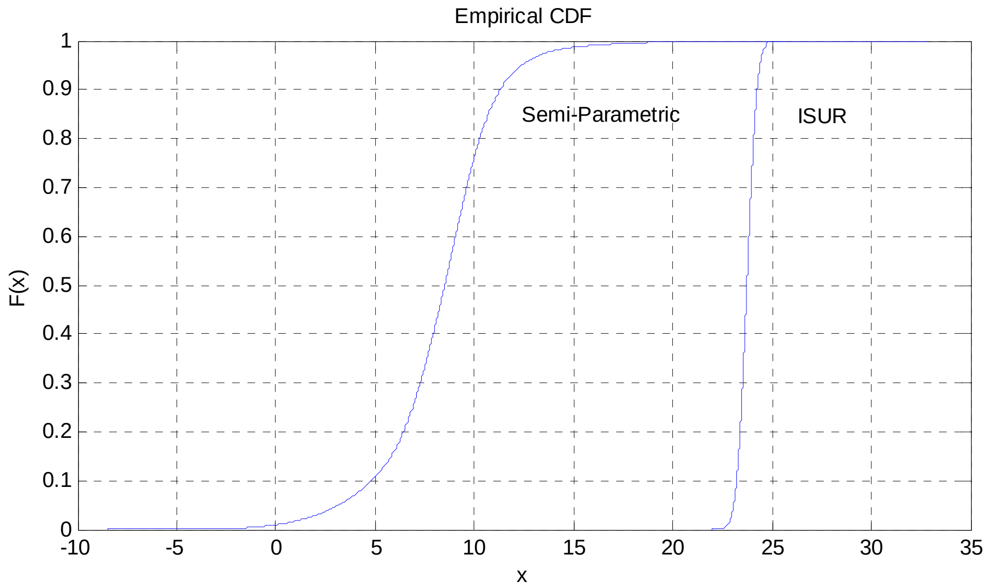



Splits = 5000




Splits = 10000

**Figure 2: Empirical Cumulative Distributions of ASPE (S = 5000, 10000, and 50000) -continued**




Splits = 50000

**Table 1: Variable Description (N=221)**

| Variables | Definition | Scale | Mean | S.D. | Min | Max |
|---|---|---|---|---|---|---|
| **Dependent** | | | | | | |
| PCGWKHR | Weekly working hours of PCG | Continuous | 37.24 | 17.99 | 1.00 | 100.00 |
| PCGChildOutdoor | Child's outdoor activity frequency with PCG | Categorical<br>1 = Never<br>2 = A few times a year or less<br>3 = About once a month<br>4 = A few times a month<br>5 = About once a week<br>6 = Several times a week<br>7 = At least once a day | 3.88 | 1.49 | 1.00 | 7.00 |
| FoodExp | Monthly food expenditures of a household | Continuous | 761.81 | 303.09 | 310 | 2200 |
| ChildBMI | BMI of the child | Continuous | 23.72 | 5.97 | 15.2 | 48.7 |
| **Independent** | | | | | | |
| PCGwage | Wage rate of PCG per hour | Continuous | 18.59 | 11.74 | 0.83 | 62.03 |
| EmpMom | If the PCG agrees that an employed mother can establish as warm and secure a relationship with her children as a mother who is not employed | Categorical<br>1 = Strongly disagree<br>2 = Disagree<br>3 = Agree<br>4 = Strongly agree | 3.24 | 0.70 | 1.00 | 4.00 |
| PCGBMI | PCG's BMI (weight in pounds *703)/(height in inches)$^2$ | Continuous | 27.77 | 6.74 | 15.94 | 54.86 |

| Variables | Definition | Scale | Mean | S.D. | Min | Max |
|---|---|---|---|---|---|---|
| PCGHealth | PCG's health status | Categorical<br>1 = Excellent<br>2 = Very good<br>3 = Good<br>4 = Fair<br>5 = Poor | 2.24 | 0.95 | 1.00 | 5.00 |
| PCGage | Age of PCG | Continuous | 42.96 | 6.03 | 29 | 58 |
| PCGedu | Completed years of education of PCG | Continuous | 13.79 | 2.42 | 0 | 17 |
| PCGwhite | If the PCG is white | Dummy | 0.76 | 0.43 | 0.00 | 1.00 |
| HDWKHR | Weekly working hours of head | Continuous | 46.30 | 11.53 | 9 | 91 |
| HDwage | Wage rate of head per hour | Continuous | 28.55 | 20.24 | 2.57 | 113.32 |
| HDBMI | Head's BMI (weight in pounds *703)/(height in inches)2 | Continuous | 28.75 | 4.70 | 19.86 | 46.11 |
| HDHealth | Household head's health status | Categorical<br>1 = Excellent<br>2 = Very good<br>3 = Good<br>4 = Fair<br>5 = Poor | 2.17 | 0.96 | 1.00 | 5.00 |
| NumChildren | Number of children in the family | Continuous | 1.82 | 0.92 | 1.00 | 7.00 |
| Lunchpro | If the child eats a complete hot lunch offered at school | Dummy<br>1 = Yes ; 0, otherwise | 0.64 | 0.48 | 0.00 | 1.00 |
| Loved | If the child feels or complains that no one loves him/her | Dummy<br>1 = Yes ; 0, otherwise | 0.82 | 0.39 | 0.00 | 1.00 |
| Childwhite | If the child is white | Dummy | 0.79 | 0.41 | 0.00 | 1.00 |

| Variables | Definition | Scale | Mean | S.D. | Min | Max |
|---|---|---|---|---|---|---|
| | | 1= Yes ; 0, otherwise | | | | |
| ActiveTime | Child's active leisure, sports and exercise time in weekdays and on weendends (in Seconds) | Continuous | 1663.98 | 4105.10 | 0 | 31020 |
| Childgender | Gender of the child | Dummy<br>1 = boy ;0 = girl | 0.51 | 0.50 | 0.00 | 1.00 |
| childage | Age of the child | Continuous | 15.38 | 1.84 | 12.08 | 19.09 |

**Table 2: ISUR Estimation of Reduced From Equations**

| | PCGWKHR Equation | | PCGChildOutdoor Equation | | FoodExp Equation | |
|---|---|---|---|---|---|---|
| Variables | Coefficients | Std.Err. | Coefficients | Std.Err. | Coefficients | Std.Err. |
| Constant | 23.87 | 13.33 | 10.52 | 1.58 | 305.88 | 320.70 |
| PCGWage | -0.21*** | 0.08 | -0.02* | 0.01 | 2.74 | 1.87 |
| HDWKHR | 0.11 | 0.07 | -0.02** | 0.01 | 2.44 | 1.62 |
| HDWage | -0.15*** | 0.04 | 0.00 | 0.01 | 4.92*** | 1.02 |
| NLabIncome | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| PCGBMI | 0.02 | 0.14 | -0.02 | 0.02 | -1.47 | 3.39 |
| HDBMI | 0.17 | 0.19 | -0.05** | 0.02 | 0.98 | 4.54 |
| HDHealth | -0.98 | 0.93 | 0.11 | 0.11 | 29.29 | 22.36 |
| PCGHealth | -1.11 | 0.96 | -0.23** | 0.11 | 15.12 | 23.18 |
| EmpMom | 3.24*** | 1.19 | 0.02 | 0.14 | 20.04 | 28.69 |
| NumChildren | -2.02** | 0.98 | 0.00 | 0.12 | 16.04 | 23.68 |
| PCGage | 0.10 | 0.17 | 0.01 | 0.02 | 0.60 | 4.01 |
| PCGedu | 0.43 | 0.41 | -0.11** | 0.05 | -3.71 | 9.92 |
| PCGwhite | -4.74 | 3.37 | 0.25 | 0.40 | 118.80 | 81.00 |
| Loved | -2.11 | 2.01 | 0.41 | 0.24 | 46.21 | 48.30 |
| Lunchpro | 4.96*** | 1.85 | -0.02 | 0.22 | 20.35 | 44.35 |
| ActiveTime | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Childwhite | 1.18 | 3.25 | -0.16 | 0.39 | -12.97 | 78.28 |
| Childgender | -1.23 | 1.73 | -0.21 | 0.21 | -20.09 | 41.63 |
| Childage | -0.17 | 0.46 | -0.17*** | 0.05 | -8.62 | 10.98 |
| R-Squared | 0.25 | | 0.18 | | 0.19 | |
| Chi-Squared | 74.57 | | 48.69 | | 53.85 | |

Notes: (*) denotes statistical significance at least at a=0.1. (**) denotes statistical significance at least at a=0.05. (***) denotes statistical significance at least at a=0.01.

## Table 3: ISUR Estimation of Children's BMI function

| Variables | Coefficients | Std.Err. |
|---|---|---|
| Constant | -9.31 | 6.84 |
| PCGWKHR | 0.03 | 0.03 |
| PCGChildOutdoor | 0.33 | 0.26 |
| FoodExp | 0.00 | 0.00 |
| HDHealth | 0.78* | 0.44 |
| PCGHealth | 0.01 | 0.46 |
| PCGBMI | 0.17*** | 0.07 |
| HDBMI | 0.18** | 0.09 |
| PCGage | 0.13* | 0.08 |
| NumChildren | 0.83* | 0.47 |
| PCGedu | -0.03 | 0.18 |
| PCGwhite | 1.71 | 1.60 |
| EMpMom | 0.44 | 0.57 |
| Loved | -0.65 | 0.96 |
| Lunchpro | 1.32 | 0.86 |
| ActiveTime | 0.00 | 0.00 |
| Childwhite | -2.43 | 1.52 |
| Childgender | 0.52 | 0.82 |
| Childage | 0.93*** | 0.22 |
| R-Squared | 0.19 | |
| Chi-Squared | 85.14 | |

Notes: (*) denotes statistical significance at least at a=0.1. (**) denotes statistical significance at least at a=0.05. (***) denotes statistical significance at least at a=0.01.

## Table 4: Semi-Parametric Polynomial Estimation of Reduced Form Equations

| | PCGWKHR Equation | | PCGChildOutdoor Equation | | FoodExp Equation | |
|---|---|---|---|---|---|---|
| Variables | Coeff. | S.E. | Coeff. | S.E | Coeff. | S.E. |
| Constant | 35.6096 | 14.9457 | 10.3239 | 1.8975 | 60.0597 | 384.1516 |
| PCGwage | -0.3088 | 0.2515 | 0.0467 | 0.0319 | 5.1350 | 6.4653 |
| HDWKHR | -0.0151 | 0.3082 | -0.0306 | 0.0391 | 11.2750 | 7.9219 |
| HDWage | -0.0336 | 0.1394 | -0.0043 | 0.0177 | 11.7314*** | 3.5823 |
| NLabIncome | 0.0003 | 0.0000 | 0.0000 | 0.0000 | -0.0002 | 0.0011 |
| PCGBMI | 0.1246 | 0.1389 | -0.0266 | 0.0176 | -1.6338 | 3.5706 |
| HDBMI | 0.0803 | 0.1871 | -0.0491** | 0.0238 | 0.5528 | 4.8093 |
| HDHealth | -0.2119 | 0.9218 | 0.0968 | 0.1170 | 32.3842 | 23.6929 |
| PCGHealth | -1.2443 | 0.9421 | -0.2235* | 0.1196 | 14.5626 | 24.2150 |
| EmpMom | 2.2194* | 1.1791 | 0.0568 | 0.1497 | 19.2197 | 30.3059 |
| NumChildren | -1.9696** | 0.9643 | -0.0129 | 0.1224 | 12.8456 | 24.7848 |
| PCGage | -0.0765 | 0.1669 | 0.0127 | 0.0212 | -0.4383 | 4.2886 |
| PCGedu | 0.2219 | 0.4096 | -0.1053** | 0.0520 | -7.4043 | 10.5281 |
| PCGwhite | -4.5752 | 3.2941 | 0.2593 | 0.4182 | 115.8031 | 84.6686 |
| Loveid | -1.0427 | 1.9823 | 0.3987 | 0.2517 | 33.3247 | 50.9519 |
| Lunchpro | 4.0893** | 1.8216 | 0.0299 | 0.2313 | 29.1662 | 46.8208 |
| ActiveTime | 0.0000 | 0.0002 | 0.0000 | 0.0000 | 0.0034 | 0.0051 |
| Childwhite | 1.9797 | 3.1910 | -0.1804 | 0.4051 | -25.3329 | 82.0186 |
| Childgender | -1.9951 | 1.7113 | -0.2227 | 0.2173 | -31.3686 | 43.9872 |
| Childage | -0.4238 | 0.4504 | -0.1585*** | 0.0572 | -5.8972 | 11.5762 |
| pcgwage2 | -0.0009 | 0.0023 | -0.0006* | 0.0003 | -0.0201 | 0.0589 |
| hrhd2 | 0.0006 | 0.0016 | 0.0001 | 0.0002 | -0.0465 | 0.0416 |
| wagehd2 | -0.0004 | 0.0007 | 0.0000 | 0.0001 | -0.0381** | 0.0187 |
| nlabincome2 | 0.0000 | 0.0000 | 0.0000* | 0.0000 | 0.0000 | 0.0000 |
| | | | | | | |
| R-Squared | 0.3632 | | 0.2039 | | 0.2139 | |
| F-value | 4.88 | | 2.19 | | 2.33 | |

Notes: (*) denotes statistical significance at least at a=0.1. (**) denotes statistical significance at least at a=0.05. (***) denotes statistical significance at least at a=0.01.

**Table 5: Semi-parametric Polynomial Estimation of Child' BMI Function**

| Variables | Coefficients | Std.Err. |
|---|---|---|
| Constant | -15.91 | 16.11 |
| PCGWKHR | 0.03 | 0.11 |
| PCGChildOutdoor | 2.16 | 2.36 |
| FoodExp | 0.00 | 0.01 |
| HDHealth | 0.85* | 0.49 |
| PCGHealth | 0.06 | 0.55 |
| PCGBMI | 0.18** | 0.07 |
| HDBMI | 0.19* | 0.11 |
| PCGage | 0.11 | 0.08 |
| NumChildren | 0.82* | 0.50 |
| PCGedu | 0.02 | 0.24 |
| PCGwhite | 1.47 | 1.73 |
| EMpMom | 0.38 | 0.64 |
| Loved | -0.67 | 1.14 |
| Lunchpro | 1.02 | 0.94 |
| ActiveTime | 0.00 | 0.00 |
| Childwhite | -2.33 | 1.61 |
| Childgender | 0.78 | 0.91 |
| Childage | 0.97*** | 0.32 |
| pcghr3 | 0.00 | 0.00 |
| pcghr4 | 0.00 | 0.00 |
| freqout3 | -0.02 | 0.04 |
| freqout4 | 0.00 | 0.00 |
| foodexp3 | 0.00 | 0.00 |
| foodexp4 | 0.00 | 0.00 |
| resid1 | -0.05 | 0.08 |
| resid2 | -0.66 | 1.28 |
| resid3 | 0.01 | 0.00 |
| | | |
| R-Squared | 0.27 | |
| F(27,193) | 2.68 | |

Notes: (*) denotes statistical significance at least at a=0.1. (**) denotes statistical significance at least at a=0.05. (***) denotes statistical significance at least at a=0.01.

**Table 6: ASPE Tests for Model Discrimination (null: the ISUR model has equal or improved predictive accuracy compared to semi-parametric model)**

| Splits | S = 5000 | S = 10000 | S = 50000 |
| --- | --- | --- | --- |
| p-value | 0.000 | 0.002 | 0.0006 |

# Appendices

## Appendix A: Beef Consumer Survey

# 1 Qualifying Questions

1.1 Do you eat beef? □ Yes □ No

**If Yes: would you like to participate in a 10 minute survey and a taste test for $10?**

**If Yes, continue; otherwise terminate.**

1.2 Are you over the age of 18? □ Yes □ No

**If Yes, continue; otherwise terminate.**

1.3 Are you the primary person who purchases food for your household?

□ Yes □ No

1.4 Are you the primary person who prepares food for your household?

□ Yes □ No

**Respondent must answer Yes to either 1.3 or 1.4 to continue; otherwise terminate.**

## 2 Beef Purchasing Behavior

2.1 Does the beef you consume at home usually come from the supermarket? □ Yes □ No

If **No**, where do you get it?

- □ Health/Natural Foods Store
- □ Farmers Market/Local Cooperative
- □ Directly from Producer
- □ Internet or Direct Mail Order

2.2 How many times a week does your household typically eat beef prepared at home?

- □ Less than once
- □ 1 – 2 times
- □ 3 or more times

2.3 How frequently do you typically purchase each of the following types of beef?

| | At least once a week | 2-3 times a month | About once a month | Less than once a month | Never |
|---|---|---|---|---|---|
| Ground beef | □ | □ | □ | □ | □ |
| Steak | □ | □ | □ | □ | □ |
| Roast | □ | □ | □ | □ | □ |

2.4 When you purchase beef, how many pounds of the following types of beef do you typically purchase at a time?

Ground beef: ___________lbs or □ Do not purchase

Steak: ___________lbs or □ Do not purchase

Roast: ___________lbs or □ Do not purchase

2.5 How much does your household spend on food that will be consumed at home during a typical week or month?

$ _____________ □ per week □ per month

2.6 Do you usually do your main supermarket shopping on one particular day of the week?

□ Yes □ No

If **Yes**, what day(s) of the week do you usually do your main supermarket shopping?

(Check all that apply)

□ Monday □ Tuesday □ Wednesday □ Thursday □ Friday □ Saturday □ Sunday

2.7 Do you usually go to the supermarket more often at a particular time of day?

□ Yes □ No

If **Yes**, when do you usually go to the supermarket of day?

□ Morning □ Noon □ Afternoon □ Evening

Other:_____________(Please specify)

2.8 What is your experience with "natural" beef? (Natural beef is minimally processed, and it cannot contain any artificial ingredients and any preservatives. Examples: Coleman's, Laura's Lean, etc.)

□ I have never heard of it.

□ I have heard of it, but never consumed it.

□ I have consumed it, but do not regularly consume it.

□ I consume it regularly.

2.9 What is your experience with "organic" beef? (Organic beef is USDA certified and it has USDA Organic seal on labels.)

□ I have never heard of it.

□ I have heard of it, but never consumed it.

□ I have consumed it, but do not regularly consume it.

□ I consume it regularly.

2.10 What is your experience with “pasture-fed,” “grass-fed” or “pasture-raised” beef?

□ I have never heard of it.

□ I have heard of it, but never consumed it.

□ I have consumed it, but do not regularly consume it.

□ I consume it regularly.

2.11 What is your expectation or impression regarding pasture-fed beef’s…

| | | | | |
|---|---|---|---|---|
| impact on *human health*? | □ Negative | □ Neutral | □ Positive | □ No expectation |
| impact on *environment*? | □ Negative | □ Neutral | □ Positive | □ No expectation |
| impact on *animal welfare*? | □ Negative | □ Neutral | □ Positive | □ No expectation |
| *taste* compared to conventional beef? | □ Worse | □ Indifferent | □ Better | □ No expectation |

## 3 Exercise and Health

3.1 How frequently do you undertake moderate or vigorous physical activities (including any activities that cause an increase in your heart or breathing rate so that you can talk but not sing, such as brisk walking, bicycling, vacuuming or other forms of exercise)?

- □ Less than once a week
- □ 1 – 2 times a week
- □ 3 or more times a week

3.2 Have you ever been diagnosed by a medical professional with any of the following? (Check all that apply)

□ Diabetes □ Heart disease. □ High blood pressure

□ High Cholesterol □ Obesity □ None of the above

3.3 Have any of your family members been diagnosed by a medical professional with any of the following? (Check all that apply)

□ Diabetes □ Heart disease. □ High blood pressure

□ High Cholesterol □ Obesity □ None of the above

3.4 How often do you read nutrition labels when deciding to buy a food product?

□ Always □ Rarely □ Never

□ Most of the time □ Sometimes □ Don't know

3.5 How often do you read health claims on packages when deciding to buy a food product? (Such as "low fat," "low cholesterol"…)

□ Always □ Rarely □ Never

□ Most of the time □ Sometimes □ Don't know

.

3.6 Please indicate whether you agree or disagree with the following statements

(1). High levels of vitamin A in the body are toxic.

□ Agree □ Disagree □ Not sure

(2). Vitamin E can help protect against the development of cardiovascular disease and cancer.

□ Agree □ Disagree □ Not sure

(3). Omega 3 fatty acids can help reduce the risk of heart attacks.

□ Agree □ Disagree □ Not sure

(4). CLA (conjugated linoleic acid) has an anti-cancer effect.

□ Agree □ Disagree □ Not sure

3.7 Please indicate whether you agree or disagree with the following statements

(1). Beta-carotene is a safe dietary source for vitamin A.

□ Agree □ Disagree □ Not sure

(2). Nuts and green leafy vegetables are good sources of Vitamin E.

□ Agree □ Disagree □ Not sure

(3). Canola and soybean oils are good sources of Omega 3 fatty acids.

□ Agree □ Disagree □ Not sure

(4). Butterfat and meat are good food sources of CLA.

□ Agree □ Disagree □ Not sure

# 4 Demographic Information

4.1 What is your gender? □ Male □ Female

4.2 What year were you born? __________

4.3 Which of the following options best describes your living arrangement?

□ Live alone □ Live with spouse / partner

□ Live with unrelated people □ Live with spouse / partner and children

□ Live with extended family □ Live with children

4.4 Including yourself, how many individuals currently live in your household? _______

a) How many infants (0-2 years old) are there in your household? _______

b) How many children (3-17 years old) are there in your household? _______

c) How many adults (between the age of 18-64) are there in your household? (Including yourself) ________

d) How many seniors (over the age of 65) are there in your household? (Including yourself) ________

4.5 What is your ethnicity?

□ White □ Native Hawaiian or other Pacific Islander

□ Black or African American □ Other___________

□ Asian □ Not Sure

□ American Indian/Alaskan Native

4.6 Are you of Hispanic or Latino background?

□ Yes □ No □ Not Sure

4.7 What is the highest level of education you have completed?

| | |
|---|---|
| □ No high school diploma or equivalent | □ Associate's degree |
| □ High school diploma or equivalent | □ Bachelor's degree |
| □ Some college/technical school | □ Graduate or professional degree |

4.8 What is your current employment status?

□ Employed part time (including students who work on campus or off campus)

□ Student (full time)

□ Employed full time

□ Unemployed

□ Homemaker (unpaid)

□ Retired

□ On disability

4.9 What is your spouse's/partner's current employment status?

□ Not applicable

□ Employed part time (including students who work on campus or off campus)

□ Employed full time

□ Unemployed

□ Homemaker (unpaid)

□ Retired

□ On disability

4.10 What is your approximate annual household income before taxes?

- □ Less than $10,000
- □ $10,000 - $19,999
- □ $20,000 - $29,999
- □ $30,000 - $39,999
- □ $40,000 - $49,000
- □ $50,000 - $59,999
- □ $60,000 - $69,999
- □ $70,000 - $79,000
- □ $80,000 - $89,999
- □ $90,000 - $99,999
- □ More than $100,000

4.11 Do you or any member of your household currently participate in any of the following food assistance programs?

□ Food Stamp Program (FSP)

□ Women, Infants and Children Program (WIC)

□ School Lunch program

□ None

# 5 Visual Test

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Lean Meat Color** | ☐ Very pale | ☐ Pale | ☐ Pink | ☐ Neutral | ☐ Red | ☐ Dark | ☐ Very dark |
| **Fat color** | ☐ Very white | ☐ White | ☐ Somewhat white | ☐ Neutral | ☐ Somewhat yellow | ☐ Yellow | ☐ Very yellow |
| **Meat Texture** | ☐ Very fine | ☐ Fine | ☐ Somewhat fine | ☐ Neutral | ☐ Somewhat coarse | ☐ Coarse | ☐ Very coarse |
| **Overall Acceptability** | ☐ Strongly like | ☐ Like | ☐ Somewhat like | ☐ Neutral | ☐ Somewhat dislike | ☐ Dislike | ☐ Strongly dislike |

# 6 Palatability Test

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Tenderness** | ☐ Very tender | ☐ Tender | ☐ Somewhat tender | ☐ Neutral | ☐ Somewhat tough | ☐ Tough | ☐ Very tough |
| **Juiciness** | ☐ Very juicy | ☐ Juicy | ☐ Somewhat juicy | ☐ Neutral | ☐ Somewhat dry | ☐ Dry | ☐ Very dry |
| **Flavor** | ☐ Very intense | ☐ Intense | ☐ Somewhat intense | ☐ Neutral | ☐ Somewhat bland | ☐ Bland | ☐ Very bland |
| **Overall Acceptability** | ☐ Strongly like | ☐ Like | ☐ Somewhat like | ☐ Neutral | ☐ Somewhat dislike | ☐ Dislike | ☐ Strongly dislike |

## 8 Pasture-fed Beef Evaluation

Overall, which sample of beef do you prefer?

□ Sample 1 (Pasture-fed beef ) □ Sample 2 (Conventional beef)
□Indifferent

If the answer is **Indifferent,** you can stop here and this completes the survey.

**Supermarket price of conventional beef: ___________/lb**

**Supermarket price of natural beef: ___________/lb**

**Supermarket price of organic beef: ___________/lb**

If you preferred conventional beef, how much would the pasture-fed beef have to be **<u>discounted</u>** compared to the price of conventional beef for you to buy it instead of conventional beef?

**$___________/lb**

If you preferred pasture-fed beef, how much **<u>more</u>** would you be willing to pay to trade your conventional beef for an equivalent amount of pasture-fed beef?

**$___________/lb**

What factors influence your preference for/against the pasture-fed beef relative to the conventional beef?
(Check all that apply)

□ Eye appeal

□ Flavor

□ Tenderness

□ Juiciness

□ Health benefits

□ Other (please specify): ______________________________________________

## Appendix B: Information Card

### Nutritional Facts about Grass-Fed Beef[2]

**Compared to the conventional beef*, grass-fed beef has:**

- **Higher concentrations of ß-carotene (also called ProVitamin A)**

*grass-fed steers incorporate higher amounts of β-carotene into muscle tissues as compared to grain-fed animals. β-carotene is a safe dietary source for vitamin A supplementation. Vitamin A is a critical fat-soluble vitamin that is important for normal vision, bone growth, reproduction, cell division, and cell differentiation.*

- **Higher concentrations of vitamin E**

*The concentration of natural vitamin E found in grass-fed beef is 2 - 4 times higher than that found in conventional beef. Vitamin E supplementation may help prevent or delay coronary heart disease, block the formation of nitrosamines, and protect against the development of cancers by enhancing immune function.*

- **Higher levels of Omega-3 fatty acids**

*Omega-3 fatty acids are essential fatty acids but cannot be produced by human body and they must thus be obtained from food. A proper balance of Omega-6/Omega-3 ratio helps maintain and improve health. Beef from cattle fed primarily on grass has approximately 60% more Omega-3 fatty acids than conventional beef and a more favorable Omega-6 to Omega-3 ratio.*

- **Higher levels of Conjugated Linoleic Acid (CLA)**

*Grass-fed cattle produce 2 to 3 times more CLA than conventional beef. Animal tests results have suggested that numerous health benefits can be attributed to CLA, including actions to reduce carcinogenesis, atherosclerosis, onset of diabetes, and fat body mass.*

* Conventional beef refers to beef produced from cattle fed in confinement on concentrate-only diets.

[2] Daley, C.A., A.Abbott, P. Doyle, G. Nader, and S. Larson. California State University, College of Agriculture, University of California Cooperative Extension Service. (2006, May). A literature review of the value-added nutrients found in grass-fed beef products.