EMPIRICAL MODELS OF ECONOMIC CHOICE PROCESSES

By

MIGUEL HENRY-OSORIO

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The members of the Committee appointed to examine the dissertation of MIGUEL HENRY-OSORIO find it satisfactory and recommend that it be accepted.

____

Ron C. Mittelhammer, Ph.D., Co-Chair

Vicki McCracken, Ph.D., Co-Chair

Jill McCluskey, Ph.D.

Levan Elbakidze, Ph.D.

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Abstract

by Miguel Henry-Osorio, Ph.D.
Washington State University
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Co-Chairs: Ron C. Mittelhammer and Vicki McCracken

The first chapter provides the first empirical attempt in using the new maximum likelihood-minimum power divergence (ML-MPD) binary response estimator. This nonparametric maximum likelihood estimator is used to model the underlying behavioral decision process leading to a person's willingness to pay (WTP) for recreation site attributes. The probit model and the Kriström/Ayer's estimators are also implemented. Based on the decision context and demographics of decision makers visiting the recreation sites, the ML-MPD approach suggests a more defensible representation of the underlying data-generating process and economic decision-making behavior.

In the second chapter, a two-stage sequential experiment was conducted in a retail grocery setting to elicit WTP for four food products. In the first stage (round), participants bid on one of the four products. In the second stage, participants bid simultaneously for the other three products. The WTP for the food items was elicited using the Becker-DeGroot-Marschak (BDM) experimental auction procedure. I examine factors that may affect participants' bidding behavior across the two rounds. One factor is the uncertainty associated with the binding product in the second round, and the other one is a potential compensation effect on participants' bidding behavior across the two rounds. Results suggest that bids are sensitive to the context of bidding and to participants' preferences. Compensation has little impact on individual's bidding decision.

However, there is some evidence that the uncertainty about which product will be binding in the second round, or the round order, can have an effect on participants' bidding decisions.

The third chapter provides a first attempt at examining household purchase dynamics for dietary fiber, using a dynamic Tobit model that accounts for censoring across households and time as well as temporal correlations between current and previous purchases by adopting a stationary Gaussian first-order autoregressive choice process. Results indicate that household purchase decisions are characterized by significant unobserved heterogeneity, statistically significant positive serial correlation, and negative and significant state dependence, implying that lagged purchases have a strong effect on current household decisions so that households purchasing previously would buy less fiber in the current period.

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CHAPTER ONE

INTRODUCTION

McFadden (2001) notes that

> "*In the 1960's, rapidly increasing availability of survey data on individual behavior, and the advent of digital computers that could analyze these data, focused attention on the variations in demand across individuals. It became important to explain and model these variations as part of consumer theory, rather than as ad hoc disturbances.*"

This doctoral dissertation embraces empirical contributions in this line and specifically on new econometric methods (information-theoretic econometrics), contingent valuation, consumer and household economics, and food economics. It discusses microeconometric analyses of choice behavior of consumers and households facing discrete and dynamic choice processes, respectively. Econometric analyses conducted in this dissertation rely on individual level cross-sectional data and household panel data.

The main objectives of this dissertation are threefold: 1) to model the underlying discrete decision process that leads to a person's willingness to pay (WTP) for recreation site attributes, 2) to model the consumers' bidding behavior for food items, and 3) to model household purchase dynamics for dietary fiber.

Since the late 1980s, the large majority of practitioners who have applied discrete choice models empirically have chosen parametric statistical procedures on the basis of precedent and readily available software. Several distribution-free estimators for estimating binary response models (BRMs) have been proposed in the literature to overcome model misspecification problems that arise when adopting an incorrectly assumed error distribution. However, none of these estimators have found widespread application in the empirical discrete choice literature. The second chapter of this dissertation provides the very first and unique empirical application of the new maximum likelihood-minimum power divergence (ML-MPD) binary response estimator in which the parametric functional form of the conditional expectation as well as the parametric family of probability distributions underlying binary responses are not specified a priori. This application models the underlying behavioral decision process that leads to a person's WTP for recreation site attributes.

Research on consumer's bidding behavior has been carried out in a wide variety of settings related to WTP, with field experiments mostly used in the last decade. In the context of food experimental economics and as documented by Lusk and Shogren (2007), an important body of research related to preference elicitation has been carried out employing incentive compatible/non-hypothetical auction mechanisms such as the first and Vickrey second price auction formats, the random n*th* price auction, and the Becker-DeGroot-Marschak (1964; hereafter, BDM) auction procedure. This study employs the BDM mechanism in two sequential and separate stages (bidding rounds) to elicit shoppers' WTP for four food items (flax-seed bread, organic milk, organic apples, and conventional milk) in a retail grocery setting. It models consumers' bidding behavior using different econometric methodologies to investigate two factors that may affect participants' bidding behavior across the two rounds. The first is the uncertainty associated with the binding product in the second round, and the other is a potential compensation effect on participants' bidding behavior across the two rounds.

The last two decades have seen growing consumer demand for a more healthful food supply. Indeed, Hasler (1998) notes that there has been a "revolution in the health-enhancing role of specific foods or physiologically-active food components”. The health-enhancing functional properties of dietary fiber (e.g., reduced risk of coronary heart disease, stroke, hypertension, obesity and certain types of cancer) has received considerable attention from nutritionists and food scientists and most recently from the U.S. government. To help consumers, nutrition labels mandate that fiber content be listed on the “Nutrition Facts” panel (NFP). Nevertheless, the average fiber intake for children and adults in the U.S. is still less than half of the recommended amounts (Slavin, 2005; Anderson *et al.,* 2009). This latter study updates existing literature on consumer/household demand for fiber, investigating what drives demand for dietary fiber in a dynamic choice process at the household level context, controlling for temporal correlations between current and previous purchases and the censoring of observations across households and over time. The main goal is to better understand U.S. household consumption dynamic decisions regarding fiber, analyzing their intertemporal purchasing behavior. Erdem, Imai and Keane (2003) argue that studying household/consumer choice in a static context might lead to serious misspecification in markets, considering that purchases by economic agents occur frequently. This research may provide new insights that ultimately improve interventions or educational policies to enhance demand for dietary fiber.

Dissertation Format and Content

This dissertation is presented as three separate, stand-alone studies. Chapter two estimates the WTP for recreation site attributes at the Caribbean National Forest in Puerto Rico using the new ML-MPD binary response estimator, the probit model and the

Kriström/Ayer's approach. Empirical choice probabilities, mean WTP measures for recreation site attributes, and marginal probability effects of decision-maker characteristics are estimated based on a real stated-preference on-site contingent valuation dataset, collected during the summers 2004 and 2005. The ML-MPD, which overcomes model misspecification issues that arise when imposing an incorrectly assumed error distribution, is free of subjective choices relating to tuning parameters, and has the flexibility to fit very robust types of shapes to the choice distribution underlying decisions made by decision makers, yields a significantly lower mean WTP estimate ($27.80) to attend the recreation sites compared to mean WTP measures obtained from the probit ($120) and Kriström/Ayer's ($97) approaches. Based on the decision context and demographics of decision makers visiting the recreation sites, the ML-MPD approach suggests a more defensible representation of the underlying data-sampling process and economic decision-making behavior. As such, it bodes well for future applications to discrete choice modeling.

Chapter three models consumer's bidding behavior for food items using a novel two-stage sequential field experiment. The experiment was conducted in a retail grocery setting to elicit WTP for flax seed bread, conventional milk, organic milk, and organic apples. In the first stage (round), participants bid on one of the four products selected randomly, while in the second round participants bid simultaneously for the other three products in a homegrown setting. After determining whether or not the participant won the first bidding round, the participants moved to the second round where they submitted bids for the other three products simultaneously. The binding product in the second round was selected randomly. The WTP for the food items was elicited using the BDM experimental auction procedure. In this study, the interest is in two factors that may affect participants' bidding behavior across the two rounds. One is the uncertainty associated with the binding product in the second round, and the other one is a potential compensation effect on participants' bidding behavior across the two rounds. Willingness to pay was modeled as a function of design variables and participant specific characteristics, obtained from a survey completed after the experiment. Econometric analyses were performed using Powell's semiparametric symmetrically censored least squares procedure, the ordinary least squares approach, Tobit I, Tobit III (Heckman two-step model), and a unconstrained Seemingly Unrelated Regression system model. Estimation results suggest that bids are sensitive to the context of bidding as well as participants' preferences for particular foods. The results also differ across estimation procedures. Compensation mainly did not impact individual's bidding decision. However, there is some evidence that the uncertainty about which product will be binding in the second round, or the round order, can have an effect on participants' bidding decisions.

Chapter three updates existing literature on consumer/household demand for fiber by examining household purchase dynamics for dietary fiber. It uses a dynamic Tobit model that allows past purchase occasions to affect current purchase decisions for fiber in a framework that captures simultaneously state dependence, unobserved households heterogeneity preferences, and serial correlation caused by a stationary first-order choice process. The model controls for the unobserved heterogeneity by adopting a Gaussian random effects specification. It also captures variations in prices over time and controls for left-censoring. The dynamic model is estimated using the *Geweke-Hajivasssiliou-Keane* recursive probability simulator and a unique dataset that contains detailed fiber purchase information of households as well as the purchase price, promotion deal, and household demographic information over time. This data design also responds to the most recent needs and newest directions in agricultural economics, as the National Research Council (2005) and Unnevehr *et al.* (2010) recognize. It was achieved by merging the 2009 Nielsen Homescan panel data and the 2005-2011 Gladson databases using heuristic algorithms and multiple sequential imputations based on product information (e.g., the Universal Product Code). Overall, household purchase decisions are found to be characterized by significant unobserved heterogeneity, statistically significant positive serial correlation, and negative and significant state dependence, implying that lagged purchases have a strong effect on current household decisions such that households purchasing previously at time period t-1 would buy less fiber at time t. Estimation results also reveal that covariates that are not integral determinants of fiber purchases are household participation in the WIC program, the age and presence of children between 13 and 17, not being Hispanic, and the employment level of the female head. Furthermore, the education level of the female head has a negative impact on fiber purchases, whereas use of coupons has the opposite effect.

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CHAPTER TWO

AN INFORMATION-THEORETIC APPROACH TO MODELLING BINARY CHOICES: ESTIMATING WILLINGNESS TO PAY FOR RECREATION SITE ATTRIBUTES

ABSTRACT

This study applies the new maximum likelihood-minimum power divergence (ML-MPD) binary response estimator developed by Mittelhammer and Judge (2011) to model the underlying behavioral decision process that leads to a person's willingness to pay for recreation site attributes. Empirical choice probabilities, willingness to pay (WTP) measures for recreation site attributes, and marginal probability effects of decision-maker characteristics are estimated based on a real stated-preference on-site contingent valuation data, collected at the Caribbean National Forest in Puerto Rico. For comparison purposes, the linear probit model and the Kriström (1990)/Ayer (1955)'s estimators are implemented. The ML-MPD method yields a significantly lower mean WTP estimate ($27.80) to attend the recreation sites compared to WTP measures obtained from the fully parametric ($120) and fully non-parametric ($97) approaches. I argue, based on the decision context and demographics of decision makers visiting the recreation sites, that the ML-MPD approach suggests a more defensible representation of the underlying data-generating process and economic decision-making behavior. As such, the ML-MPD estimator suggests future potential for improved econometric analyses of discrete behavioral decision choice processes.

1. Introduction

Economists have used diverse valuation techniques[1] to analyze choice processes in a wide variety of settings related to willingness-to-pay (WTP) for private or public goods and related policy analyses (Adamowicz, 2004). Among these tools, stated preference techniques, also known as direct or contingent valuation (CV) methods, stand out because of their frequent application and complexity compared with revealed preference methods (Adamowicz and Deshazo, 2006).[2]

Behavioral models have become the dominant framework in the theoretical and empirical choice literature for understanding the underlying decision processes that lead to a person's WTP. These models are also useful for estimating welfare measures based on stated preference data. As Louviere, Hensher and Swait (2000) point out, these choice models and their underlying assumptions, stemming from McFadden's seminal work on random utility maximization theory, form the theoretical context for discrete choice models, including binary response models (BRMs).

Since the late 1980s, the large majority of practitioners who have applied discrete choice models empirically have chosen parametric statistical procedures on the basis of precedent and readily available softwares. Typical methods of analysis require a full parametric functional specification of the relationship between the regressors and the response variable, and more importantly, a full specification of a parametric distribution of the disturbances (e.g., the probit (normal) or logit cumulative distribution functions [CDFs]). Although some distributional assumptions can be benign, especially if the

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[1] Hanemann, Loomis and Kanninen (1991), Cameron (1992), Englin, Lambert and Shaw (1997), Brownstone and Train (1999), and Atkinson, Healey and Mourato (2005) constitute very few of many applications of these valuation techniques.

[2] For a more comprehensive review of the CV instrument, see Hausman (1993), Diamond and Hausman (1994), Hanemann (1994), and Venkatachalam (2004).

parameterization is flexible enough to describe behavior adequately (McFadden, 1994; McFadden and Train, 2000), the implementation of an incorrect parametric functional form can lead to spurious statistical inferences due to biased and inconsistent estimates. Moreover, underlying economic theory provides little guidance for these functional specifications, so there is insufficient information regarding the appropriate distribution to adopt in practice (Mittelhammer, Judge and Miller, 2000; Crooker and Herriges, 2004). Thus, any (parametric) functional specification for either the stochastic error or the utility differences used in these methods is in general uncertain and questionable (Creel and Loomis, 1997).

This study applies the new ML-MPD binary response estimator, developed by Mittelhammer and Judge (2011), in which the parametric functional form of the conditional expectation as well as the parametric family of probability distributions underlying binary responses are not specified a priori. The ML-MPD estimator begins in a nonparametric context regarding model specification. Then, information theoretic methods are applied to orthogonality relationships in the form of sample moments that lead to a parametric family of probability distributions, a conditional expectation function for the BRM, and estimators for the unknowns of the model. Unlike most nonparametric methods, the ML-MPD does not employ the usual kernel density estimation methodology with the attendant implementation choices relating to bandwidth, kernel function, and other tuning issues. The ML-MPD approach effectively avoids using model specification information that the econometrician generally does not really have, and thereby reduces the potential for specification errors. The ML-MPD estimator is ultimately based on a large varied family of CDFs, relies only on a minimal set of orthogonality conditions, and is free of user specified tuning parameters.

Several distribution-free estimators for estimating BRMs have already been proposed in the literature to overcome model misspecification issues (e.g., Manski, 1975; Turnbull, 1976; Cosslett, 1983; Horowitz, 1992; Matzkin, 1992; Klein and Spady, 1993; Li, 1996; Chen and Randall, 1997; Creel and Loomis, 1997; Huang, Nychka and Smith, 2008). However, none of these estimators have found widespread application in the empirical discrete choice literature for a number of reasons that may include: 1) users' lack of understanding regarding the estimation and inference gains of the approach in empirical applications; 2) difficulty in interpreting results of the analysis; 3) nonidentification of model parameters (e.g., the Klein and Spady (1993) estimator[3] [KS]); and 4) ambiguity and/or uncertainty regarding the appropriate choices for tuning parameters and other estimator implementation-computational issues.

Creel and Loomis (1997) underscore that the required scale and local normalizations for the identification of KS parameter estimates are questionable because they go beyond restrictions implied by demand theory. Moreover, it has been found that other suggested semiparametric methods do not achieve root-*n* consistency (e.g., the Manski [1985] and Horowitz [1992] estimators), and their finite sample behavior is in question (e.g., the Cosslett [1983], KS and Ichimura [1993] estimators).[4] And while fully non-parametric estimation techniques tend to be more robust to incorrect functional specifications of conditional expectation functions as well as probability distributions, they involve various choices of tuning parameters, kernels, and other implementation choices.

[3] The KS estimator is considered a "best" semiparametric estimator because its asymptotic covariance matrix has been shown to achieve the semiparametric efficiency bound.
[4] See Chen and Khan (2003) for more details.

Sampling behavior in smaller-sized samples is also problematic. Crooker and Herriges (2004) state that the gains and losses from using non-parametric and semi-parametric estimators to recover WTP measures relative to the standard parametric approaches are still unknown. There remains a continuing need to seek robust and efficient methods for analyzing discrete choice behavior.

The empirical application in this study relates to a stated-preference CV on-site dataset collected at the Caribbean National Forest (CNF) in Puerto Rico (other researchers who have used this data include Gonzalez, Loomis and Gonzalez-Caban (2008) and Santiago and Loomis [2009]). In order to compare the new ML-MPD estimator to other leading methods for analyzing BRMs, I implemented two prominent alternative estimation methods, including a fully parametric and a fully nonparametric estimator that have been employed in the CV literature, in particular, the linear index probit model and the Kriström (1990)/Ayer *et al.* (1955) approach.

In the next section, I describe and characterize the dataset utilized in this study. Section 3 presents the implementation of the ML-MPD estimator in detail. In section 4, I discuss the estimation results, and I provide concluding remarks in section 5.

2. Data

The dataset is comprised of 718 in-person interviews acquired at ten different recreation sites along the Mameyes and Espiritu Santo rivers at the CNF in Puerto Rico during the summers of 2004 and 2005. The data was collected through dichotomous-response CV surveys, employing the single-bounded[5] bidding approach as the elicitation protocol,

[5] This approach has the potential to be less efficient than the double-bounded protocol, however, McFadden (1994) and Cooper, Hanemann and Signorello (2001) have documented that the single-bounded CV question eliminates the response inconsistency and its associated bias.

which is also referred to in the literature as the "*closed-ended*" CV approach or the "*take-it-or-leave-it"* approach. Additional details of the survey and its design are given in Gonzalez-Sepulveda (2008).

The survey asked each recreation user the following CV question: "*Taking into consideration that there are other rivers as well as beaches nearby where you could go visit, if the cost of this visit to this river was $____more than what you have already spent, would you still have come today?___Yes___No*". The hypothetical cost of the visit was randomly drawn from a pool of 18 bid thresholds for each respondent, and ranged from $1 to $200 (see appendix). Information on site attributes (road quality, volume and speed of water in the pools, and size of rocks around the pools), the recreation user's income, and trip information (travel cost and travel time) were also collected. Previous work demonstrated that when including trip information in the models, the signs of the estimated coefficients for "travel cost" and "travel time" were not consistent with theoretical expectations. By including travel time information as an indicator (= 1 if the travel time to the CNF is more than 30 minutes and equal to 0 otherwise), as Cameron and James (1987) propose, I obtain theoretically consistent results. Tables 2.1 and 2.2 summarize the variables included in the estimated model, along with selected descriptive statistics.

The socio-demographic information in table 2.2, indicate that lower income, moderately educated, middle-aged male visitors dominated the sample outcomes.

3. Model and Estimation Framework

I present the ML-MPD estimation procedure in this section. The linear probit model and the nonparametric[6] estimators are well documented in the literature and are not reviewed here. All of the statistical approaches used in this study allow one to model the underlying decision-makers' choices made from a single, finite and exhaustive choice set with mutually exclusive alternatives. I calculated a compensated WTP measure as an aggregate net estimate of WTP for the probit ML and ML-MPD models based on a grand constant term (see Hanemann, 1984, 1989). Regarding the Kriström/Ayer's approach, I estimated the mean WTP through numerical integration of the estimated survivor function (i.e., WTP probability distribution), excluding the possibility of negative bids. The median WTP, in turn, is derived by finding the amount whose acceptance probability equals 0.5.

This study makes the usual assumption that the observable discrete responses are the outcomes of utility-maximizing choices made by decision-makers. The behavioral decision process is assumed to be based on a linear and additive utility index, $\mathbf{Y}_{\mathbf{i}}^{*} = \mathbf{x}_{i.}\boldsymbol{\beta} + \boldsymbol{\varepsilon}_{\mathbf{i}}^{*}$, also known as a latent index model or a discrete choice behavioral-Random Utility Maximization model, so that recreators choose the alternative that generates the greatest indirect utility.

3.1 Minimum Power Divergence Distributions

To motivate the ML-MPD estimator, note that the n-dimensional vector of unknown Bernoulli probabilities corresponding to the BRM,

[6] Boman, Bosted and Kriström (1999) show how Kriström/Ayer's approach can be reinterpreted as an approximation of Dupuit's consumer surplus. This describes what consumers would be willing to pay for obtaining some units of a good.

$$P\left(y_i = 1 \mid x_i\right) = p_i = 1 - F\left(-\mathbf{x}_{i.}\boldsymbol{\beta}\right) = F_*\left(\mathbf{x}_{i.}\boldsymbol{\beta}\right),\ i = 1,\ldots,n, \tag{1}$$

is associated with an unknown *link or transformation function* $\mathrm{F}(\cdot)$ of factors affecting the decision environment and that in practice is expressed in terms of an *index function*[7] that is often linear. However, more generally, one can always characterize the Bernoulli random variables $\left[Y_1, Y_2, \ldots, Y_n\right]^{\mathrm{T}} \in \mathbb{R}^{\mathrm{n}}$ as being defined by $Y_i = p_i + \varepsilon_i, \forall i$, with zero-mean error, $E\left(\varepsilon_i\right) = 0$. Without knowledge of the particular distributional specification of the link function, the traditional ML approach is not available. One might then consider a Quasi-ML approach, but this method does not assure the full set of attractive ML sampling properties (Mittelhammer, Judge and Miller 2000), and moreover, it is difficult to characterize the actual sampling properties in any given application. Alternatively, one might consider the two-stage Generalized Method of Moment (GMM) estimator; however, the approach is not appealing for the current application due to the ill-posed, underdetermined nature of the estimating equations of the problem (see equation (2) ahead).

I pursue an empirical likelihood type estimator of $\boldsymbol{\beta}$ instead. Unlike classical estimation procedures, these estimators rely on Kullback's (1959) information theoretic minimum discrimination information principle[8] as well as on data-moment constraints, as

[7] This index is usually a function of the covariates $\mathbf{x}$ and a vector of $\boldsymbol{\beta}$ unknown parameters, which is estimated along with the link function. Although non-linear specifications and the linear Box-Cox utility function are also possible, the commonly used linear index representation $\mathbf{x}_{i.}\boldsymbol{\beta} \equiv \beta_0 + \mathbf{x}\boldsymbol{\beta}_1$, with $\boldsymbol{\beta}_1$ being a vector of parameters, is considered in this study.

[8] An alternative to this principle is the maximum entropy principle, also known as the Shannon's (1948) entropy measure or the generalized maximum entropy approach. Although there are some recent theoretical and empirical contributions in the econometric literature using the latter approach (e.g., Golan, Judge and Perloff, 1996; Crooker and Herriges, 2004; Marsh and Mittelhammer, 2004) a user of the method is also confronted with a notable number of "tuning parameter" type of decisions to make, for which the performance consequences are not well known currently.

defined in Mittelhammer and Judge (2011). The basic estimation principle is to jointly estimate the unknown parameters of the model along with the empirical sampling distributions that exhibit minimum discrepancy relative to a reference distribution. The ML-MPD approach is robust in terms of the uncountably infinite number of candidate distributions (such as symmetric, skewed, uniform) that are members of the distribution class. It also maintains the full set of familiar ML estimation and inference sampling behavior under familiar regularity conditions, and has been shown to be potentially mean square error (MSE) superior to probit and logit estimators. Moreover, the ML-MPD approach has been shown to be MSE superior to the best semiparametric (KS) estimator under certain sampling conditions. All of the aforementioned properties make this estimation procedure an appealing alternative relative to currently known parametric and semiparametric alternative estimating procedures.

The application of the ML-MPD procedure can be conceptualized in two stages, although implementation of the estimation methodology can be performed in one computational step. One begins with an ill-posed inverse problem consisting of the nonparametric moment model $\mathbf{Y_i} = \mathbf{p_i} + \boldsymbol{\varepsilon}_\mathbf{i}$ noted above, along with generally applicable orthogonality conditions between explanatory variables and model noise of the general form $E\left[\mathbf{g}\left(\mathbf{X}\right)'(\mathbf{Y}-\mathbf{p})\right] = \mathbf{0}$. A minimum power divergence solution for the probabilities is found that identifies a complete set of probability distributions (i.e., the MPD solution) for the BRM. In a second stage, based on the MPD class of probability distributions, ML estimation is used to estimate the unknowns that occur in the class of probability distributions. The results of ML estimation produce estimates of the effects of explanatory variables on the conditional Bernoulli probabilities, and also identify a link function for those probabilities. In effect, the method estimates the form of the probability model along with estimates of the unknowns in the model.

Regarding the first stage of the method, the Cressie-Read (CR)[9] power-divergence family of statistics (see Read and Cressie, 1988; Imbens, Spady and Johnson, 1998) measures the discrepancy between probabilities to be estimated and a reference distribution for those probabilities. Including sample moment constraints based on zero-mean theoretical population conditions, the minimum power divergence extremum problem is specified as:

$$\begin{aligned} &\operatorname*{Min}_{\mathbf{p}}\left\{\mathrm{CR}\left(\mathbf{p},\mathbf{q},\gamma\right)\right\} \\ &\text{s.t. } n^{-1}\left(\mathbf{g}\left(\mathbf{x}\right)'(\mathbf{y}-\mathbf{p})\right)=\mathbf{0} \\ &\quad 0\le p_i\le 1,\ \forall i,\ i=1,\dots,n \end{aligned} \tag{2}$$

where $\mathrm{CR}\left(\mathbf{p},\mathbf{q},\gamma\right)$ is a member of the CR family, $\mathbf{q}=\left[q_1,q_2,\dots,q_n\right]^{\mathrm{T}}\in\mathop{\times}\limits_{i=1}^{n}\left[0,1\right]$is an n-dimensional vector of reference Bernoulli probabilities, and $\gamma\in\left(-\infty,\infty\right)$ is the scalar power parameter of the divergence measure. The sample moment constraint vector equation $n^{-1}\left(\mathbf{g}\left(\mathbf{x}\right)'(\mathbf{y}-\mathbf{p})\right)=\mathbf{0}$ is of dimension $m\times 1$ where $g:\mathbb{R}^k\to\mathbb{R}^m$ is a real-valued measurable function. The inequality constraints on the probability values are non-negativity constraints and $p=\left[p_1,p_2,\dots,p_n\right]^{\mathrm{T}}\in\mathop{\times}\limits_{i=1}^{n}\left[0,1\right]$ represents an n-dimensional

[9] This goodness-of-fit measure contains the empirical likelihood statistic as a special case when $\gamma=0$ and encompasses in its basic form the maximum entropy, the Kullback-Leibler statistic $\left(\gamma=-1\right)$and the Pearson's χ^2-statistic $\left(\gamma=-1\right)$, among others. As γ ranges from $-\infty$ to ∞ the CR divergence measure leads to different information theoretic estimators (see Mittelhammer, Judge and Miller 2000, Chapter 13.4; Lee, Chao and Judge, 2010).

vector of updated conditional-on-x Bernoulli probabilities (estimated empirical/sample distribution) underlying the binary decisions.

Mittelhammer *et al.* (2004) point out that some potential candidates for specifying $\mathbf{g}(\mathbf{x})$ are the $n \times k$ matrix $\mathbf{x}$ of explanatory variables as well as powers and cross products of the same matrix. If one or more explanatory variables are determined simultaneously with the dependent variable or some regressors are statistically dependent with the unobservable stochastic noise component (i.e. $E\left[n^{-1}\mathbf{x}'\boldsymbol{\varepsilon}\right] \neq 0$), then instrumental variables whose elements are uncorrelated with the noise component but correlated with the endogenous entries in $\mathbf{x}$ should be included in the specification of the orthogonality conditions (Mittelhammer and Judge, 2009). In the current application, the explanatory variables are exogenous and the function $\mathbf{g}(\mathbf{x}) = \mathbf{x}$ was utilized.

The estimation objective function in (2) relies on the information theoretic CR power-divergence criterion, which in the binary case takes the following form (Mittelhammer and Judge, 2011):

$$\mathrm{CR}(\mathbf{p},\mathbf{q},\gamma) = \frac{\sum_{i=1}^{n}\left\{p_i\left(\left(\frac{p_i}{q_i}\right)^{\gamma}-1\right)+(1-p_i)\left(\left(\frac{1-p_i}{1-q_i}\right)^{\gamma}-1\right)\right\}}{\gamma(\gamma+1)} \tag{3}$$

The discrepancy measure is always positive valued unless $p_i = q_i$, no matter the choice of γ, becomes larger the more divergent are p_i and q_i, is convex in the $p_i's$, and is second order continuously differentiable. On the basis of the constrained minimization problem specified in (2) and (3), the MPD family of CDFs solution for this extremum problem is given by:

$$
\begin{aligned}
p\left(w_i;q_i,\gamma\right) &= \arg_{p_i}\left\{\left[\left(\frac{p_i}{q_i}\right)^{\gamma}-\left(\frac{1-p_i}{1-q_i}\right)^{\gamma}\right]-w_i\gamma=\mathbf{0}\right\} \text{ when } \gamma<0 \\
&\Rightarrow \arg_{p_i}\left\{Ln\left(\frac{p_i}{q_i}\right)-Ln\left(\frac{1-p_i}{1-q_i}\right)-w_i=\mathbf{0}\right\} \text{ when } \gamma=0 \qquad (4)\\
&\Rightarrow \arg_{p_i}\left\{\begin{matrix} 1 \\ \left(\frac{p_i}{q_i}\right)^{\gamma}-\left(\frac{1-p_i}{1-q_i}\right)^{\gamma}-w_i\gamma=\mathbf{0} \\ 0 \end{matrix}\right\} \text{when } \gamma>0 \text{ and } w_i\left\{\begin{matrix} \geq \gamma^{-1}q_i^{-\gamma} \\ \in\left(-\gamma^{-1}\left(1-q_i\right)^{-\gamma},\gamma^{-1}q_i^{-\gamma}\right) \\ \leq -\gamma^{-1}\left(1-q_i\right)^{-\gamma} \end{matrix}\right\}
\end{aligned}
$$

where $w_i = \mathbf{x}_{i.}\boldsymbol{\lambda}$, and $\boldsymbol{\lambda}$ represents the $m \times 1$ vector of Lagrange multipliers of the moment constraints when the problem is expressed in Lagrange form. The definition in (4) characterizes an uncountably infinite number of distributions, with argument w_i, indexed by the values of γ and q_i. For example, when $\gamma = 0$ and $q_i = 0.5$, the standard logit model is subsumed by the family of distributions. It is clear that the inverse cumulative distribution function of the MPD family always exists in closed form, but except for a measure zero set of possibilities for γ and q_i, the probabilities themselves must be solved for numerically. Fortunately, strict monotonicity properties of the terms involving the p_i's in (4) make for a relatively straightforward numerical solution procedure that is guaranteed to solve for the appropriate p_i for any admissible argument, w_i, of the CDF. Further discussion of the MPD family of distributions, including their myriad different shapes and characteristics, can be found in Mittelhammer and Judge (2011).

3.2 The ML-MPD estimator

The family of probability distributions in (4) was used as a basis for specifying the likelihood function associated with the data outcomes in the usual way, leading to a log-likelihood function of the general form

$$L(\boldsymbol{\beta},\mathbf{q},\gamma)=\sum_{i=1}^{n} y_i \ln\left(p\left(\mathbf{x}_{i.}\boldsymbol{\beta};q_i,\gamma\right)\right)+\left(1-y_i\right)\ln\left(1-p\left(\mathbf{x}_{i.}\boldsymbol{\beta};q_i,\gamma\right)\right) \qquad (5)$$

where I define $\boldsymbol{\beta}=\boldsymbol{\lambda}$.[10] In the implementation of the distribution family, I specify $q_i = q \;\forall i$, which is tantamount to assuming that the same basic probability distributional form is used across the observations in forming the conditional Bernoulli probabilities. In this context, it is the $\mathbf{x}_i\text{'}s$, and thus the arguments of the distributions, that change the probabilities across decisions makers. The likelihood function was maximized using the non-gradient based Nelder-Mead simplex minimization algorithm proposed by Nelder and Mead (1965) (the negative of the likelihood function was minimized to obtain the maximum).[11] This optimization method belongs to the general class of "direct search methods" and has become one of the most widely used techniques for non-linear unconstrained optimization. It does not rely on gradients or Hessians, so it tends to be faster between iterations than search methods that depend on derivatives of the objective function (e.g., Newton-Raphson). The Nelder-Mead approach is also immune to numerical problems caused by highly nonlinear and sometimes unstable gradient and/or Hessian calculations from iteration to iteration.

[10] A formal argument of equating the Lagrange multiplier vector $\boldsymbol{\lambda}$ and the unknown parameter vector $\boldsymbol{\beta}$ is given in Judge and Mittelhammer (2012), Chapter 10.
[11] A detailed explanation of this algorithm and its implementation can be found in Nelder and Mead (1965) and Jacoby, Kowalik and Pizzo (1972).

In order to promote both stability and accuracy in the search for the ML optimimum, while guarding against converging to local optima, I first implemented a recursive grid search approach in the γ direction with increments of ± 0.2. In particular, I set the global values of γ external to the rest of the optimization problem, and sequentially updated the starting values based on the lagged recursive solutions for the previous value of γ, beginning with the standard logit solution ($\gamma = 0, q = .5$ in the MPD family of distributions). The recursive method does not guarantee a global optimum but reduces the possibility of not searching in the neighborhood of the global optimum. I also embedded a search for the optimal q along the grid from 0.01 to 0.99, in .01 increments. The likelihood function was ultimately maximized at the values $\hat{\gamma}^* = -4.4$ and $\hat{q}^* = .88$ (see section 4.3).

Upon identifying the ML solution, the variance-covariance matrix of $\boldsymbol{\beta}$ was estimated by substituting the optimized ML estimates $\hat{\gamma}^*$ and $\hat{q}^*$, and the optimized ML-MPD parameter estimates $\hat{\boldsymbol{\beta}}^*$ into the definition of the MPD distribution in (4).[12] The resulting expression is the value of a *profile likelihood function for the parameter vector* $\boldsymbol{\beta}$, which can be used to calculate the asymptotic covariance matrix of the ML estimates, and for conducting inference. Since p_i is implicit in (4), the variance-covariance matrix is derived using implicit differentiation and the p_i's are solve for numerically. The variance-covariance matrix was estimated using the "outer-product-of-gradients" approach, based

[12] Notice that if the optimized gamma is > 0, the resulting MPD CDF will be a model with finite bounded support, whereas for < 0, as is the case here, the MPD CDF has infinite support in both the positive and negative directions.

on the computation of the inverse of $\left(\frac{\partial \mathbf{L}(\beta)}{\partial \beta}\right)'\left(\frac{\partial \mathbf{L}(\beta)}{\partial \beta}\right)$, where $\frac{\partial \mathbf{L}(\beta)}{\partial \beta}$ is the $n \times k$ matrix of derivatives of the log of the profile likelihood function contributions, $L_i(\beta)$, $i = 1,\ldots,n$ with respect to $\boldsymbol{\beta}$.

For implementing all of the preceding procedures relating to the MPD estimator, as well as the implementation of the probit maximum likelihood estimator (MLE), I used Aptech Systems' GAUSS™ 11. The Kriström/Ayer estimator was implemented using the software environment for statistical computing and graphics R (R Development Core Team, 2009).

4. Results and discussion

All of the models discussed in this section utilize the seven explanatory factors that are defined in table 2.1.

4.1 Parametric Model Results

Using the conventional parametric structure of the probit model, I adopted the Berndt-Hall-Hall-Hausman (BHHH) estimator (Berndt *et al.,* 1974) to find the maximum likelihood estimator of the linear probit model, and the results are displayed in table 2.3. The "bid" variable is highly significant and its sign is aligned with economic theory, indicating that the higher the visit price to the park, the less willing respondents are to pay. According to the CV literature (see e.g. Hanemann, 1984; Haab and McConnell, 2002; Gonzalez, Loomis and Gonzalez-Caban, 2008), income has typically, but not necessarily, been dropped in these types of studies due mainly to the lack of statistical significance. However, based on the dichotomous indicator, the "income" variable was found to be significantly different from zero in the parametric approach. The variables "bid", "size" (size of the rocks around the pool) and "road" (non-paved roads) contribute to the explanation of the dependent variable at the 0.01 level of type I error. "Income" and "volume" are both positively related to the probability of paying the bid amount, whereas the variables "discharge", "road", "size" and "non-residents" are negatively associated.

Table 2.3 also reports the mean economic value of a visit to the rivers at the CNF per group and its corresponding confidence intervals (CIs). Employing the parametric and non-symmetric CI Krinsky and Robb (1986)[13] simulation method for the mean WTP and Hanneman's approach (see section 3), the (net) mean WTP measure is \$120 and the 95% CI ranges from \$107 to \$136.25. Note that either of these levels of WTP for the types of recreators surveyed, as well as the type of recreation experience obtained by a visit to the CNF, appears to be unrealistically high.

4.2 Nonparametric Model Results

Relating to the non-parametric estimation approach, figure 2.1 illustrates both the proportion of individual WTPs for each ordered bid class (a so-called empirical survivor function or Ayer function) and the *monotonized empirical survivor function* F(p) using the non-parametric technique.[14] Both curves were derived by setting the probability of a

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[13] Under this simulation procedure, draws of coefficient estimates are taken from their asymptotic distribution (i.e., $\hat{\beta}_r \sim N\left(\beta, \mathrm{VCOV}\left(\beta\right)\right)$, $r = 5{,}000$), after calculating the Cholesky decomposition (p) of the VCOV matrix, calculating a vector of parameter estimates such that $\hat{\beta} = \hat{\beta}_r * p + \hat{\beta}'$, and computing the WTP of interest. Park, Loomis, and Creel (1991) constitute an application of this simulation technique in CV studies.

[14] This distribution-free estimator has desirable ML properties, represents a closed-form solution to the Non-Parametric ML problem for single-bounded discrete choice data, and yields a monotonically non-increasing sequence of likelihoods of accepting the bid (i.e., $F\left(p\right) = P\left\{WTP \geq bid\right\}$, $\mathrm{p} \equiv \mathrm{bid}$). If the sequence is not monotonic in some regions for some bids, then the pool-adjacent-violators (PAVA)

"yes" response equal to one at $0 and the maximum bid amount as the truncation upper limit point (T = $200 ; see the frequencies of "yes" responses for each bid level and the distribution-free Maximum Likelihood estimates of the probability for acceptance in the appendix). The monotonized function represents a set of ML estimates (or maximizing set) of desired probabilities, which provides a continuous linear smoothed function with a non-constant slope. In the context of the current study, each ML estimate symbolizes the survival probability of WTP given a specific bid level. As the sample size becomes infinite, the estimated proportions will converge in probability to the true probability of success and the new sequence will provide a distribution-free nonparametric maximum likelihood estimator of the probability of success (Ayer *et al.*, 1955).

Two findings can be derived from figure 2.1. First, to obtain the monotonic survivor function, constraining WTP to be non-negative upon assuming that $\pi = 1$ and 0 when the bid is $0 and $200, respectively, appears to be a reasonable approximation of behavior between the known points ("bids"). That is, if the bid is zero, then the probability of accepting the payment is unity and if the price is $200 the probability is zero since it is understood to be too high and, therefore, no one will be willing to accept the offered price. Second, the plot indicates that as the bid increases, the probability of WTP decreases.

Although the selection of the truncation point is an empirical problem in the non-parametric literature (see Duffield and Patterson [1991]) and its sensitivity must be noted, I integrated the smoothed survivor function up to the maximum bid level to obtain the mean WTP, following the approach of Creel and Loomis (1997). Using numerical

algorithm is applied. This smoothing procedure is repeated until a monotonic sequence of aggregated proportions emerges at each bid level. For more details on this technique, see Robertson, Wright and Dykstra (1988).

integration $\left(E[WTP]=\int_0^{T=200}\left[1-F(p)\right]dp\right)$ and bootstrap pair resampling, the unconditional truncated mean compensated variation (WTP) is \$97 and the 95% bootstrap CI ranges from \$66.5 to \$124. Note that the mean fully nonparametric WTP estimate does not fall within the 95% confidence interval for the mean WTP (\$107, \$136.25), constructed for the fully parametric estimator, and that while the level of mean WTP is lower than that of the parametric approach, the nonparametric WTP value still seems unrealistically high for the types of recreators surveyed and the type of recreation experience obtained.

4.3 ML-MPD Model Results

The value of the ML estimate, $\hat{\boldsymbol{\beta}}_{ML-MPD}$, of the $\boldsymbol{\beta}$ vector corresponding to the ML estimates of $\hat{\gamma}^*=-4.4$ and $\hat{q}^*=.88$, is presented in table 2.3. Substituting these point estimates into the MPD definition in (4) for $\gamma<0$ yields the estimated WTP probability distribution:

$$p\left(w(\mathbf{x}_{i.});\hat{q}^*,\hat{\gamma}^*\right)=\arg_p\left\{\left[\left(\frac{p}{0.88}\right)^{-4.4}-\left(\frac{1-p}{1-0.88}\right)^{-4.4}\right]+4.4w(\mathbf{x}_{i.})=\mathbf{0}\right\} \tag{6}$$

where $w(\mathbf{x}_{i.})\equiv\mathbf{x}_{i.}\hat{\boldsymbol{\beta}}_{ML-MPD}$, and $\mathbf{x}_{i.}$ denotes a $1\times k$ row vector contained within the $n\times k$ matrix $\mathbf{x}$ of covariates, or any other vector value of interest relating to the explanatory variables.

There is no closed form solution for the probabilities in (6). Accordingly, the derivatives of $p\left(w;\hat{q}^*,\hat{\gamma}^*\right)$ with respect to $\boldsymbol{\beta}$ needed to form the asymptotics covariance matrix are derived via implicit differentiation. The resulting $n \times k$ matrix of derivatives is given by

$$\frac{\partial \mathbf{p}}{\partial \boldsymbol{\beta}} = \left(\frac{1}{(\mathbf{p})^{-5.4} \cdot (0.88)^{4.4} + (1-\mathbf{p})^{-5.4} \cdot (1-0.88)^{4.4}} \right) \odot \mathbf{x} \tag{7}$$

where $\odot$ denotes the Hadamard (elementwise) product operator, all the division operations are Hadamard (elementwise) division, and $\mathbf{p}$ is the $n \times 1$ vector of estimated probabilities. As indicated in section 3, the outer product of the gradient method is then used to define the $k \times k$ variance covariance matrix as $\left[\left(\frac{\partial \mathbf{L}(\boldsymbol{\beta})}{\partial \boldsymbol{\beta}} \right)' \left(\frac{\partial \mathbf{L}(\boldsymbol{\beta})}{\partial \boldsymbol{\beta}} \right) \right]^{-1}$.

The empirical probabilities in (6) were recovered numerically using the interval bisection method. Interested readers are referred to Mittelhammer and Judge (2011) for additional detail on the computational methodology.

Table 2.3 summarizes estimated coefficients, asymptotic standard errors, and willingness to pay results for the MPD-ML estimator. A number of interesting findings can be deduced from the results reported in this table. First of all, based on the goodness-of-fit measures reported (pseudo R^2, AIC, BIC, and deviance statistics), the ML-MPD model performs better than the probit model despite the fact that both models do not exhibit misspecification problems according to the outcome of the deviance goodness-of-fit test. Second, the parameter estimates in these two models have the same signs, except for the "income" variable. As mentioned previously, this dichotomous income indicator is positively related to the probability of paying the bid amount based on the probit model, but when using the ML-MPD approach, a negative effect of income is estimated, although the effect is not statistically significant. Third, there are sizeable differences in the magnitudes of the coefficients, where most of the ML-MPD estimates tend to be larger compared to the probit point estimates, although this by itself is not remarkable, given the notably different probability distribution functions for which the explanatory factors are arguments. Fourth, the MPD approach does not produce uniformly smaller estimated standard errors relative to probit. Under the fully parametric model the variables that are statistically significantly at the .01 level are the “bid”, "size", and “road” regressors. However, under the ML-MPD approach, only “bid” is significant at that level, although “size” and “road” are significant at the .05 level. The outcome of having just "bid" statistically significant at the .01 level is consistent with Gonzalez-Sepulveda (2008)'s findings. The "discharge" variable is insignificant at conventional levels in the ML-MPD case, but is nearly significant at the 0.10 level, suggesting its effect should not necessarily be ignored.

4.4 Comparison of Marginal Effects and WTPs

Using the estimating parameters derived from the probit and ML-MPD models, marginal effects[15] of changes in the explanatory variables on mean WTP were calculated from table 2.3. It should be mentioned that marginal effects from the Kriström (1990)/Ayer *et al.* (1955) approach were not computed, considering the fact that the essence of this

[15] Marginal effect values are obtained for the probit and ML-MPD cases using the mean marginal effect approach. In the estimation procedure, there is potentially a different marginal effect at every observation if the observations evaluate different probabilities. For the probit model, the marginal effect representation is given by $n^{-1}\sum_i \phi\left(\mathbf{x}_{i.}\hat{\boldsymbol{\beta}}\right)\hat{\beta}_j$, i=1,...,n, j=2,...,k and $\phi(\cdot)$ is the standard Normal probability density function, while in the case of ML-MPD the marginal effects are represented by $n^{-1}\sum_i\left[\frac{\hat{\beta}_{(ML-MPD)j}}{(p_i)^{\hat{\gamma}^*-1}\left(\hat{q}^*\right)^{-\hat{\gamma}^*}+(1-p_i)^{\hat{\gamma}^*-1}\left(1-\hat{q}^*\right)^{-\hat{\gamma}^*}}\right]$ for $\gamma<0$, where j=2,...,k, $\hat{\gamma}^*$, $\hat{q}^*$, and $\hat{\beta}_{(ML-MPD)}$ are the optimized ML point estimates reported above, p_i are the empirical probabilities, and i=1,...,n.

empirical method consists only to serve as a mean or median WTP estimation technique given by the area under the empirical survivor function.

Based on the probit results, visitors were willing to pay -\$58 and -\$65 for increasing in-stream flows and non-paved roads, respectively, as well as -\$3 for increasing size of rocks or sand around the pools. This indicates that increased stream flows, non-paved roads, and larger rock/sand sizes provide disutility to recreation users. The volume of water in the pools positively influences the WTP of recreation users, being the marginal effect \$0.37. These marginal effects on WTP across site attributes become larger when employing the ML-MPD approach. For instance, visitors are willing to pay -\$33 and -\$40 for increasing in-stream flows and non-paved roads, respectively. The amount relating to the size of rocks or sand becomes -\$2, whereas the marginal effect associated to the volume of water in the pools is \$0.25.

I also calculated marginal effects on the mean probabilities of acceptance of bids as a function of one unit changes in the levels of explanatory factors from the probit and ML-MPD models (see table 2.4).

These marginal effect outcomes were not calculated for the fully nonparametric approach, following the same argument previously mentioned. It is evident from table 2.4 that the effects on probabilities of one-unit changes in explanatory variables is notably different in magnitude for the probit and ML-MPD approaches, albeit except for income, the directional effects are the same. For income, the mean marginal effects contrast both in sign and magnitude. The impact of a one-unit change in travel time (i.e., indicating that travel time to the CNF takes over 30 minutes) is -0.06 for probit and -0.02 for ML-MPD. For every additional millimeter of grain size, the probability of bid acceptance decreases by 0.088 and 0.070 for the probit and ML-MPD methods, respectively. The probability of visiting recreational sites decreases substantially for non-paved roads and for increased water discharge based on both estimation approaches, although relatively speaking, the effects for the probit model, -.1662 and -.1858 respectively, are much higher than for the ML-MPD approach, being -.1125 and -.1345.

As for the (net) mean WTP for a visit to the CNF per group, the ML-MPD WTP of $27.80 is substantially *lower* than the results of the probit ($120) and nonparametric ($97.00) approaches. Note that a 95% CI under ML-MPD as well as the mean WTP measure were computed in a similar manner, as I described previously in section 4.1. It is apparent from the fact that the CI's are non-overlapping that the mean WTPs are estimated to be statistically different via the two approaches (this is true at any typical level of confidence [including 99%]). To formally test whether there is a difference in WTP *distributions* for the probit and ML-MPD (i.e. H_o: $WTP_{probit} = WTP_{ML\text{-}MPD}$), I implemented the nonparametric *complete combinatorial convolution* approach of Poe, Giraud and Loomis (2005). A two-tailed p-value equal to 0.00082 rejects the null hypothesis convincingly, and it can be concluded that the two empirical WTP distributions are statistically different. In terms of providing information on mean WTP, the ML-MPD is more informative and precise than the probit and fully nonparametric approach. For a 95% nominal coverage, the average CI length for the ML-MPD approach is $15.53, whereas for probit and Kriström/Ayer's estimators this interval is wider at $29.23 and $57.52, respectively.

5. Implications and Conclusion

A major finding of this study is that the ML-MPD approach yields a substantially lower estimate of the mean WTP ($27.80) for visiting the recreation sites compared to WTPs obtained from the fully parametric ($120) and fully non-parametric approaches ($97). I argue, based on the decision context and demographics of decision makers, that the lower WTP value is a much more reasonable and defensible estimate of the WTP for visiting the recreation sites. Gonzalez-Sepulveda (2008; Chapter three), using the same dataset and compensated WTP measures, but a smaller subsample of the data, arrived at a related insight with regard to the level of WTP when comparing the Travel Cost Model (TCM) with the parametric logit model (CV method). Sampling issues affecting TCM and CV estimates are potentially part of the explanation for the difference in the WTP estimates obtained from these two approaches, including spatial truncation of TCM recreation markets and endogenous stratification of CV respondents in the sample. Estimates from the ML-MPD approach suggest yet another reason for the difference in WTP values -- relaxing the rigid distributional assumptions of the conventional parametric methods produce substantially lower WTP estimates.

Another implication worthy of note is that income, expressed in terms of an income indicator of a $20,000 threshold, was statistically significant under the parametric approach, but insignificant, and nominally estimated to have a negative effect, based on the ML-MPD methodology. Income effects are often disregarded in CV studies, mainly due to insignificance of the model parameter. Carson and Hanemann (2005) identify several sources of measurement errors that have contributed to biasing estimated income effects downward. While treating the effect of income as an indicator variable is not a common practice in CV, Aiew, Nayga and Woodward (2004) recognized how attractive an exploration of this type of specification might be, especially when understanding that the WTP distribution across income groups might be important from a policy perspective. Champ *et al.* (2002) conducted one of very few CV published studies that included income as an indicator variable. A negative effect of an income threshold over $20,000 is suggestive of wealthier Puerto Ricans not preferring visiting water pools, but possibly preferring other types of recreation (e.g., boating to nearby islands, visiting resorts). While the negative effect is not statistically significant, the ML-MPD result seems more plausible than the result obtained with the probit model, especially when considering that more than half of the respondents who report that visiting the water pools was the main purpose of the trip had an annual income of less than $15,000. The negative income effect is also consistent with the mean ML-MPD WTP value of $27.80 compared to the substantially higher WTP values obtained using the other two approaches, which appear patently unrealistic relative to the demographics of the individuals who visit the water pools.

In contrast to many alternative estimators, the ML-MPD procedure is free of subjective choices relating to various tuning parameters, has the flexibility to fit a wide range of varied distributional shapes to conform to the choices observed, and proceeds by imposing minimal assumptions on the information contained in the data. In addition, sampling experiments conducted by Judge and Mittelhammer (2012) to investigate the small sample properties of a range of MPD-based estimators and parametric methods (e.g. the probit model) indicate that the former ones compare more favorably in terms of MSE relative to parametric methods. As such, the new ML-MPD approach to estimation of BRMs appears to have potential for providing a more defensible representation of the underlying data-generating process and economic decision-making behavior, and improved econometric analyses of discrete choice processes.

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Table 2.1. Variables Used in the Analyses

Variable Name	Description
Choice	= 1 if willing to pay the visit price = 0 otherwise
Bid	Offered U.S. dollar amount (threshold)
Road	= 1 if non-paved road;= 0 otherwise
Discharge	Mean annual speed of water in the pool (cubic feet)
Size	Median grain size (millimeters) around the pools
Volume	Volume of the pool (cubic feet)
Income	= 1 if family annual income (U.S. dollars) is greater than $20,000 = 0 otherwise
Travel Time	= 1 if travel time (TT) exceed 30 minutes; = 0 otherwise

Note: The variables volume, size, and income were scaled by 100, 10 and 1000, respectively, in estimation to support numerical stability and accuracy in calculations, and allow similar orders of magnitude for parameter estimates.

Table 2.2. Descriptive Statistics for Selected Unscaled Quantitative Variables

Variable Name	Obs	Mean	Std.Dev.	Minimum	Maximum
Bid	718	63.53	58.27	1	200
Discharge	718	0.83	0.5711	0.11	1.67
Size	718	509.22	628.17	102	2337
Volume	718	446.74	414.00	42	1868.4
Income	718	28652	21893.50	5000	75000
Travel Time	718	63.52	59.62	1	990

Table 2.3. Estimation Results for the Probit and ML-MPD Models

Variable Name	PROBIT-MLE	ML-MPD
BID	-.00964***	-. 05612***
	(.00088)	(.0140)
DISCHARGE	-.56115**	-1.85838
	(.281)	(1.198)
SIZE	-.02974***	-.11546**
	(.0108)	(.047)
VOLUME	.00365	.014319
	(.00261)	(.012)
INCOME	.23559**	-.08717
	(.108)	(.339)
ROAD	-.62744***	-2.22201**
	(.228)	(1.081)
Travel Time	-.20266	-.25873
	(.114)	(.351)
INTERCEPT	1.84962***	4.15471**
	(.328)	(1.659)
McFadden R^2	.1596	.1935
AIC	772.7821	742.2593
BIC	809.3939	778.8711
Deviance statistic	756.7822	726.2593
	{0.1088}	{0.3278}
Krinsky Robb		
Mean WTP ($)	120.35	27.80
LCIL	107.02	18.39
UCIL	136.25	33.92
Log Likelihood	**-378.39**	**-363.13**

BHHH standard errors are shown in parentheses. AIC and BIC are the Akaike information criterion and Schwarz's information criterion, respectively. The deviance statistic is a chi-squared test for goodness-of-fit with n-k degrees of freedom and defined by -2*LLH, where LLH is the log-likelihood, n is the sample size and k is the number of unknown parameters. Its associated p-value is reported in curly brackets. Lower and Upper Krinsky and Robb Confidence Interval Levels for the mean WTP, shown through LCIL and UCIL for 95% confidence levels, respectively, are calculated using the empirical convolutions method proposed by Poe, Giraud and Loomis (2005) and 5,000 repetitions. For the computational implementation of the probit model, an iterative algorithm with analytical gradients and analytical Hessian were implemented in GAUSS 11.

*** Statistically significant at 99% confidence level; ** statistically significant at 95% confidence level. $t_{0.01,704} = -2.5828$, $t_{0.05,704} = -1.9633$

Table 2.4. Marginal Probability Effects of Regressors on WTP for Recreation Site Attributes

Variable Name	PROBIT-MLE	ML-MPD
BID	-0.0029	-0.0034
DISCHARGE	-0.1662	-0.1125
SIZE	-0.0088	-0.0070
VOLUME	0.0011	0.0009
INCOME	0.0698	-0.0053
ROAD	-0.1858	-0.1345
TRAVEL TIME	-0.0600	-0.0157

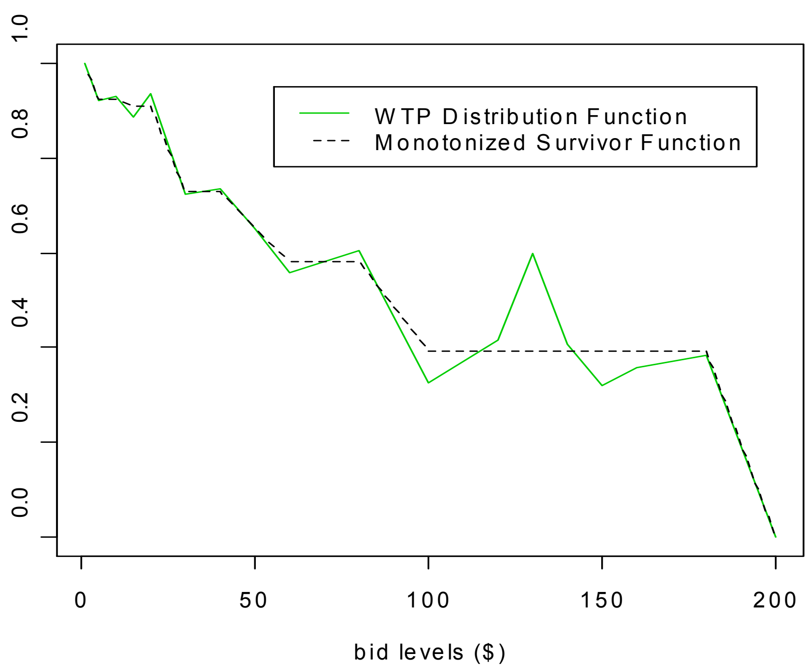

Figure 2.1. WTP Distribution Function and the Monotonized Empirical Survivor Function.

Appendix

A. Proportions of yes – answers and estimates of the probability for acceptance

Bid($)	Proportion Yes	P("yes")
1	2/2	1
5	69/75	.925
10	66/71	.925
15	54/61	.911
20	58/62	.911
30	39/54	.729
40	39/53	.729
50	28/43	.651
60	24/43	.581
80	26/43	.581
100	13/40	.393
120	15/36	.393
130	3/5	.393
140	11/27	.393
150	8/25	.393
160	10/28	.393
180	10/26	.393
200	13/24	.000
Sub-total	488/718	

CHAPTER THREE

MODELING CONSUMER BIDDING BEHAVIOUR ON FOOD ITEMS: EVIDENCE FROM A TWO-STAGE SEQUENTIAL BDM FIELD EXPERIMENT

ABSTRACT

A two-stage sequential experiment was conducted in this study at the point of purchase (retail grocery setting) to elicit willingness to pay (WTP) for four food products: flax seed bread, conventional milk, organic milk, and organic apples. In the first stage (round), participants bid on one of the four products selected randomly, while in the second round participants bid simultaneously for the other three products in a homegrown setting. The WTP for the food items was elicited using the Becker-DeGroot-Marschak (1964) experimental auction procedure. In this study, I am interested in two factors that may affect participants' bidding behavior across the two rounds. One factor is the uncertainty associated with the binding product in the second round, and the other factor is a potential compensation effect on participants' bidding behavior across the two rounds. WTP was modeled as a function of design variables and participant specific characteristics, obtained from a survey completed after the experiment. Econometric analyses were performed using Powell's semiparametric symmetrically censored least squares procedure, the ordinary least squares approach, Tobit I, Tobit III, and a Seemingly Unrelated Regression system model. Estimation results suggest that bids are sensitive to the context of bidding as well as participants' preferences for particular foods. Compensation has little impact on individual's bidding decision. However, there is some evidence that the uncertainty about which product will be binding in the second round, or the round order, can have an effect on participants' bidding decisions.

1. Introduction

An increasing number of economic experiments[16] have been conducted in a field context rather than in a laboratory setting in the last decade to address a wide range of different economic research questions (e.g. see List and Lucking-Reiley, 2000; Lusk and Fox, 2003; List 2004; Ding, Grewal and Liechty, 2005; Landry *et al.,* 2006; Marette, Roosen and Blanchemanche, 2008). When research questions pertain to measuring willingness to pay (WTP)[17] for food products, an obvious field experiment setting is in-store valuation of consumer WTP where grocery store visitors are recruited to take part in the experiment. As Lusk *et al.* (2001) note, "in-store valuation has demonstrable and potential advantages for the experimenter compared to a lab setting".

In the context of food experimental economics and as documented by Lusk and Shogren (2007), an important body of research related to preference elicitation has been carried out employing incentive compatible/non-hypothetical[18] auction mechanisms such as the first and Vickrey second price auction formats, the random n*th* price auction, and the Becker-DeGroot-Marschak (1964; hereafter, BDM) auction procedure. This study employs the BDM mechanism to elicit adult shoppers' values for four perishable food items (a functional[19] bread item, organic milk, organic apples, and conventional milk). The BDM method, while theoretically equivalent to the second price auction, random n*th* price auction and English auctions (Lusk, Feldkamp and Schroeder, 2004; Lusk and

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[16] Field economic experimentation emerged in the past decade (Levitt and List, 2009). For this period, Harrison and List (2004) classify field experiments into three categories (artefactual, framed, and natural field experiments) of which the second type is conducted in this research.
[17] WTP is defined as the maximum amount a person is willing to pay or exchange to obtain a good.
[18] *Incentive compatibility* is referred to the property that participants in the experiment admit a unique dominant strategy as the truthful revelation of private values, while *non-hypothetical* implies experimental settings involving a transaction of actual goods and/or actual cash.
[19] In this study, I define "functional food" as food with some added functionality. On the other hand, we refer to "conventional food" as food not being organic and dietary supplement (e.g. vitamins, minerals, herbs and other botanicals, amino acids, enzymes, etc.).

Rousu, 2007) is not without critics.[20] Nevertheless, its rules are simple compared to other incentive compatible auction mechanisms, and it avoids many of the concerns associated with hypothetical valuation procedures.[21] In addition, as Noussair, Robin and Ruffiex (2004) note, based on Rutström (1998)'s experimental results, the bias towards high bidding is less severe in the BDM than in the Vickrey second price auction format.

This research contributes to the literature in four ways. First, the BDM mechanism is used to elicit participants' WTP "homegrown" values[22] in a retail grocery setting, in contrast to most BDM studies, including certain field settings (e.g. Rozan, Stenger and Willinger, 2004). Lusk and Fox (2003) conducted a BDM experiment in a field setting; however, the study was carried out on a university campus and focused only on cookies with different attributes. To my knowledge, the only published studies eliciting homegrown values that have used experimental auction procedures similar (except for the offered compensation, auction food items, and bidding context) to that used in this study are by Lusk *et al.* (2001) and Corrigan and Rousu (2008). Lusk *et al.* (2001) elicited participants' WTP for steak tenderness in three urban retail grocery stores, located in the Midwestern United States. In contrast to this study, they allowed for only one bidding round, endowment effects, informational effects, and exchange for a steak upgrade using the endow-and-upgrade methodology as the incentive mechanism. Corrigan and Rousu (2008) also elicited WTP at grocery stores, but they used bananas and chocolate bars as

[20] See Karni and Safra (1987), Noussair, Robin and Ruffiex (2004), Horowitz (2006), and Buckley *et al.* (2009) for formal discussions about the strengths and weaknesses of the BDM method.

[21] Several studies (e.g. Cummings, Harrison and Rutstrom, 1995; Fox *et al.,* 1998; List and Shogren, 1998; Lusk and Schroeder, 2004) indicate that hypothetical techniques tend to overestimate the true WTP due to the hypothetical context in which the data are collected.

[22] Experimental subject's values that are independent of those induced by the experimenter (Smith, 1976). Lusk and Shogren (2007) refer to them as "values that people bring into an experiment for real-world goods".

auction food items, employed actual money as the monetary incentive, and allowed for informational effects in a second round. These authors designed the BDM experiment in a similar manner to our experiment; however, contrarily to our study, participants bid on the same type and same number of food items in both rounds, allowed for multiple participants per bidding round, and participants did not know they would have a second opportunity to bid.

Second, and similar in spirit to Corrigan and Rousu (2008)'s work, in the current study participants moved sequentially through two separate bidding rounds, as opposed to numerous BDM experiments, which are mostly run as a single-round auction (see e.g. Lusk, Feldkamp and Schroeder, 2004) or in multiple repeated rounds (see e.g. Urbancic, 2011). Unlike Corrigan and Rousu (2008), however, our experimental design introduces a single-item shopping scenario (item selected randomly) in the first round, and multiple food items of different types in the second bidding round. In other words, unlike prior literature that relies on BDM, the context between rounds in our study changes. The binding product in the second round was selected randomly and revealed to the participants after they submitted their bids.

Third, and as an empirical matter, researchers have included a different number of goods to be auctioned during the experimentation. List (2002) examines preferences across joint and separate decision modes in the sportscard market. Comparing bidding behavior of participants under the two decision modes (joint and separate) and using the random *n*th-price auction mechanism, he reports that valuations of the good under study differ significantly depending on whether the goods are seeing isolated or juxtaposed. To the best of my knowledge, no BDM based study has been used to elicit WTP for a single food item in isolation, and with full bidding for multiple dissimilar products in a sequential setting.

Fourth, to my knowledge, no other studies have implemented and compared the Powell's semiparametric symmetrically censored least squares (SCLS) and the Seemingly Unrelated Regression (SUR) system estimation procedures with the standard approaches (e.g. the Tobit model) using data from economic experiments.

In this study, I am interested in two factors that may affect participants' bidding behavior across the two rounds. One is the uncertainty associated with the binding product in the second round, and the other is a potential compensation effect on participants' bidding behavior across the two rounds. With regards to the first, I hypothesize that bidding rounds matter and, therefore, I examine product bid sensitivity across the two rounds by testing whether the round that a product was bid on, impacted the bid amount. Regarding the second factor, all participants were compensated prior to engaging in bidding with a $10 store gift certificate. When they moved into the second round and before bidding for the other three products, however, they had differing amounts of money, depending upon whether they won the auction in the first round and the amount that was spent in the first round. Hence, I formally tested for the compensation effect on participants' bidding behavior in the second round. Even though the participants were not restricted to spending no greater than the allocated $10, I hypothesize that the participants may still behave as if they were constrained by the allocated funds. Brosig and Reiβ (2007) found that bidding behavior is significantly affected by the opportunity cost of early bid submission under sequential auctions games, while Phillips, Battalio and Kogut (1991) show that the more bidding opportunities a participant has, the more likely sunk costs[23] will be ignored by the decision makers. Experimental evidence generated by Arkes and Blumer (1985) show that once an investment in money, effort, or time has been made the commitment to an endeavor is manifested with more vigor.

In pursuit of these two objectives, I employed different econometric estimation procedures, including the ordinary least square (OLS) approach, Tobit I and Tobit III models, the SCLS estimator, and the SUR model. I used different estimators in order to compare results across techniques and verify robustness of the results. In addition, given our small sample size, the actual effect of the theoretical large sample properties (particularly consistency) of the OLS and fully parametric Tobit models on the results is not known.

The remainder of this chapter is organized as follows. In section 2, I describe and characterize the experiment. Section 3 presents the auction data collected in the experiment, and section 4 discusses our modeling strategy. In section 5, I report the experimental results. Concluding remarks as well as some limitations of this study and suggestions for future research are detailed in section 6.

2. The Experiment

The experiment was conducted in two separate and sequential BDM rounds (experimental treatments), followed by participants completing a questionnaire.[24] The experimental auctions were conducted in a retail grocery setting in October, 2009 in the

[23] Payment made or committed as a result of an earlier decision, e.g., the opportunity cost associated with the time spent in the experiment or the purchase out-of pocket of the food items.
[24] The questionnaire was taken at the end of the experiment to be consistent in not sensitizing the respondent to the characteristics of the product as would be done if they had the survey before the experiment.. The complete questionnaire is available on request from authors.

Pacific Northwest, United States. Prior to the actual experiment, a pilot study was conducted to finetune the details of the experiment.

The experiment proceeded as follows:

In Step 1, shoppers were recruited for participation in the experiment near the entrance (or inside) of the selected store. Potential participants were informed that university researchers were conducting an "in store consumer study". After agreeing to participate in the experiment, each participant was assigned an identification number to preserve the participant's anonymity. Each participant took part in a "practice round" (see the experimental instructions in the appendix).

In Step 2, researchers again provided participants with oral and written instructions about the BDM mechanism. They were told that they would be bidding for four different food items[25] in two separate bidding rounds. The identity of the products (flax seed bread, conventional milk, organic milk, and Fuji organic apples) was not revealed to the participants at this point of the experiment.

In Step 3, each participant bid separately for only one of the four products. The food product was randomly assigned to the participant and displayed (revealing the milk or bread labels, or that apples were organically produced), as the participant was asked to submit his/her bid.

In Step 4, a binding price for the food product being auctioned in the previous step was determined at random by drawing a number from a bowl containing prices

[25] These products were selected because they provided variation in attributes and were of economic importance to the region. None of them were major brands, and the organic and conventional milk products were selected based on similar colored labels with 2% of fat. The loaf of bread was selected to be a functional food and it was labeled as such (i.e. high fiber with omega-3 fatty acids). The apples were identified by variety (i.e. organic Fuji apples) and presented in groups of three (approximately one pound).

ranging from \$0.10 to \$6.00 in \$0.10 increments. This randomly drawn price was used to determine if the participant won or not in the first round.

In Step 5, monitors placed each of the other three products on display to show the participant exactly what he/she would be bidding on in the next step.

In Step 6, monitors informed the participant that the same bidding mechanism would be used, but that now bids on these three food products would be submitted simultaneously. Each participant was informed that only one product (randomly selected and identified after bidding) would be binding.

In Step 6, the participant's bid for the binding product was compared to a randomly drawn binding price for this product to determine if the participant won or did not win in the second round.

In Step 7, participants were asked to complete the questionnaire specific to the binding product.

In Step 8, the experiment ended and the participant signed a form that he/she received the compensation. He/she was also asked not to discuss his/her results with others in the store.

The two rounds and the auction elicitation mechanism used in this study are explained more fully in the appendix (see the experimental instructions). The experiment was designed to be balanced in terms of the total number of cross-sections per food item, and as completely randomized design having one-treatment structure with repeated measures (four food items). The products were randomized across individuals by round. Participants were asked to bid in a common context (reflecting on product value at that specific point of time) and all participated in both rounds (within-participant experimental design). They did not bid against one another, but one at a time as is customary for the BDM mechanism. Each participant recorded the bids on a paper clip pad that was collected by the monitors when the experiment ended. Participants not winning in either of the two rounds received the $10 gift certificate, while those winning in one or the two rounds had the “market” price deducted from the $10 gift certificate and were given the food products they won during the experiment. If the binding price is lower or equal than the participant’s bid, then participants were obligated to buy the binding product at the randomly determined binding price. Lastly, participants were not informed about the prices that the food products being auctioned were being sold in the store.

3. Data Description

The experiment described in the previous section resulted in 136 cross-sectional observations. Table 3.1 summarizes the demographics and other characteristics of the participants included in our experiment. This table shows that female, middle and old age, educated participants dominate the sample. Moreover, 94 percent are white (non-Hispanic), 81 percent are non-students and most of the sample is concentrated in the range of middle/low income (i.e. less than or equal to $60,000). Also, 73.5 percent are primary shoppers and a similar percentage is not currently or has not previously been employed in an agricultural occupation. Even though it is not reported in table 3.1, the majority of the participants (85%) indicated they do not to have infants or children between 2-7 years old.

Table 3.2 shows summary statistics of bids per food item over the two rounds. In general, the bids are slightly right-skewed despite the mean response for organic milk being smaller than the median. The skewness and kurtosis tests based on Snedecor and Cochrane (1989) and the coefficients of skewness and kurtosis reported in table 3.2 suggest that the bid distributions for each food product are not symmetric and present non-normal kurtosis characteristics.

Some extreme[26] values were identified for milk, organic apples, and organic milk. These identified extreme bid values were compared with participants' self-reported "field prices" for the same products. In more than 50 percent of the cases the extreme values and the self-reported field prices for conventional milk and organic apples coincide in terms of magnitude, and in 60 percent of the identified extreme bid values the major food shopper intended to buy the product. This result is consistent with theory (Corrigan and Rousu, 2008) in the sense that the field auction is demand-revealing. For those cases in which the extreme values were not close to the self-reported field prices, participants did not intend to purchase the food items, overstating their WTP for organic milk and some of the conventional milk items. According to Corrigan and Rousu (2008), the latter result would not be consistent with theory. One possible explanation for this would be that participants were not familiar with the "market" price of the product. Note that most of the auction bids are concentrated between \$0 and \$2. Out of the 544 bids, 41 of them (i.e. 7.54 percent) are equal to zero - 4 correspond to bread, 14 to milk, 5 to organic apples, and 18 to organic milk. The larger number of zeros for the organic milk product might indicate that participants did not intend to purchase these food products at that particular moment.

[26] The term "extreme" is not formally defined in the statistical literature, but I refer to extreme observations as observations that deviate from the rest of the sample and are not necessarily outliers. As noted in Hawkins (1980) "the intuitive definition of an outlier would be 'an observation that deviates so much from other observations as to arouse suspicions that it was generated by a different mechanism'."

Figure 3.1 shows the average bid for each food product across the two bidding rounds under study. For this experimental application, bids tend to increase across the two rounds, being the difference between the bids in round 1 and bids in round 2 not statistically significant according to the nonparametric Wilcoxon-Mann-Whitney two-sample test (p-value = 0.1107).

Auction bid price distributions by food product are reported in figure 3.2 for the first and second rounds. The distributions for round 1, where participants bid for one food item in isolation, illustrates that bid prices for the flax-seed bread are higher relative to the other food items ($4 being the maximum), whereas in round 2, where participants bid in a multi-good auction setting, bid prices increased to $5 for both flax-seed bread and organic apples. In round 1, the distribution of the bids for bread and organic milk tend to be more uniform, but in round 2 none of the distributions per product have a similar pattern. In addition, participants were willing to pay a minimum bid price for bread of $1 in the first round, but when this functional food was juxtaposed with other two food items some participants placed a zero bid on it. This analysis suggests that valuation in isolation and full-bidding differ at least from an exploratory prospective similar to List (2002) who used random n*th* price auctions.

The intra-respondent WTP responses exhibit some degree of positive correlation across the four food products under study, being larger between organic milk and conventional milk (correlation coefficient = 0.7). This outcome is not surprising considering that conventional milk and organic milk are highly substitutable. The existing correlation across responses might be explained due to common unobservables for a given respondent, whose interaction with some regressors might lead to heteroskedastic errors. The fact of having four different cross-sectional responses from the same participant is critical in terms of modeling so that we allowed for cross-equation error correlations in the error terms using the unconstrained SUR estimation procedure.

4. Modeling Strategy and Variables

Section 3 presented the bid data, emphasizing that the variable to study is observed only on some interval of its support. As Lusk and Fox (2003) note, we surmise that possible reasons that lead participants to have a zero WTP could be budgetary considerations or disengaged behavior in the experiment itself; however, this is uncertain in our study. We conjecture that some zero WTP records are linked to some participants disliking some of the auctioned goods under study (e.g. organic foods). In the econometric literature, zeros are also treated as corner solutions where the issue is not data observability but instead the distribution of the response variable given the covariates (Wooldridge, 2002; Chapter 16). This may be inapplicable to our case, since participants were not income constrained in the experiment as they were compensated with a \$10 gift certificate and, therefore, all of them could bid positive amounts. Otherwise, then they might bid zero as they realized that the \$10 could help them to purchase other foods with more need or priority.

Our data structure suggests that our sample is left *fixed*-censored at zero and the censoring[27] mechanism belongs to the Type II class. Chay and Powell (2001) indicate that when censoring occurs, it is expected that the variation of the variable to be explained will lead to an understatement of the effect of the explanatory variables on the "true" dependent variable. Censoring renders OLS coefficient estimates biased and

[27] The distinction between censoring and truncation is usually loose among practitioners. In statistical parlance, the term "censoring" is a property of the sample itself, whereas "truncation" is a property of the distribution. As Maddala (1983) points out a *censored distribution* is rarely used.

inconsistent (Greene, 1981), thus yielding misleading statistical results. In fact, the linearity assumption is violated so that the least square method becomes inappropriate (Maddala, 1983).

Given the left-censored nature of the dependent variable and that our data are realizations of a discrete and continuous processes, a Tobit maximum likelihood estimator (MLE) might seem most appropriate; however, this commonly used fully parametric estimation technique for fixed censoring is not without critics. First, this nonlinear method, also known as censored regression normal model or Tobit I, is a very restrictive approach, since it does not allow for different covariates in the two parts (continuous and discrete) of the model. As Haines, Guilkey and Popkin (1988), state "ignoring the two-step nature of the decision process may hamper understanding of true behavioral patterns, lead to erroneous conclusions, and generate incorrect policy recommendations". Second, the Tobit model and all its generalizations (e.g. Heckman's two-step procedure) become inconsistent under heteroskedasticity and non-normality (see Amemiya (1984) among others). Third, these models require a full specification of a parametric distribution of the disturbances. Unfortunately, researchers usually have insufficient information regarding the actual distribution of the errors, and theory provides very little guidance for a reasonable structural specification of the heteroskedasticity. Powell (1986) points out that this is a serious concern, since the adoption of an incorrect parametric functional form can lead to spurious statistical inferences due to biased and inconsistent estimates.

Following Cameron and Trivedi (2009), I formally tested for homoskedasticity and normality using conditional moment tests, which are based on generalized residuals for censored regression. The statistical results (Normality test: p-value = 1.85e-14; homoskedasticity test: p-value = 4.991e-21) from these tests reveal departures from the Tobit model assumptions, rendering inconsistent ML-Tobit coefficient estimates. Next, I tested for the Tobit specification against a somewhat more general model using the likelihood ratio (LR) test proposed by Ruud (1984).[28] Given that the log-likelihood values for the Tobit model and the two-part (hurdle) model are -628.29419 and -594.5086, respectively, and the $\mathrm{LR} = 67.572 > \chi^2_{0.05,29} = 42.55$, we reject the null hypothesis $(\mathrm{H_o}: \text{Tobit model is correct})$. That is, the two-part model is preferred to the Tobit model. For these model diagnostics, I pooled the data over food items and included the variables specified in table 3.1 as well as intercept shifters for all food items among other variables.

Although OLS and the ML frameworks are inconsistent, the extent of the consequences is not clear given the sample size in this study. Therefore, results based on OLS, Tobit I, and Heckman two-step (Tobit III) estimators in a product-by-product context are presented. I also present an alternative single equation approach to the fully parametric techniques known as the Powell's (1986) SCLS estimator, which provides consistent coefficients for censored data, even when the noise term is non-normal and/or exhibits non-sphericity. This estimation procedure is semiparametric[29] in nature, and relatively well-established in the statistics and economics literature (see e.g. Kwak, Lee

[28] $\mathrm{LR} = -2 \cdot \left[\mathrm{LLH}_{\text{Tobit Model}} - \left(\mathrm{LLH}_{\text{Probit Model}} + \mathrm{LLH}_{\text{Truncated Regression Model}}\right)\right] \sim \chi^2_{n-1}$, where LLH is the log-likelihood value and *n* is the sample size. A number of alternative tests are also available in the econometric literature such as Nelson (1981) and Lin and Schmidt (1984).

[29] The term *semiparametric* typically involves a parametric and a nonparametric specification. The former refers to an underlying regression function assumed to be linear in the covariates, while the second part involves not imposing specific parametric family of distributions on the unobservable idiosyncratic error term.

and Russell, 1997; Chay and Powell, 2001; Yoo, Kim and Lee, 2001; Wilhelm, 2008). Despite the statistical advantages of the SCLS approach, an important disadvantage of this method is that by trimming (discussed in the next section) the sample we might eliminate valuable information of individuals' decisions.

Lastly, I provide an empirical econometric application of the SUR model, developed by Zellner (1962), in a system context since the model errors of the four WTP equations are very likely correlated. Due to our sample size, the SUR system estimation is conducted using the iterated feasible generalized least-squares (IFGLS) rather than using the two-step FGLS or ML approach.

Since the single equation SCLS approach for Tobit models is novel to the experimental and food economics literature, I will briefly review it next.

4.1 Symmetrically Censored Least Squares Estimator

I start by introducing notation. Let y_i be the bid for participant i for a specific product (e.g. milk), $\mathbf{x}_i$ be a $1 \times K$ matrix of observed explanatory variables that may influence the participant's bid, $i = 1, \ldots, n$ (the number of total participants in the experiment), $\boldsymbol{\varepsilon}_\mathbf{i}$ - the disturbance term – are factors that the econometrician cannot observe, y_i^* is the true (latent) dependent variable, and K is the number of unknown parameters. Then, assuming that censoring from below at zero is present and the parametric distribution of the disturbance term is unknown, the censored sample counterpart of y_i is given by:

$$y_i = \max\left\{0, \mathbf{x}_\mathbf{i}^{'}\boldsymbol{\beta} + \varepsilon_i\right\} = \max\left\{0, y_i^*\right\} \tag{1}$$

where y_i is non-negative, asymmetrically distributed due to left-censoring, and its value is determined by its latent variable y_i^*.

Considering that the error distribution family remains unknown, the moment-based approach appears to be appealing for solving this problem. However, since (1) is censored, then $\varepsilon_i \geq -x_i^{'}\beta$ so that the orthogonality condition is violated. Assuming that the conditional density function of $\boldsymbol{\varepsilon} \mid \mathbf{x}$, $f_{\boldsymbol{\varepsilon}|\mathbf{x}}$, is symmetric and unimodal around zero, Powell (1986) suggests a way to restore the orthogonality condition by "trimming" the error density.

To “trim” equation (1), extreme values of y_i are replaced with a maximum value $\left(2\mathbf{x}_\mathbf{i}^{'}\boldsymbol{\beta}\right)$ such that the resulting distribution of the censored sample is symmetrically distributed around $\mathbf{x}_\mathbf{i}^{'}\boldsymbol{\beta}$. By doing so, we are able to restore symmetry of y_i. That is to say, we censor the upper tail of $f_{\boldsymbol{\varepsilon}|\mathbf{x}}$ in the opposite direction to allow us to estimate least squares coefficients consistently. As Santos Silva (1998) describes, under the symmetry restriction, the SCLS estimator induces the following model:

$$y_i^* = \mathbf{x}_\mathbf{i}^{'}\boldsymbol{\beta} + \varepsilon_i^*,\ 1\left(\mathbf{x}_\mathbf{i}^{'}\boldsymbol{\beta} > 0\right),\ \forall i,\ i = 1,\ldots,n \tag{2}$$

where $1(\cdot)$ is an indicator function equal to 1 if the condition is satisfied and $\varepsilon_i^* = \begin{Bmatrix} -\mathbf{x}_\mathbf{i}^{'}\boldsymbol{\beta} \\ \varepsilon_i \\ \mathbf{x}_\mathbf{i}^{'}\boldsymbol{\beta} \end{Bmatrix} \text{ if } \begin{Bmatrix} y_i^* = 0 \\ 0 < y_i^* < 2\mathbf{x}_\mathbf{i}^{'}\boldsymbol{\beta} \\ y_i^* = 2\mathbf{x}_\mathbf{i}^{'}\boldsymbol{\beta} \end{Bmatrix}$. To solve for this inverse problem the moment-based approach is invoked so that a set of theoretical (population) moment conditions are specified by $\mathrm{E}\left[1\left(\mathbf{x}_\mathbf{i}^{'}\boldsymbol{\beta}>0\right)\left(y_i^*-\mathbf{x}_\mathbf{i}^{'}\boldsymbol{\beta}\right)\cdot\mathbf{x}_\mathbf{i}\right]=\mathbf{0}$ and its corresponding sample estimating equation-moment is given by:

$$n^{-1}\sum_{i=1}^{n}1\left(\mathbf{x}_\mathbf{i}^{'}\boldsymbol{\beta}>0\right)\cdot\left(\min\left\{y_i,\mathbf{2x}_\mathbf{i}^{'}\boldsymbol{\beta}\right\}-\mathbf{x}_\mathbf{i}^{'}\boldsymbol{\beta}\right)\cdot\mathbf{x}_\mathbf{i}=\mathbf{0},\ \forall i,\ i=1,\ldots,n \tag{3}$$

Since equation (3) is discontinuous we can expect more than one solution to this moment condition. However, under the generalized method of moments framework we can choose $\boldsymbol{\beta}$ for which equations (3) are as close to the zero vector as possible. In pursuit of this task, the SCLS estimator is an implicit solution to the following minimization problem with respect to $\boldsymbol{\beta}$:

$$S(\beta)=$$
$$(1/n)\sum\left(y_i-\max\left\{0.5y_i,x_i^{'}\beta\right\}\right)^2+(1/n)\sum1\left(y_i>2x_i^{'}\beta\right)\cdot\left[\left(0.5y_i\right)^2-\left(\max\left\{0,x_i^{'}\beta\right\}\right)^2\right] \tag{4}$$

In this study, equation (4) was implemented using Aptech Systems' GAUSS 11 and numerically solved using an iterative optimization routine.

4.2 Variables

Dummy variables for *gender* and *primary food shopper* (*pfs*) as well as dichotomous indicators for bachelor's and graduate or professional degrees (see table 3.1) as *educ_d5* and *educ_d6*, respectively, were included in the specifications of the models. Education levels 1, 2, 3 and 4 (see table 3.1) were omitted and incorporated as a reference category subsumed into the intercept term, since they were identified as being collinear. As for *household income*, dummy variables were constructed to capture income-specific variation, omitting the first income group indicator *income_d1* (i.e. less than $20,000) from the model for estimation purposes. The variable *age* was represented by the midpoint of the age categories. A lin-log specification for *age* was introduced as a regressor. *Race*, *student*, *current agricultural occupation* (*ao)*, and *household size* were initially considered, but excluded from the models reported here because they were shown to be insignificant variables across the models or were collinear with other included variables.

The questionnaire also included six Likert-type scale[30] questions on participants' perceptions about the quality attributes of the organic apples (nutrition, taste, appearance, safety, and environmentally sound practices) relative to conventional ones and seven binary questions about participants' shopping habits for organic apples (the store under study, other supermarkets and grocery stores, natural foods markets, food Co-ops, warehouse retailers (e.g. Costco), farmers markets, and other type of stores different than the previous ones). To reduce the number of variables representing this information, the forward stepwise model selection approach was used, with a significance level for adding and deleting a variable equal to 0.05 and 0.01, respectively. As a result, four variables from the two sets were retained (*oa_tb*: taste better, *oa_n*: more nutritious, *wr*: warehouse retailers, and *osgs*: other type of stores).

In addition to the variables discussed above, three indicators were included into the corresponding models for the specific product, indicating 1 if the corresponding product category was generally purchased when shopping at the store under study. That is, *breads* was included in the bread model, *dairy* was included in the conventional milk model, and *onf* (organic or natural foods) was included in both the organic apple and organic milk models.

The following two variables were constructed to address the two major objectives of the study: a dummy variable *dp1* (= 1 if product *m*=1,2,3,4 is being auctioned in the first

[30] 5 "strongly agree", 4 "agree", 3 "not sure", 2 "disagree" and 1 "strongly disagree".

round for the participant; 0 otherwise) and a numerical variable *gain1* indicating the amount of gift certificate available when the product appeared in the auction (= \$10 minus the dollar amount a participant spent in the first round). The variable *gain1* was equal to \$10 for all first round products (*dp1=1*). To examine bid sensitivity across the two rounds and compensation effects I tested the following hypotheses:

$$H_o : \beta_{dp1} = 0 \text{ vs. } H_1 : \beta_{dp1} \neq 0 \tag{5}$$

$$H_o : \beta_{gain1} = 0 \text{ vs. } H_1 : \beta_{gain1} \neq 0 \tag{6}$$

where β_{dp1} and β_{gain1} are the associated unknown parameter estimates for *dp1* and *gain1,* respectively. To test theses hypotheses, I conducted the traditional parametric *t*-test for each product estimate, separately, with each participant represented once in each food product equation. For the SUR system, the product datasets were stacked, resulting in a balanced multiple-equation system with each product having their own set of coefficients.

5. Results and Discussion

The appendix (see B-E) reports parameter estimates and standard errors for all the variables included in the equation-by-equation models (i.e. OLS, Tobit I, Tobit III, and SCLS) for each of the four products under study. F in the appendix displays the SUR system results. Due to the limited variation in several independent variables in the sample and limited amount of censoring for the dependent variable for bread and organic apples, the Tobit III model is not presented for these two products.

Based on our estimation results (see B-F) and statistical trade-offs of using the different techniques, it is difficult to choose the best method in terms of modeling participants' bidding behavior, even when utilizing the robust semiparametric estimator with which a 16.3% of the sample is trimmed (two observations from bread, five from milk, nine from organic milk, and five from organic apples). For this application, the SUR system model losses less efficiency relative to the maximum likelihood estimation procedures, OLS approach, and SCLS estimator.

Overall, the signs of the estimated coefficients (directional effects) were generally the same across techniques. Consistent with prior expectations, the contribution of the explanatory variables to the explanation of the participant's WTP and the magnitude of these effects depends upon the food product and vary by estimation method. This is why it is important to recognize the statistical advantages and disadvantages of using different econometric methodologies. Also important, and especially when having limited data as in our case, is to recognize that we as researchers do not have enough information about the underlying data sampling process to make strong assumptions for the appropriate functional specifications.

Regarding parameter significance, the coefficient associated to household income at level 4 (i.e., \$60,001 - \$80,000) is the only one that is significantly different from zero across all the methods in the bread model (see B in the appendix). This indicates that this income category differs in impact from the reference category (i.e. household income at level 1: less than \$20,000), but household income at levels 2, 3, 5 and 6 do not. No variable in the bread model has a statistically significant impact at the 0.01 level. For the conventionally produced milk model (see C in the appendix), the variables "age" and "wr" (i.e., consumers' shopping habits for organic apples at warehouse retailers) were found to have negative and significant effects on participants' WTP in all of the models. However, "age" is the only statistically significant variable at a 99% level of confidence.

For the organic apples model (see D in the appendix), “age”, “household income at level 6 (i.e., greater than $100,000)”, and “wr” were found to be significant and negatively related to the bids across all estimation methods, whereas “oa-tb” (i.e., consumers' perceptions about the quality of the organic apples relative to conventional ones in the sense of tasting better) was found to have a positive and significant effect on the bids over all methods. Nonetheless, “age” has the strongest effect on participants’ WTP. This effect can be also observed in the organic milk model (see E in the appendix). In addition, the variable “oa_n” (i.e., consumers' perceptions about the quality of the organic apples relative to conventional ones in terms of more nutrition) also contributes to the explanation of the dependent variable in all the models. The variable “age” is negatively associated with participant’s WTP, while “oa_n” is positively related. These results suggest that participants’ WTP for the food products under study are largely explained by their age, possibly somewhat capturing the impact that habit has on food purchases.

Focusing on the results from the system approach, I find that household income has a positive and significant effect on participant’s WTP for organic apples and bread, while, interestingly the variable “age” has a statistically significant and negative impact on WTP for both organic food items (i.e., organic apples and organic milk). This last outcome suggests that the older participants are, the less willing they are to pay higher prices for organic foods. The variable “age” is insignificant at 0.05 confidence level in the bread model, but is nearly significant at the 0.10 level, suggesting its effect should not necessarily be ignored.

Table 3.3 summarizes parameters' estimated values for the main variables of interest, (*dp1* and *gain1*) across food products and estimation procedures. Recall that “*dp1”* is the dummy variable for whether the product was in the first round, and "*gain1*" indicates the amount of the gift card compensation that was available to the participant when the product was being bid on.

It is evident in table 3.3 that individual equation estimation results show similarities to the system framework in terms of parameter significance for organic apples and organic milk, but not for bread and conventional milk. Focusing on "*dp1*", I find that this indicator variable is negatively related to participant's bidding behavior and its coefficient is only statistically different than zero (with at least 95% confidence) in organic apples, across all models. Therefore, we reject the null hypothesis for this case, implying that rounds can matter. The negative coefficient indicates that participants are willing to pay less if the product is auctioned in the first round than if it is auctioned in the second round, which might be explained by a learning effect of the auction mechanism or by the uncertainty associated with the food products that would be bid in the second round. Participants might realize they have lost an opportunity to purchase the product at a lower price.

Parametric t-tests for the single product models for bread, milk and organic milk indicate that we cannot reject the null hypothesis at any significance level. For the system approach we cannot reject the null hypothesis for milk and organic milk, but reject it for bread and organic apples. Overall, the results suggest that non-hypothetical bids are sensitive to the context of bidding, participants' preferences for particular food items and to the approach to estimation of the model.

Focusing on the Tobit III model for milk and organic milk, the inverse mills ratio (IMR) variable was found to be insignificant for both products at the 0.05 level.

However, the IMR is "close" to being significant at the 0.10 level for conventional milk. The apparent insignificance of the IMR variable for organic milk could be due to the multicollinearity, a typical problem in this type of datasets.

In general, we cannot reject the null hypothesis of no compensation effect (see equation [6]) when using individual and system estimations. According to our results (see table 3.3), the variable "*gain1*" is never statistically significant, except for milk in the SUR system. This overall outcome suggests that compensation effects have little impact on individual's bidding decision. I argue that this might be explained due to the uncertainty associated with the lack of information about the products that would be bid in the second round and due to the fact that participants were not actually income constrained during the experiment. However, there is some evidence that the uncertainty about which product will be binding in the second round, or the round order, can have an effect on participants' bidding decisions.

It seems that participants perceived the amount they spent for the food items as an opportunity cost. Thirty out of 136 participants (i.e., 22 percent) won the single good-auction in the first round, being the conventionally produced milk the least frequently purchased product and the average cost (from the gift certificate) across all products purchased was near $1. The average earning for the entire sample at this stage of the decision process was $9.8. Even though every participant could potentially win the auction and the opportunity of learning was allowed in the current setting, the resulting decision behavior might be explained by the uncertainty associated with the binding product in the second round. This result provides evidence that compensation effects in the context of our experiment have mostly no impact on individual's bidding decision.

6. Conclusions and Future Research

This research reports a field experiment in which participants are asked to value goods in a homegrown value elicitation context with no pre-assigned induced value. Individual bidding behavior in multi round BDM auctions with uncertainty about the binding product in one of the rounds has not been analyzed in economic literature.

Participants proceed sequentially through two rounds where they bid on one food product in the first stage (round) and then bid simultaneously for other three different products in the second round. The estimation results show different effects of participant demographics and participants' perceptions about the quality attributes of the organic apples (nutrition and taste) relative to conventional ones and participants' shopping habits for organic apples (warehouse retailers and other type of stores). For instance, the variable “age”, which is most consistently highly significant across all the estimation procedures considered in this study, is negatively associated to participants’ WTP for both organic food items (i.e., organic apples and organic milk).

I find that bids are sensitive to the context of bidding and participants' preferences for particular foods. The results also differ across estimation procedures. Compensation mainly did not impact individual's bidding decision, implying that since the participants were not constrained in terms of how much money they could spend during the experiment, outcomes of the first round and associated spending in the first round did not have an effect on the behavior in the second round. This means that participants rational decisions are not affected by a potential “latent” constraint that may be argued to be present when the participants are compensated with a certain amount of money as long as the rules of the experiment do not explicitly restrict the participants spending amounts.

There are two limitations that need to be pointed out with regard to this research; however, none of them have significant implications to successfully complete the research objectives of this study. First, it is true that this first attempt at modeling consumer's bidding behavior using the IFGLS-SUR system model allows us to account for the error correlation across equations and, therefore, take advantage of the fact that four WTP values for four different food products come from the same participant. However, this approach does not control for the censoring, and as such, an avenue of future research would be to implement a system approach that is able to account simultaneously for both the error correlation across equations and the censoring without imposing parametric assumptions that can lead to biased and inconsistent estimates and distort our statistical inferences.

Another limitation of this study is associated with the order in which the bidding rounds were implemented in the experiment. In our study, the order of the bidding rounds was the same for all participants. The first round was always for a single product auction, and the second round was always for the multi-product auction. An important consideration in future research with a greater number of participants would be to allow for randomization of the bidding sequence. This will allow to separate the effects of uncertainty and round order on participant behavior.

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Table 3.1. Features of Participants

Variable	Description	Min	Max	Mean	Std.Deviation	N
Age	Age of participant in years	1	6	3.84	1.82	**136**
	= 1 if 18-24					24
	= 2 if 25-34					16
	= 3 if 35-44					11
	= 4 if 45-54					24
	= 5 if 55-64					28
	= 6 if 65+					33
Gender		0	1	0.59	0.49	**136**
	= 1 if female					80
	= 0 otherwise					56
Education	Highest level of formal education of participant	1	6	3.80	1.48	**136**
	= 1 if less than 12th grade					3
	= 2 high school graduate					25
	= 3 if some college					47
	= 4 if associate degree					5
	= 5 if bachelor degree					32
	= 6 if graduate or professional degree (e.g. MS, MA, PhD, MD, JD)					24
Race	Race/ethnicity background of participant	1	6	4.96	0.58	**136**
	= 1 American Indian or Alaska Native					1
	= 2 if Asian-American, Native Hawaiian or Pacific Islander					1
	= 3 if Black or African American					2
	= 4 if Hispanic or Latino					1
	= 5 if White (non-Hispanic)					128
	= 6 if International					0
	= 7 Other					3
Income	Household income (before taxes) in US dollars	1	6	2.98	1.63	**133**
	= 1 if less than $20,000					30
	= 2 if $20,001 - $40,000					31
	= 3 if $40,001 - $60,000					26
	= 4 if $60,001 - $80,000					17
	= 5 if $80,001 - $100,000					16
	= 6 if greater than $100,000					13
hs	Household size	1	6	2.35	1.22	**136**
pfs	Primary food shopper?	0	1	0.70	0.53	**136**
	= 1 if Yes					100
	= 0 otherwise					36
ao	Currently or previously employed in an agricultural occupation?	0	1	0.27	0.45	**136**
	= 1 if Yes					37
	= 0 otherwise					99
Student	Are you currently a student?	0	1	0.19	0.39	**129**
	= 1 if Yes					24
	= 0 otherwise					105

Table 3.2. Summary Statistics of Bids over the two Rounds

Food Item	Mean	Median	S. D.	Min	Max	$\sqrt{b_1}$	b_2
Bread	2.20	2.00	0.99	0	5	0.27	2.95
Milk	1.21	1.16	0.74	0	4	0.62	4.12
O. milk	1.38	1.50	0.86	0	4	0.26	3.09
O. apples	1.38	1.25	0.79	0	5	1.23	6.03

Note: S.D. is the standard deviation, $\sqrt{b_1} = m_3 / m_2^{3/2}$ is a measure of skewness, and $b_2 = m_4 / m_2^2$ is a coefficient of kurtosis as defined in Pearson and Harley (1970), where $m_r = \sum_{i=1}^{n} \frac{(x_i - \bar{x})^r}{n}$, $\bar{x} = \sum_{i=1}^{n} \frac{x_i}{n}$, $r \geq 2$, and m_r is the r^th moment of the observations. The Mean, Median, Min and Max statistics are in U.S. dollars.

Table 3.3. Summarized Results for Selected Variables across Food Products and Estimation Procedures

Estimation Procedure	Coefficient	Bread	Milk	Food Product Organic Apples	Organic Milk
OLS_1	$\hat{\beta}_{dp1}$	-.2221	-.0066	**-.3354****	-.1584
	$\hat{\beta}_{gain1}$	.0017	-.0239	-.1231	-.1473
OLS_2	$\hat{\beta}_{dp1}$	-.3361	-.1509	**-.3449****	.0263
	$\hat{\beta}_{gain1}$	.0933	.0768	-.1402	-.0460
Tobit I	$\hat{\beta}_{dp1}$	-.2063	.0214	**-.3529****	-.1767
	$\hat{\beta}_{gain1}$	-.0092	-.0465	-.1220	-.1686
Tobit III	$\hat{\beta}_{dp1}$		-.0518		.0438
	$\hat{\beta}_{gain1}$		-.0169		-.0324
SCLS	$\hat{\beta}_{dp1}$	-.2625	.0262	**-.3542****	-.1646
	$\hat{\beta}_{gain1}$	.0121	.0165	-.0830	-.1564
SUR System	$\hat{\beta}_{dp1}$	**-.3689****	-.0989	**-.3333*****	-.1603
	$\hat{\beta}_{gain1}$	.1432	**.2232****	.0318	.1343

OLS_1: ordinary least square using the full sample; OLS_2: ordinary least square using the uncensored sample; Standard errors and the way they were computed are denoted in tables B-F in the appendix.
***Statistically significant at 99% confidence level;**statistically significant at 95% confidence level

Figure 3.1. BDM Average Bids across the two Bidding Rounds for each Type of Food

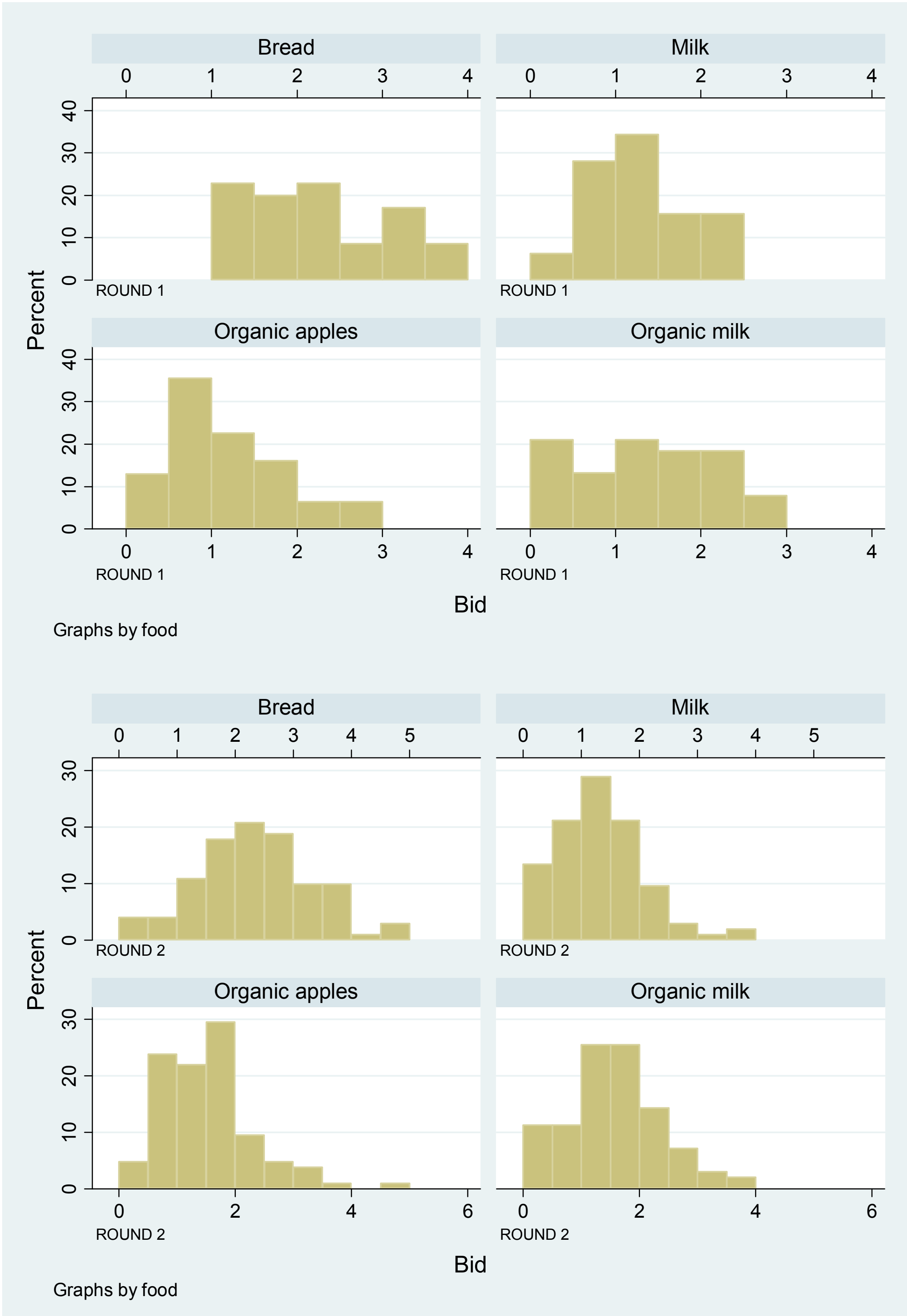

Figure 3.2. Histograms of Bid Prices per Round and Type of Food

Appendix

A. Experimental Instructions

General Instructions:

My name is__________ and I am part of team researchers from Washington State University.

We are conducting a market study, which consists of two parts: an experiment and a short questionnaire. If you participate, we will compensate you for your time with a gift certificate worth $10. This will take 15-20 minutes and you will receive *your gift certificate* upon completion of the experiment and questionnaire. Would you be willing to participate?

Specific Instructions:

You will have the opportunity to buy some products without spending any more money on the purchases than you want to.

How this will work?

- We will show you a variety of products, and give you the opportunity to bid individually on each of the products like you would in an auction.
- We do not have anyone for you to bid against, so the opposing bid will be determined by drawing a price from this (bowl) of random prices.
- Just like in an auction, <u>if your bid is greater than or equal to the price we draw</u>, you win the auction and the right to **buy** the product.
  - Different from an auction, if you win the auction, the price that you pay for the product is the lower drawn price
- Just like in an auction, <u>if your bid is lower than the drawn price</u>, you don't win the auction and you **don't get to buy** the product.
- You only get to bid once, and if you win we expect you to buy the product.
  - <u>Example</u>:
    - Suppose for example that we showed you a bottle of wine and you submit a <u>bid of $10.</u>
    - If the <u>price that we drew was $5,</u> then your bid is higher and you win the auction and get to **buy the bottle of wine for $5.**
    - Suppose that you <u>submit a bid of $10 for the bottle of wine, and we draw a price of $12.</u>
    - Your bid is lower than the drawn price, so you don't win the auction and **don't get to buy** the bottle of wine.
- If you value the product and would like to buy it today, it is in your best interest to bid your true value for the product. <u>If you bid more than you value</u> the product you might end up paying more than you wanted for the product. <u>If your bid is</u>

lower than your true value, you may miss the opportunity to buy the product for a low price.

The experiment will consist of **two rounds** of bidding using the auction procedure that I just explained.

Round 1:

- You have a chance to buy this *product* (e.g. one pound of organic apples).
- Your price offer for the product should be the highest amount you would be willing to pay to have the product right now.
- After you submit your bid, you will draw a price from this bowl that contains prices ranging from $0.10 to $6.00 in $0.10 increments.
- If your price offer is higher than the price you draw, you will be obligated to buy the product (from us) at the drawn price. If your price offer is lower than the price you draw, you will not be able to buy the product.
- Inform the participant(s) of the results, and discuss if necessary.

Round 2:

- You have the opportunity to bid on each of these products individually.
- The auction will work the same as in round 1, but this time you will bid on three products simultaneously.
- You will not have to buy all three products. One of the three products has been randomly predetermined to be the *binding product*. After you submit your three bids, we will reveal the binding product and randomly draw a price for the product.
- Inform the participant(s) of the results.

Thank you for your participation in the experiment. We would now like to complete a questionnaire. Take as much time as you need and feel free to ask (person at the other table) for clarification of any question.

You will receive your compensation and products from (person at the other table) upon completion of the questionnaire.

Flow chart of the BDM experimental auction mechanism

B. Estimation Results for Bread

	OLS_1	OLS_2	Tobit I	Tobit III	SCLS
dp1	-0.2221	-0.3361*	-0.2063		-0.2625
	(0.2068)	(0.1929)	[0.1954]		{0.1777}
gain1	0.0017	0.0933	-0.0092		0.0121
	(0.2598)	(0.2415)	[0.1503]		{0.1961}
breads	0.3197*	0.2675	0.3266*		0.3191**
	(0.1852)	(0.1750)	[0.1775]		{0.1603}
ln(age)	-0.3238	-0.1852	-0.3460*		-0.3410*
	(0.2176)	(0.2050)	[0.2087]		{0.1886}
gender	0.1851	0.1997	0.1797		0.1896
	(0.1897)	(0.1769)	[0.1804]		{0.1825}
income_d2	0.2439	0.1613	0.2575		0.2400
	(0.2547)	(0.2384)	[0.2443]		{0.2146}
income_d3	-0.1011	-0.1142	-0.1027		-0.0988
	(0.2814)	(0.2645)	[0.2724]		{0.2552}
income_d4	0.6481*	0.7593**	0.6404*		0.6711**
	(0.3436)	(0.3265)	[0.3306]		{0.3393}
income_d5	0.4856	0.4429	0.4939		0.4744
	(0.3183)	(0.2970)	[0.3055]		{0.3494}
income_d6	-0.2930	-0.2822	-0.2979		-0.3221
	(0.3798)	(0.3603)	[0.3635]		{0.3720}
pfs	-0.2346	-0.3548*	-0.2215		-0.2162
	(0.2065)	(0.1946)	[0.1971]		{0.1970}
educ_d5	-0.1952	-0.3087	-0.1776		-0.1855
	(0.2295)	(0.2139)	[0.2212]		{0.1875}
educ_d6	-0.1597	-0.1114	-0.1618		-0.2036
	(0.2804)	(0.2618)	[0.2687]		{0.2895}
osgs	0.2693	0.2099	0.2748		0.2860
	(0.1864)	(0.1760)	[0.1785]		{0.1809}
wr	-0.1866	-0.2204	-0.1861		-0.2221
	(0.1935)	(0.1810)	[0.1853]		{0.1954}
oa_n	0.0259	0.0033	0.0310		0.0389
	(0.1164)	(0.1088)	[0.1095]		{0.1231}
oa_tb	0.0463	0.0643	0.0449		0.0336
	(0.1251)	(0.1171)	[0.1195]		{0.1267}
intercept	2.9327	1.7949	3.0800*		2.8863
	(2.7200)	(2.5307)	[1.7821]		{2.1145}

OLS_1: ordinary least square using the full sample (N=136); OLS_2: ordinary least square using the uncensored sample (N=132); Standard errors for OLS are in parenthesis and were computed by deriving the adjusted sampling variance of the residuals. Standard errors in square brackets were calculated based on the inverse of the negative Hessian, while standard errors in curly brackets were estimated with the covariance matrix $\left[E\left\{1\left[|\varepsilon|<x'\hat{\beta}_{SCLS}\right]xx'\right\}\right]^{-1} E\left\{1\left[x'\hat{\beta}_{SCLS}>0\right]\min\left(\varepsilon^2,\left(x'\hat{\beta}_{SCLS}\right)^2\right)xx'\right\}\left[E\left\{1\left[|\varepsilon|<x'\hat{\beta}_{SCLS}\right]xx'\right\}\right]^{-1}$.

***Statistically significant at 99% confidence level;**statistically significant at 95% confidence level; *statistically significant at 90% confidence level.

$t_{0.01}=-2.62393,\ t_{0.05}=-1.98304,\ t_{0.1}=-1.65964$

C. Estimation Results for Conventionally Produced Milk

	OLS_1	OLS_2	Tobit I	Tobit III	SCLS
dp1	-0.0066	-0.1509	0.0214	-0.0518	0.0262
	(0.1591)	(0.1394)	[0.1478]	(0.1550)	{0.1566}
gain1	-0.0239	0.0768	-0.0465	-0.0169	0.0165
	(0.1314)	(0.1125)	[0.1310]	(0.1269)	{0.1391}
dairy	0.2144	0.0328	0.2564	0.2145	0.2008
	(0.1519)	(0.1382)	[0.1574]	(0.1870)	{0.1701}
ln(age)	-0.3658**	-0.3941***	-0.3729**	-0.4040***	-0.3885**
	(0.1625)	(0.1434)	[0.1677]	(0.1428)	{0.1509}
gender	-0.0229	-0.0346	-0.0107	-0.0009	-0.0331
	(0.1432)	(0.1257)	[0.1244]	(0.1273)	{0.1634}
income_d2	-0.1081	-0.1342	-0.1016	-0.1024	-0.0593
	(0.1874)	(0.1637)	[0.1924]	(0.1644)	{0.1579}
income_d3	-0.0541	0.0434	-0.0756	-0.0662	-0.0661
	(0.2088)	(0.1855)	[0.2156]	(0.1998)	{0.1927}
income_d4	0.1832	0.2754	0.1818	0.2860	0.2876
	(0.2590)	(0.2388)	[0.2699]	(0.2378)	{0.2890}
income_d5	-0.1279	-0.1803	-0.1206	-0.1442	-0.0448
	(0.2370)	(0.2042)	[0.2445]	(0.2047)	{0.1990}
income_d6	-0.3230	-0.5564**	-0.2774	-0.3723	-0.2539
	(0.2849)	(0.2535)	[0.2919]	(0.2831)	{0.2544}
pfs	-0.1625	-0.2421*	-0.1504	-0.1810	-0.1335
	(0.1551)	(0.1380)	[0.1587]	(0.1438)	{0.1598}
educ_d5	-0.2399	-0.0996	-0.2683	-0.2554	-0.2618*
	(0.1727)	(0.1534)	[0.1786]	(0.1873)	{0.1456}
educ_d6	-0.2301	0.1425	-0.2997	-0.1779	-0.4291
	(0.2103)	(0.1960)	[0.2186]	(0.2967)	{0.2659}
osgs	0.1112	0.0561	0.1205	0.0830	0.1657
	(0.1355)	(0.1222)	[0.1403]	(0.1230)	{0.1434}
wr	-0.2675*	-0.2614**	-0.2808*	-0.3212**	-0.3159**
	(0.1465)	(0.1308)	[0.1514]	(0.1367)	{0.1388}
oa_n	0.0873	0.0559	0.0993	0.0958	0.1296*
	(0.0866)	(0.0800)	[0.0901]	(0.0843)	{0.0725}
oa_tb	-0.0880	0.0335	-0.1177	-0.0650	-0.1529
	(0.0960)	(0.0893)	[0.0997]	(0.1123)	{0.1011}
intercept	2.9842*	2.1467	3.2142**	2.9814**	2.6696
	(1.5289)	(1.3299)	[1.5801]	(1.4458)	{1.7805}
IMR				0.9656	
				(0.6739)	

OLS_1: ordinary least square using the full sample (N=136); OLS_2: ordinary least square using the uncensored sample (N=122); Standard errors for OLS are in parenthesis and were computed by deriving the adjusted sampling variance of the residuals. Standard errors in square brackets were calculated based on the inverse of the negative Hessian, while standard errors in curly brackets were estimated with the covariance matrix $\left[E\left\{1\left[|\varepsilon| < x'\hat{\beta}_{SCLS}\right]xx'\right\}\right]^{-1} E\left\{1\left[x'\hat{\beta}_{SCLS} > 0\right]\min\left(\varepsilon^2, \left(x'\hat{\beta}_{SCLS}\right)^2\right)xx'\right\}\left[E\left\{1\left[|\varepsilon| < x'\hat{\beta}_{SCLS}\right]xx'\right\}\right]^{-1}$.

***Statistically significant at 99% confidence level;**statistically significant at 95% confidence level; *statistically significant at 90% confidence level.

$t_{0.01} = -2.62393,\ t_{0.05} = -1.98304,\ t_{0.1} = -1.65964$

D. Estimation Results for Organic Apples

	OLS_1	OLS_2	Tobit I	Tobit III	SCLS
dp1	-0.3354**	-0.3449**	-0.3529**		-0.3542**
	(0.1572)	(0.1571)	[0.1521]		{0.1418}
gain1	-0.1231	-0.1402	-0.1220		-0.0830
	(0.1358)	(0.1335)	[0.1312]		{0.1236}
onf	-0.1710	-0.2507*	-0.1547		-0.1455
	(0.1556)	(0.1512)	[0.1508]		{0.1246}
ln(age)	-0.4733***	-0.3440**	-0.5027***		-0.4903***
	(0.1625)	(0.1614)	[0.1569]		{0.1475}
gender	0.0366	0.1385	0.0075		0.0784
	(0.1440)	(0.1421)	[0.1669]		{0.1306}
income_d2	-0.2515	-0.3850**	-0.2273		-0.2134
	(0.1893)	(0.1875)	[0.1819]		{0.2021}
income_d3	-0.1568	-0.2639	-0.1538		-0.1488
	(0.2601)	(0.2062)	[0.1987]		{0.2569}
income_d4	-0.1409	-0.3291	-0.1077		-0.0947
	(0.2601)	(0.2560)	[0.2484]		{0.2856}
income_d5	-0.0951	-0.1667	-0.0718		-0.0359
	(0.2343)	(0.2321)	[0.2227]		{0.2522}
income_d6	-0.5173*	-0.6197**	-0.4990*		-0.4562*
	(0.2832)	(0.2748)	[0.2746]		{0.2723}
pfs	-0.1442	-0.1451	-0.1330		-0.1361
	(0.1527)	(0.1509)	[0.1484]		{0.1530}
educ_d5	0.2121	0.2360	0.2078		0.1928
	(0.1711)	(0.1683)	[0.1648]		{0.1864}
educ_d6	0.1845	0.1602	0.1894		0.2071
	(0.2077)	(0.2006)	[0.1989]		{0.1821}
osgs	0.2226*	0.1574	0.2352*		0.2376*
	(0.1333)	(0.1313)	[0.1284]		{0.1419}
wr	-0.2899**	-0.2865**	-0.3025**		-0.2697**
	(0.1450)	(0.1416)	[0.1396]		{0.1169}
oa_n	-0.1052	-0.1276	-0.0963		-0.0950
	(0.0849)	(0.0824)	[0.0822]		{0.0945}
oa_tb	0.2309**	0.2022**	0.2425***		0.2275**
	(0.0944)	(0.0920)	[0.0913]		{0.0985}
intercept	4.2025**	4.1768***	4.2166***		3.7547**
	(1.6134)	(1.5860)	[1.5617]		{1.4896}

OLS_1: ordinary least square using the full sample (N=136); OLS_2: ordinary least square using the uncensored sample (N=131); Standard errors for OLS are in parenthesis and were computed by deriving the adjusted sampling variance of the residuals. Standard errors in square brackets were calculated based on the inverse of the negative Hessian, while standard errors in curly brackets were estimated with the covariance matrix $\left[E\left\{1\left[|\varepsilon|<x'\hat{\beta}_{SCLS}\right]xx'\right\}\right]^{-1}E\left\{1\left[x'\hat{\beta}_{SCLS}>0\right]\min\left(\varepsilon^2,\left(x'\hat{\beta}_{SCLS}\right)^2\right)xx'\right\}\left[E\left\{1\left[|\varepsilon|<x'\hat{\beta}_{SCLS}\right]xx'\right\}\right]^{-1}$.

***Statistically significant at 99% confidence level;**statistically significant at 95% confidence level; *statistically significant at 90% confidence level.

$t_{0.01}=-2.62393,\ t_{0.05}=-1.98304,\ t_{0.1}=-1.65964$

E. Estimation Results for Organic Milk

	OLS_1	OLS_2	Tobit I	Tobit III	SCLS
dp1	-0.1584	0.0263	-0.1767	0.0438	-0.1646
	(0.1736)	(0.1571)	[0.1842]	(0.1782)	{0.1809}
gain1	-0.1473	-0.0460	-0.1686	-0.0324	-0.1564
	(0.1483)	(0.1251)	[0.1573]	(0.1423)	{0.1556}
onf	-0.1507	-0.1786	-0.1380	-0.1790	-0.2783**
	(0.1704)	(0.1534)	[0.1812]	(0.1542)	{0.1329}
ln(age)	-0.5658***	-0.4786***	-0.6193***	-0.4544**	-0.5746***
	(0.1779)	(0.1589)	[0.1895]	(0.1988)	{0.1784}
gender	0.0435	0.0786	0.0351	0.0795	0.1406
	(0.1562)	(0.1395)	[0.1590]	(0.1403)	{0.1729}
income_d2	0.0101	-0.1311	0.0443	-0.1564	-0.0777
	(0.2059)	(0.1814)	[0.2148]	(0.2202)	{0.1691}
income_d3	-0.0449	-0.1351	-0.0258	-0.1460	-0.1915
	(0.2289)	(0.2089)	[0.2307]	(0.2165)	{0.2444}
income_d4	0.2961	0.2606	0.3599	0.2288	0.3658
	(0.2847)	(0.2575)	[0.3032]	(0.3019)	{0.2852}
income_d5	-0.0031	-0.1615	0.0482	-0.1887	-0.0322
	(0.2554)	(0.2232)	[0.2759]	(0.2607)	{0.2861}
income_d6	0.0375	-0.4052	0.1642	-0.4896	0.1849
	(0.3090)	(0.2662)	[0.3276]	(0.4917)	{0.3274}
pfs	-0.2451	-0.3407**	-0.2329	-0.3466**	-0.2880*
	(0.1673)	(0.1488)	[0.1774]	(0.1523)	{0.1524}
educ_d5	-0.3084*	-0.1359	-0.3717*	-0.1006	-0.3678
	(0.1863)	(0.1678)	[0.1996]	(0.2413)	{0.2360}
educ_d6	-0.1494	0.0320	-0.1984	0.0688	-0.4014*
	(0.2297)	(0.2018)	[0.2443]	(0.2709)	{0.2436}
osgs	0.2588*	0.1415	0.2984*	0.1263	0.4014**
	(0.1477)	(0.1317)	[0.1575]	(0.1517)	{0.1629}
wr	-0.2580	-0.2221	-0.2977*	-0.2073	-0.2088
	(0.1620)	(0.1438)	[0.1727]	(0.1616)	{0.1624}
oa_n	0.2113**	0.1762**	0.2347**	0.1650***	0.2365***
	(0.0917)	(0.0805)	[0.0973]	(0.0976)	{0.0877}
oa_tb	-0.0598	0.0099	-0.0645	0.0161	-0.0195
	(0.1038)	(0.0959)	[0.1107]	(0.1011)	{0.1073}
intercept	4.7316***	3.5956**	5.0025***	3.4329**	4.5741**
	(1.7224)	(1.4712)	[1.8295]	(1.6788)	{1.9098}
IMR				-0.1585	
				(0.7747)	

OLS_1: ordinary least square using the full sample (N=136); OLS_2: ordinary least square using the uncensored sample (N=118); Standard errors for OLS are in parenthesis and were computed by deriving the adjusted sampling variance of the residuals. Standard errors in square brackets were calculated based on the inverse of the negative Hessian, while standard errors in curly brackets were estimated with the covariance matrix $\left[E\left\{1\left[|\varepsilon|<x'\hat{\beta}_{SCLS}\right]xx'\right\}\right]^{-1}E\left\{1\left[x'\hat{\beta}_{SCLS}>0\right]\min\left(\varepsilon^2,\left(x'\hat{\beta}_{SCLS}\right)^2\right)xx'\right\}\left[E\left\{1\left[|\varepsilon|<x'\hat{\beta}_{SCLS}\right]xx'\right\}\right]^{-1}$.

***Statistically significant at 99% confidence level;**statistically significant at 95% confidence level; *statistically significant at 90% confidence level.

$t_{0.01}=-2.62393,\ t_{0.05}=-1.98304,\ t_{0.1}=-1.65964$

F. IFGLS-SUR System Estimation Results

	BREAD	MILK	ORGANIC APPLES	ORGANIC MILK
dp1	-0.3689**	-0.0989	-0.3333***	-0.1603
	(0.1671)	(0.1120)	(0.1247)	(0.1194)
gain1	0.1432	0.2232**	0.0318	0.1343
	(0.2110)	(0.1063)	(0.1130)	(0.1196)
breads	0.1784			
	(0.1472)			
dairy		0.0853		
		(0.1049)		
onf			-0.1699	-0.0442
			(0.1284)	(0.1196)
ln(age)	-0.2984	-0.3247**	-0.4453***	-0.5300***
	(0.2027)	(0.1536)	(0.1517)	(0.1673)
gender	0.2022	-0.0079	0.0527	0.0342
	(0.1770)	(0.1350)	(0.1341)	(0.1467)
income_d2	0.1928	-0.1371	-0.2604	0.0207
	(0.2367)	(0.1775)	(0.1763)	(0.1936)
income_d3	-0.1540	-0.0506	-0.1559	-0.0276
	(0.2622)	(0.1978)	(0.1940)	(0.2155)
income_d4	0.6369**	0.2264	-0.1306	0.3628
	(0.3211)	(0.2450)	(0.2426)	(0.2674)
income_d5	0.4952***	-0.1227	-0.0868	0.0282
	(0.2966)	(0.2241)	(0.2193)	(0.2420)
income_d6	-0.3433	-0.3305	-0.5385**	0.0223
	(0.3548)	(0.2697)	(0.2649)	(0.2921)
pfs	-0.2379	-0.2083	-0.1593	-0.2948**
	(0.1923)	(0.1464)	(0.1427)	(0.1580)
educ_d5	-0.1714	-0.2491	0.2188	-0.3182**
	(0.2144)	(0.1634)	(0.1602)	(0.1765)
educ_d6	-0.1577	-0.2731	0.1926	-0.2007
	(0.2616)	(0.1987)	(0.1944)	(0.2162)
osgs	0.2466	0.1291	0.2286*	0.2640*
	(0.1721)	(0.1276)	(0.1247)	(0.1386)
wr	-0.1920	-0.2588*	-0.2912**	-0.2702*
	(0.1811)	(0.1385)	(0.1357)	(0.1516)
oa_n	0.0486	0.1012	-0.0917	0.2215**
	(0.1080)	(0.0814)	(0.0793)	(0.0869)
oa_tb	0.0319	-0.0747	0.2264**	-0.0625
	(0.1168)	(0.0899)	(0.0881)	(0.0972)
intercept	1.5614	0.4602	2.5438*	1.8197
	(2.2540)	(1.2851)	(1.3773)	(1.4410)

Standard errors are in parenthesis.
***Statistically significant at 99% confidence level;**statistically significant at 95% confidence level; *statistically significant at 90% confidence level.

$t_{0.01} = -2.62393,\ t_{0.05} = -1.98304,\ t_{0.1} = -1.65964$

CHAPTER FOUR

ASSESSING U.S. HOUSEHOLD PURCHASE DYNAMICS FOR DIETARY FIBER

ABSTRACT

This chapter provides a first attempt at examining household purchase dynamics for dietary fiber, using a dynamic Tobit model that accounts for censoring across households and time as well as temporal correlations (state dependence and unobserved household heterogeneous preferences) between current and previous purchases by adopting a stationary Gaussian first-order autoregressive choice process. Our study uses a unique longitudinal dataset, created by merging household-level scanner data and nutritional datasets through heuristic algorithms and multiple sequential imputations. In order to avoid the multidimensional integration nature of the dynamic censored likelihood function and overcome computational burden of the estimator, I used the Geweke-Hajivasssiliou-Keane (GHK) recursive probability simulator in the estimation of the model. Estimates for the unknown parameters are used to compute dynamic demand elasticities for fiber purchases. Empirical results indicate that household purchase decisions are characterized by significant unobserved heterogeneity, statistically significant positive serial correlation, and negative and significant state dependence, implying that lagged purchases have a strong effect on current household decisions so that households purchasing in the previous period would buy less fiber in the current period. I also found that covariates that are not integral determinants of fiber purchases are household participation in the Women, Infants, and Children (WIC) program, the age and presence of children between 13 and 17, not being Hispanic, and the employment level of the female head. Furthermore, the education level of the female head has a negative impact on fiber purchases, whereas coupons have the reverse effect.

1. Introduction

The last two decades have seen growing consumer demand for a more healthful food supply (Hasler, 2000; Menrad, 2003). Indeed, Hasler (1998) notes that there has been a "revolution in the health-enhancing role of specific foods or physiologically-active food components". As a result of this demand, estimates of this market range from \$20 to \$60 billion (Siro *et al.,* 2008). Some demand drivers for this food include escalating health care costs and increasing public awareness of health-related concerns (Milner, 2000; International Food Information Council, 2011). The U.S. Department of Agriculture (USDA) has estimated that improved dietary patterns could save \$43 billion in medical care costs (Frazao, 1995).

The health-enhancing functional properties of dietary fiber (e.g., reduced risk of coronary heart disease, stroke, hypertension, obesity and certain types of cancer)[31] received considerable attention from nutritionists and food scientists and most recently from the U.S. government. To help consumers, nutrition labels mandate that fiber content be listed on the "Nutrition Facts" panel (NFP). However, despite well-established disease-reversal benefits of this physiologically-active food component, along with the fact that "nine out of ten adults are at increased risk of diet-related chronic disease" (American Public Health Association, 1993), that the fiber content is listed on the NFPs, and that the dietary fiber has received widespread publicity (Variyam, Blaylock and Smallwood, 1996), the average fiber intake for children and adults in the U.S. is still less than half of the recommended amounts (Slavin, 2005; Anderson *et al.,* 2009). Nayga (1996) points out that this low intake may be a result of consumers' difficulties in translating their awareness into appropriate food choices. Smith (2004) argues that while it is possible to view diet as the result of a trade-off between considerations of future health consequences and

[31] For a more comprehensive review of these properties interested readers refer to The National Academies (2006) and Anderson *et al.* (2009).

immediate pleasure of consumption, the current dietary choice outcomes may actually be the result of choosing the foods sub-optimally due to an "evolutionary mismatch".[32]

This research updates existing literature on consumer/household demand for fiber (Ippolito and Mathios, 1991; Blisard, Blaylock and Smallwood, 1994; Nayga, 1996; Variyam, Blaylock and Smallwood, 1996; and Variyam, 2008). What drives demand for dietary fiber is investigated in a dynamic choice process at the household level, controlling for temporal correlations between current and previous purchases and the censoring of observations due to nonpurchases across weeks. Our goal is to better understand U.S. household dynamic consumption decisions regarding fiber, analyze their intertemporal purchasing behavior, and perhaps explain why consumption remains at under half the recommended values. Erdem, Imai and Keane (2003) argue that studying household/consumer choice statics might lead to serious misspecification in markets, considering that purchases by economic agents occur frequently. This research may provide new insights that ultimately improve interventions or educational policies to enhance demand for dietary fiber.

Previous studies have focused on different research questions using consumption survey data at the consumer level in a static context, ignoring the effect of price on fiber consumption due to data availability (see section 2). Polinsky (1977) indicates that omitting significant variables such as price might lead to inconsistent parameter estimates. On the other hand, though the use of micro-level data avoids the problem of aggregation over consumers and often provides a large and statistically rich sample (Heien and Wessells, 1990), static frameworks cannot capture the intertemporal dependence of decisions over time. Keane (1997) refers to this phenomenon as the *temporal persistence* of consumer choices. Ignoring this temporal correlation and its sources

[32] Maladaptive behavior made possible by modern technology (Smith, 2011). Interested readers on this theory refer to Smith and Tasnadi (2007).

(*state dependence*[33] and *heterogeneity of preferences*) will also yield inconsistent parameter estimates (Dong, Chung and Kaiser, 2004) and spurious demand elasticities (Hendel and Nevo, 2006). Heckman (1981) and Hajivassiliou (1994) state that by ignoring household heterogeneity preferences and allowing for state dependence, it may represents a source of misspecification leading to *spurious state dependence*. Contrarily, by ignoring state dependence and allowing for household heterogeneity will lead to overestimate the degree of heterogeneity (Keane, 1997).

The use of micro-level data usually involves data censoring, i.e., unrecorded observations for a given household due to nonpurchases. Controlling for censoring is also necessary to avoid bias and inconsistency in parameter estimates. Chay and Powell (2001) indicate that when censoring occurs, it is expected that the variation of the variable to be explained will lead to an understatement of the effect of the explanatory variables on the "true" dependent variable.

To address the previous issues, the purchasing choice process was modeled following the spirit of Hyslop (1999) for non-linear models. That is to say, I allowed past purchase occasions to affect current purchase decisions for fiber in a framework that captures simultaneously state dependence, unobserved households heterogeneity preferences, and *serial correlation*[34] caused by a stationary first-order choice process. The proposed model controls for the unobserved heterogeneity by adopting a Gaussian random effects specification. It also captures variations in prices over time and controls for left-censoring. The dynamic model is estimated using the *Geweke-Hajivasssiliou-Keane* (GHK) recursive probability simulator and a unique dataset that contains detailed fiber purchase information of households as well as the purchase price, promotion deal, and household demographic information over time. This data design also responds to the most recent needs and newest directions in agricultural economics, as the

[33]The term state dependence is also referred in the marketing literature as *purchase carryover* effect or *habit persistence*.
[34]Hyslop (1999) defines *serial correlation* as the "transitory individual differences in the propensity to participate".

National Research Council (2005) and Unnevehr *et al.* (2010) recognize. It was achieved by merging the 2009 Nielsen Homescan panel data and the 2005-11 Gladson databases using heuristic algorithms and multiple sequential imputations based on product information (e.g., the Universal Product Code).

The reminder of this chapter is organized as follows. The next section describes the background of relevant research. Section 3 characterizes the dataset utilized in this study, and section 4 presents the econometric model and estimation framework. In section 5, I discuss estimation results, and I provide concluding remarks in section 6.

2. Background

A limited but important body of economic literature on dietary fiber includes Ippolito and Mathios (1991); Blisard, Blaylock and Smallwood (1994); Nayga (1996); Variyam, Blaylock and Smallwood (1996); Kim, Nayga and Capps (2000); and Variyam (2008).

Ippolito and Mathios (1991) focused on health claims in advertising. By using the USDA's 1985 Continuing Survey of Food Intakes by Individuals (CSFII) for women and the Food and Drug Administration's Health and Diet Surveys conducted in different periods of time in the 1980s, these authors found that most consumers increased their awareness about the relationship between cereal fiber intake and colon cancer risk from 8.5% in 1984 to 32% in 1986, when manufacturers were allowed to promote the well-established disease-reversal benefits of dietary fiber.

On the other hand, Variyam (2008) examined the impact of thirteen nutrients (e.g., fiber) on consumer diets that are displayed in the NFP and mandated by the Nutrition Labeling and Education Act. The dataset used by this author was the USDA's 1994-1996 CSFII and the Diet and Health Knowledge Survey (DHKS) over two to three-day period. By adopting a full parametric functional specification of the relationship between the regressors and the response variable (maximum likelihood Heckman procedure), this author showed that when consumers use the labels, the NFP improves fiber intake of consumers by 0.69 grams per 1000 calories (about 7% increase in consumption from the mean intake level). Variyam attributes this result to the influence of the labels on the choice of ready-to-eat breakfast cereals, considering that these food items are a major source of total fiber intake in the diets of adult Americans. Using the same data set for the same period of time and similar research question, but a different parametric approach (endogenous switching regression), Kim, Nayga and Capps (2000) reported that the NFP improves the average daily fiber intake of consumers by 7.51 grams.

These results seem optimistic; however, they contrast with the current underconsumption of fiber. Jacoby, Chestnut and Silberman (1977) indicate that although most consumers were aware of and intended to use the nutritional information displayed on the labels, "the vast majority of consumers neither use nor comprehend nutrition information in arriving at food purchase decisions" (page 126). Therefore, other factors such as food cost, consumption habit, and demographics may also play an important role in fiber intakes.

Published studies examining the determinants of fiber intake include Blisard, Blaylock and Smallwood (1994); Nayga (1996); and Variyam, Blaylock and Smallwood (1996). The first and third study rely on the same datasets (i.e., the USDA's 1989-1990 CSFII and the DHKS on a three-day period), while the second uses the Individual Intake phase of the USDA's 1987-1988 Nationwide Food Consumption Survey and the Human Nutrition Information Service database over a one, two or three-day period. Blisard, Blaylock and Smallwood (1994), adopting a three-equation system framework, found that meal planners who consume less fiber than average tend to be African American, reside in the North Central States or the West, live in large households, smoke, and/or participate in the Food Stamp program or the WIC program. On the other hand, meal planners who consume more fiber than average tend to be Hispanic males with higher levels of education and live in rural areas. Variyam, Blaylock and Smallwood (1996) conducted an informational effect study on dietary fiber intake using the same data and theoretical background as Blisard, Blaylock and Smallwood (1994), but a different estimation procedure (structural equation model). They found that household income, meal planner age, smoking status, vegetarian status, race, and ethnicity are integral determinants of knowledge, awareness, and attitude, and dietary fiber intake. For example, household income has a significant negative total effect on dietary fiber intake. Unlike Blisard, Blaylock and Smallwood (1994), Variyam, Blaylock and Smallwood (1996) point out that females have a higher consumption of fiber relative to males and household size does not have much direct or indirect effect on fiber intake. Finally, Nayga (1996) reports that height, diet status, living in the Western United States, and income positively and significantly affect fiber intake away-from-home, while age, household size, and living in the Northeast have a negative effect. Conversely, he also found that weight, Hispanic ethnicity, diet status, age, and income are positively related to the average daily intake of dietary fiber and are statistically significant in the away-from-home food market. Weight squared, height squared, living in the Northeastern U.S., being African American, being male, household size, consumption on the weekend, and living in non-metro areas are negatively related to the average daily intake of dietary fiber and statistically significant in the at-home food market.

As I mentioned above, these existing studies on fiber consumption ignored price effect and the effect of consumption habits over time. These are two important factors in determining consumer food demand.

3. Data and Variables

The data set I have constructed to address the goal of this study was obtained by merging the Dry[35]-2009 Nielsen Homescan food purchase panel data with another data designed by the Economic Research Service (2011) (see appendix). The Homescan panel data offer national coverage, excluding Alaska, Hawaii, and all off-shore U.S. territories, and include detailed household characteristics and purchase information (e.g. household expenditure, consumers' socio-demographic characteristics). The second data set provides information for an extensive group of products sold in the U.S. on nutritional and front-of-package claims.

The merged data contain more than 47,000 households with their demographic variables such as income, household size, residence type, ethnicity, race, age, education, employment, household participation in the WIC program, and the age and number of children. Seasonal and regional factors as well as detailed information on households' daily food purchases such as purchase date, quantity purchased, expenditure, whether used coupon, and the fiber quantity contained in each of the purchased food products are also contained in the merged data. To reduce the computational burden of model estimation without losing the household dynamic purchase feature, I aggregated the data from daily to weekly, based on the purchase date.

After eliminating observations with incomplete information, our data reduced to 46,935 households with each household having 52 weeks of fiber purchase information. The weekly fiber quantity is calculated for each household from all the food products that contain fiber and are purchased during the week by the household. The price is the average price of the foods used to calculate the fiber quantity, which is computed from the observed food purchase quantity and

[35] The Dry Grocery category includes all product modules that do not fit into the Dairy products; Frozen foods, produce, and meat; and Random weight products. The term *random weights* refer to non-UPC labeled items (e.g. fresh fruits and vegetables).

expenditure. It should be mentioned that our data is censored at zero. Therefore, it is expected to find households with no purchase of fiber in some of the 52 weeks.

Figure 4.1 gives the fiber purchase frequency across households over the 52 weeks in 2009. The average number of weeks across households is 36.71 with a standard deviation of 9.13. It should be mentioned that for non-purchase weeks, we do not have purchase information to calculate the price of fiber. For these cases, however, I used the average price from other purchase weeks for the same household. In this study, I also included the coupon value information in the demand to capture the food deal or promotional effect on fiber. The coupon value in US dollars is calculated from all the coupons used when making purchases on any of the food products that contain fiber in a given week.

Table 4.1 lists all the variables considered in this study, whereas table 4.2 provides descriptive statistics for the quantitative variables.

The demographic information shown in table 4.2 indicates that the average age of the female head in the household is 54, the mean income across households is about \$61,000, and the average household size is between 2 and 3 people. Even though is not reported in table 4.1, the majority of the U.S. households are composed by non-Hispanic people (95%), where the prominent age and presence of children is in the range of 13 and 17 (46.5%). The percentage of age and presence of children between 0 and 6 and 7-13 is 19.2% and 34.2%, respectively. 0.6% of the sample participates in the WIC program, 85.1% are white, 8.6% are African American, and most of them are located in the South region with 35.9% of participation.

Table 4.2 also shows that the computed average price of fiber is \$0.4 with a standard error of 3.3, indicating that the price variation across purchases is large enough. Regarding purchase quantity, the weekly amount of fiber consumed by households ranges from zero to 454,257.9

grams with a mean purchase across all the households and over all the weeks of 254.9 grams. This mean value represents about 16 grams per day per person for households with an average size of 2.33. According to the USDA (2005) energy guidelines, the recommended fiber intake amount is 28 grams/day for adult women and 36 grams/day for adult men. Figure 4.2 shows the frequency of fiber purchase quantities across households. About 94% of households purchased 500 or less grams of fiber per week.

Figure 4.3, panel a displays the change of purchase frequency across households over 52 weeks, while panel b shows the variation of average fiber purchase quantities across households over 52 weeks. Figure 4.3 makes it evident that there is certain variation across the 52 weeks. As illustrated here, the average fiber purchase declines at the end of the winter season until the beginning of summer, reaching its peak during January and through in May. During summer the fiber purchase tends to increase to then stabilize it during fall. However, the seasonal effects are not significant.

4. Model and Estimation Framework

Equipped with panel data, we are able to account for temporal correlations that might exist between fiber purchases made by households. However, these data usually bring censoring problems that need to be solved to avoid model selectivity bias. The panel Tobit model introduced below accounts for both the temporal correlation and the censoring bias.

Let q_{it} be the fiber purchases made by household i at week t and X_{it} be a $1\times K$ matrix of observed explanatory variables that may influence household fiber purchases. X_{it} can be household demographic and socio-economic variables (e.g., household income, size, age, etc.) as well as marketing variables faced by the household (e.g., food price and coupon). $t = 1,\ldots,T$ (the number of weeks per household), $i = 1,\ldots,N$ (the number of total households), and K is the number of total explanatory variables. The dynamic panel Tobit specification, capturing the intertemporal dependence of decisions over time, is given by[36]

$$\begin{aligned} q_{it}^{*} &= X_{it}\beta + q_{it-1}\gamma + u_{it}, \\ q_{it} &= \max\left(q_{it}^{*}, 0\right), \\ u_{it} &= \alpha_i + \varepsilon_{it},\ \varepsilon_{it} = \rho\varepsilon_{it-1} + e_{it}, \end{aligned} \tag{1}$$

where q_{it}, the observed fiber purchases by household *i* at week *t*, is nonnegative and its value is determined by its latent variable q_{it}^{*}. q_{it-1} is the observed fiber purchases made by household *i* at week *t*-1 (the lag purchase), β and γ are parameters to be estimated, and u_{it} is the composite error vector consisting of the unobserved household heterogeneity effect (α_i) and serially correlated first-order autoregressive error component (ε_{it}) for each *t*. $\rho \in [-1,1]$ is the autocorrelation coefficient. Notice that the unobserved household specific heterogeneity effect α_i is constant over time, whereas ε_{it} varies across time and households. e_{it} is assumed to be Gaussian white noise and the $T \times 1$ composite error u_i for household *i* is $\mathbf{N}(\mathbf{0}, \mathbf{\Omega}_i)$, where $\mathbf{\Omega_i}$ is a $T \times T$ variance-covariance matrix.

In this framework, the dynamic feature of the model is characterized by the presence of the lagged-dependent variable q_{it-1} (state dependence), the household heterogeneity effect over time (α_i), and the first-order autoregressive process of ε_{it}. State dependence, which is due to the accumulation of products with fiber content derived from past purchases, is captured by the parameter γ, while unobserved household heterogeneous preferences for fiber are represented by the term α_i. In order to tackle the unobserved heterogeneity α_i, I assumed that the random

[36] Dong, Schmit and Kaiser (2012) provide a similar model, except the first-order autoregressive choice process assumed in our study.

effects assumption holds. Specifically, the unobserved household-specific effects are assumed to be uncorrelated with the observed regressors so that econometric endogeneity problems can be avoided. Under this specification, parameterization of the distribution of the individual-specific effects is appealing (Arellano and *Honoré,* 2001). Following Hajivassiliou (1994) and McFadden (1998), I assumed that $\alpha_i \sim N(0,\sigma_\alpha^2), \forall i$, $e_{it} \sim N(0,\sigma_e^2)$, $\varepsilon_{it} \sim N(0,\sigma_\varepsilon^2)$, and α_i, e_{it}, and ε_{it} are mutually orthogonal. From stationarity we know $\sigma_\varepsilon^2 = \dfrac{\sigma_e^2}{1-\rho^2}$.

Without loss of generality, the $T \times T$ variance-covariance matrix of the composite error u_i for household i is stationary and can be represented by (Hajivassiliou 1994, Hajivassiliou and Ruud 1994):

$$\underset{T\times T}{\mathbf{\Omega}_i} = \mathrm{E}\left[\mathbf{u}_i\mathbf{u}_i'\right] = \sigma_\varepsilon^2 \begin{pmatrix} 1 & \rho & \rho^2 & \cdots & \rho^{T-1} \\ \rho & 1 & \rho & \cdots & \rho^{T-2} \\ \rho^2 & \rho & \cdots & \cdots & \vdots \\ \vdots & \vdots & \cdots & 1 & \rho \\ \rho^{T-1} & \rho^{T-2} & \cdots & \rho & 1 \end{pmatrix} + \sigma_\alpha^2 \mathbf{J}_T \qquad (2)$$

where $\mathbf{J}_T$ is a $T \times T$ matrix with unity in every element. This covariance-stationary matrix representation, also known in the econometric literature as the *one-factor analytic* Gaussian AR(1) structure, introduces intertemporal linkages and is invariant across households.

It should be mentioned that an important difficulty of using our model, and any dynamic Tobit model, is associated with the so-called *initial conditions problem*. This issue might have a strong impact on the path of the observations if it is ignored and, as noted by Arellano and *Honoré* (2001), it occurs "if one starts observing the individuals when the process in question is already in progress, then the first observation will depend on the dependent variable in the period before the sample starts" (page 3282). Instead of assuming that the initial condition is fixed/exogenous or that the stochastic process underlying our model is in equilibrium (steady state), I assumed that the initial time period is correlated with other periods through the assumed parametric distribution of all the error terms in order to control for endogenous initial condition.

This study assumes that household fiber purchase decisions over time, defined in equation (1), are outcomes of utility-maximizing choices made by households.

4.1 Model Estimation Procedure

Dynamic Tobit estimates from the formulation in equation (1) were obtained via maximum likelihood estimation. As stated in this specification, the noise vector $\mathbf{u}$ has a T-dimensional multivariate normal distribution. For representation convenience, the T-week observations for the ith household can be partitioned into two mutually exclusive sets. Therefore, $T = T_{i0} + T_{i1}$, where T_{i0} and T_{i1} denote the nonpurchase and purchase weeks, respectively. Given the parametric specification of our model, a likelihood function for the parameters of the model $\left(\underset{m\times 1}{\boldsymbol{\theta}} = \left[\underset{(K\times 1)}{\beta} \ \gamma \ \sigma_{\varepsilon}^{2} \ \sigma_{\alpha}^{2} \ \rho \right]; \ m = K \times 4 \right)$ and household i under this particular purchase pattern over T weeks, can be specified as

$$
\begin{aligned}
l_i(\boldsymbol{\theta}) &= \left(q_{i0}, q_{i1} \mid q_{i0} = 0, q_{i1} > 0\right) \qquad i = 1, \ldots, N \\
l_i(\boldsymbol{\theta}) &= f_1(u_{i1}) \int_{-\infty}^{-x_{i0}\beta - q_{i0-1}\gamma} f_{0|1}(u_{i0})\, du_{i0}
\end{aligned} \tag{3}
$$

where q_{i0} and u_{i0} are the observed weekly nonpurchases and the disturbance term associated with the nonpurchase weeks, respectively. On the other hand, the term q_{i1} denotes the observed weekly purchases, whereas u_{i1} is the error term associated with the purchase time periods. $f_1(u_{i1})$ is the multivariate Normal probability density function (PDF) of u_{i1} with zero-mean error vector and a $T_{i1} \times T_{i1}$ variance-covariance matrix $\mathbf{\Omega}_{i11}$, associated with purchase weeks. $f_{0|1}\left(u_{i0}\right)$ denotes the conditional multivariate Normal PDF of u_{i0} given u_{i1}. By letting the $T \times 1$ vector $\mathbf{u}$, its corresponding mean vector $\boldsymbol{\mu}$, and the household-specific variance-covariance matrix of the errors, $\mathbf{\Omega}_i$, be partitioned as

$$\mathbf{u}_{it} = \begin{bmatrix} u_{i0} \\ u_{i1} \end{bmatrix}, \ \boldsymbol{\mu} = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \ \mathbf{\Omega}_i = \begin{bmatrix} \underset{T_{i0}\times T_{i0}}{\mathbf{\Omega}_{i00}} & \underset{T_{i0}\times T_{i1}}{\mathbf{\Omega}'_{i01}} \\ \underset{T_{i0}\times T_{i1}}{\mathbf{\Omega}_{i01}} & \underset{T_{i1}\times T_{i1}}{\mathbf{\Omega}_{i11}} \end{bmatrix} \tag{4}$$

the conditional distribution u_{i0} given u_{i1} is Normal with mean vector $u^i_{0|1} = \mathbf{\Omega}'_{i01}\mathbf{\Omega}^{-1}_{i11}u_{i1}$ and covariance matrix $\mathbf{\Omega}^i_{0|1}$, where $\mathbf{\Omega}^i_{0|1} = \mathbf{\Omega}_{i00} - \mathbf{\Omega}_{i01}\mathbf{\Omega}^{-1}_{i11}\mathbf{\Omega}'_{i01}$. Then, the likelihood function for N households is specified as

$$L(\boldsymbol{\theta}) = \prod_{i=1}^{N} l_i(\boldsymbol{\theta}) = \prod_{i=1}^{N} f_1(u_{i1}) \int_{-\infty}^{-x_{i0}\beta - q_{i0-1}\gamma} f_{0|1}(u_{i0})\, du_{i0}$$

(5)

The difficulty in equation (5) stems from the evaluation of the T_{i0}-fold integrals. These are analytically and computationally intractable when T_{i0} exceeds 3 or 4 under the current form of $\mathbf{\Omega}_i$ by using the conventional numerical integration (Hajivassiliou and McFadden 1998). Notice that the order of the probability integrals equals the total number of nonpurchase weeks (T_{i0}) for household *i*. As shown in figure 4.1, the average purchase week across households is 36.7. Therefore, we are not able to use the conventional procedures to estimate the model. In order to make it estimable, practitioners assume that the errors are iid or equicorrelated, which can be undesirable (Keane, 1994). Alternatively, I approximated the multivariate integrals (choice probabilities) rather than evaluating them by adopting a simulation-based approach (the GHK recursive simulator). According to Hajivassiliou, McFadden, and Ruud (1996), this algorithm was found to be the most accurate and reliable simulator, in terms of mean square error, among several simulation-based inference methods for normal rectangle probabilities. The GHK approach yields simulated probability values that are bounded away from 0 and 1 (Borsch-Supan and Hajivassiliou 1993).

As Geweke, Keane, and Runkle (1994) and Hajivassiliou, McFadden, and Ruud (1996) note, the GHK simulator relies on sampling from recursive truncated univariate normals and evaluation of univariate integrals after extracting a Cholesky factor of $\mathbf{\Omega}_i$. Considering that simulation estimation relies on the fact that integration over a density is a form of averaging, choice probabilities can be numerically approximated by (Breslaw, 1994):

$$\frac{1}{R}\sum_{r=1}^{R}\prod_{i=1}^{m}Q_{ir} \tag{6}$$

where R is the number of GHK replications, and Q_{ir} is the probability of the ith recursive truncated normal for replication r. The univariate truncated normal implemented in this study follows Geweke, Keane, and Runkle (1994) closely and it is specified as

$$\in \ = \Phi^{-1}\left[\left(\Phi(b)-\Phi(a)\right)\odot U+\Phi(a)\right] \tag{7}$$

where Φ^{-1} is the inverse of a standard normal distribution, U is a uniform random variate on [0,1], $\odot$ denotes the Hadamard (elementwise) product operator, and $\in\sim N(0,1)$, $a\leq\in\leq b$. Details of this approach are given in Breslaw (1994).

Upon identifying the dynamic Tobit estimates, the asymptotic variance-covariance matrix of $\boldsymbol{\theta}$ was constructed using the "outer-product-of-gradients" approach, based on the computation of the inverse of $\left(\frac{\partial\mathbf{L}(\boldsymbol{\theta})}{\partial\boldsymbol{\theta}}\right)'\left(\frac{\partial\mathbf{L}(\boldsymbol{\theta})}{\partial\boldsymbol{\theta}}\right)$, where $\frac{\partial\mathbf{L}(\boldsymbol{\theta})}{\partial\boldsymbol{\theta}}$ is the $n\times m$ matrix of derivatives of the likelihood function contributions $l_i(\boldsymbol{\theta})$, $i=1,...,N$ with respect to $\boldsymbol{\theta}$. For implementing all of the preceding procedures, I used Aptech Systems' GAUSS^{TM} 10 and 100 GHK replications.

4.2 Demand Elasticity Estimation

After obtaining the estimates of $\boldsymbol{\theta}$, we can predict household purchases for fiber under several circumstances. For instance, we can predict the unconditional expected purchases of fiber for household *i* at time period *t* as follows

$$E[q_{it}] = P(q_{it} > 0) \cdot E[q_{it} \mid q_{it} > 0] \tag{8}$$

Where the expected probability of purchase and the conditional expected purchase given a purchase are defined, respectively, by

$$P(q_{it} > 0) = 1 - \Phi\left(-\frac{X_{it}\beta + q_{it-1}\gamma}{\sigma}\right) = \Phi\left(\frac{X_{it}\beta + q_{it-1}\gamma}{\sigma}\right) \tag{9}$$

and

$$E[q_{it} \mid q_{it} > 0] = X_{it}\beta + q_{it-1}\gamma + \sigma \cdot \frac{\phi\left(\frac{X_{it}\beta + q_{it-1}\gamma}{\sigma}\right)}{\Phi\left(\frac{X_{it}\beta + q_{it-1}\gamma}{\sigma}\right)} \tag{10}$$

where $\sigma = \sqrt{\sigma_\alpha^2 + \sigma_\varepsilon^2}$, $\Phi(\cdot)$ is the standard normal cumulative distribution function (CDF), and $\phi(\cdot)$ is the standard normal PDF.

The effects of explanatory variables on household fiber purchases can be captured by calculating purchase elasticities, based on the predicted values given above. We can evaluate the elasticities for the continuous variables, based on the computation of numerical first derivatives (marginal effects). For example, the elasticity for a vector $\mathbf{x}$ of continuous variables can be written as

$$\eta_{\text{continuous}} = \frac{\partial E[q_{it}]}{\partial \mathbf{x}} \odot \frac{\mathbf{x}}{E[q_{it}]} \tag{11}$$

For indicator variables, the elasticities are computed using differences in the dependent variables, holding all the variables constant except the dependent variable and the indicator variable under consideration. Thus, the resulting elasticity can be written as

$$\eta_{indicator} = \frac{E[q_{it} \mid d=1] - E[q_{it} \mid d=0]}{E[q_{it}]} \tag{12}$$

where d is the binary variable under consideration and the $E[q_{it}]$ is given by equation (8).

For computational purposes, it is worth mentioning that the actual elasticity estimates for the continuous and binary variables are obtained using the mean elasticity approach. Therefore, the elasticity across households for a given week t is $\bar{\eta}_{jt} = N^{-1}\sum_{i=1}^{N}\eta_{jit}$, where j is the associated explanatory variable and N is the number of households in the sample. For instance, at week 1, elasticities are summed up across households and then its average is computed by dividing the total number of households. This routine can be repeated for all the 52 weeks, or the average of elasticities can be taken across weeks for the corresponding variable.

Standard errors for the elasticities are estimated using the Delta method, based on the computation of the square root of $\nabla f(b)' \left[\left(\frac{\partial \mathbf{L}(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}}\right)' \left(\frac{\partial \mathbf{L}(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}}\right)\right] \nabla f(b)$, where $\left[\left(\frac{\partial \mathbf{L}(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}}\right)' \left(\frac{\partial \mathbf{L}(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}}\right)\right]$ is the $m \times m$ variance-covariance matrix of $\boldsymbol{\theta}$, denoted in section 4, and the $m \times 1$ gradient vector $\nabla f(\boldsymbol{\theta}) = \frac{\eta|_{\theta} - \eta|_{\theta_1}}{\theta_1 - \theta}$.

In order to take advantage of the dynamic nature of the model specified in section 4, I also derived the following set of conditional expectations:

$$E\left[q_{it} \mid q_{it-1}=0\right]=P\left(q_{it}>0 \mid q_{it-1}=0\right)\cdot E\left[q_{it} \mid q_{it}>0, q_{it-1}=0\right] \tag{13}$$

$$E\left[q_{it} \mid q_{it-1}>0\right]=P\left(q_{it}>0 \mid q_{it-1}>0\right)\cdot E\left[q_{it} \mid q_{it}>0, q_{it-1}>0\right] \tag{14}$$

where

$$P\left(q_{it}>0 \mid q_{it-1}=0\right)=1-\frac{\Phi_2\left(-\delta_{it},-\delta_{it-1},\varphi\left(u_{it},u_{it-1}\right)\right)}{\Phi\left(-\delta_{it-1}\right)} \tag{15}$$

$$P\left(q_{it}>0 \mid q_{it-1}>0\right)=1-\frac{\Phi\left(-\delta_{it}\right)-\Phi_2\left(-\delta_{it},-\delta_{it-1},\varphi\left(u_{it},u_{it-1}\right)\right)}{1-\Phi\left(-\delta_{it-1}\right)} \tag{16}$$

$$E\left[q_{it} \mid q_{it}>0, q_{it-1}=0\right]=\left(X_{it}\beta+q_{it-1}\gamma\right)+ \sigma\cdot\frac{\phi\left(-\delta_{it}\right)\left(1-\frac{\Phi\left(\delta_{it-1}+\delta_{it}\varphi\left(u_{it},u_{it-1}\right)\right)}{\sqrt{1-\left(\varphi\left(u_{it},u_{it-1}\right)\right)^2}}\right)+\varphi\left(u_{it},u_{it-1}\right)\phi\left(\delta_{it-1}\right)\left(1-\frac{\Phi\left(-\delta_{it}-\delta_{it-1}\varphi\left(u_{it},u_{it-1}\right)\right)}{\sqrt{1-\left(\varphi\left(u_{it},u_{it-1}\right)\right)^2}}\right)}{1-\Phi\left(-\delta_{it}\right)-\Phi\left(\delta_{it-1}\right)+\Phi_2\left(-\delta_{it},\delta_{it-1},\varphi\left(u_{it},u_{it-1}\right)\right)} \tag{17}$$

$$E\left[q_{it} \mid q_{it}>0, q_{it-1}>0\right]=\left(X_{it}\beta+q_{it-1}\gamma\right)+ \sigma\cdot\frac{\phi\left(-\delta_{it}\right)\left(1-\frac{\Phi\left(-\delta_{it-1}+\delta_{it}\varphi\left(u_{it},u_{it-1}\right)\right)}{\sqrt{1-\left(\varphi\left(u_{it},u_{it-1}\right)\right)^2}}\right)+\varphi\left(u_{it},u_{it-1}\right)\phi\left(-\delta_{it-1}\right)\left(1-\frac{\Phi\left(-\delta_{it}+\delta_{it-1}\varphi\left(u_{it},u_{it-1}\right)\right)}{\sqrt{1-\left(\varphi\left(u_{it},u_{it-1}\right)\right)^2}}\right)}{1-\Phi\left(-\delta_{it}\right)-\Phi\left(-\delta_{it-1}\right)+\Phi_2\left(-\delta_{it},-\delta_{it-1},\varphi\left(u_{it},u_{i,t-1}\right)\right)} \tag{18}$$

$\delta_{it}=\frac{\left(X_{it}\beta+q_{it-1}\gamma\right)\big|_{t=30}}{\sigma}$, $\delta_{it-1}=\frac{\left(X_{it}\beta+q_{it-1}\gamma\right)\big|_{t=29}}{\sigma}$, $\varphi\left(u_{it},u_{it-1}\right)=\frac{\sigma_\varepsilon^2\rho+\sigma_\alpha^2}{\sigma}$, and $\Phi_2\left(\cdot\right)$ is the bivariate normal CDF for q_{it} and q_{it-1}.

Previous results are used as illustrated in equations (11) and (12) to compute the corresponding demand elasticities.

5. Estimation Results

As shown in table 4.3, the model includes six (HHSize, mpHHInc, mpAgeF, q_{it-1}, Coupon, and Lnprice) and sixteen (feduc, femploy, WIC, House, c06, c712, c1317, Hispanic, black, others, summer, fall, winter, east, central, and west) continuous and discrete regressors, respectively.

Column 1 shows parameters' estimates for household demographic and socio-economic variables (HHSize, mpHHInc, mpAgeF, feduc, femploy, WIC, House, c06, c612, c1317, Hispanic, black, others, summer, fall, winter, east, central, and west), marketing variables (Lnprice and Coupon), and regression coefficients (intercept, σ_ε, σ_α, and ρ). Column 2 reports the corresponding standard errors for the parameters' estimated values. As noted, most of the regressors become statistically significantly different from zero with 95 and 99% confidence. The error variance due to the random household heterogeneity effect σ_α is strongly significant with 99% confidence and equal to 1.054 with a standard error of 0.0036. The autocorrelation coefficient ρ is also highly statistically significant at level 0.01 and equals to 0.059. Thus, equicorrelation is rejected, implying that household choice is not a zero-order process. Allenby and Lenk (1994) report that by adopting a zero choice order process (i.e. independent purchase occasions), the variability in household preferences gets inflated.

Notice that the covariance between u_{it} and u_{it-1} is

$$\begin{aligned} Cov\left[u_{it}, u_{it-1}\right] &= E\left[u_{it} - E\left(u_{it}\right)\right]\left[u_{it-1} - E\left(u_{it-1}\right)\right] \\ &= E\left[\left(\alpha_i + \rho\varepsilon_{it-1} + v_{it}\right)\left(\alpha_i + \varepsilon_{it-1}\right)\right] \\ &= E\left(\alpha_i^2\right) + \rho E\left[\varepsilon_{it-1}^2\right] \\ &= \mathrm{Var}\left(\alpha_i\right) + \rho \mathrm{Var}\left(\varepsilon_{it-1}\right) \end{aligned} \qquad (19)$$

With stationarity, the $\mathrm{Var}\left(\varepsilon_{it-1}\right) = \mathrm{Var}\left(\varepsilon_{it}\right)$, which implies that $Cov\left[u_{it}, u_{it-1}\right] = \sigma_\alpha^2 + \rho\sigma_\varepsilon^2$. Thus, the serial (intraclass) correlation is

$$\varphi(u_{it},u_{it-1})=\frac{Cov(u_{it},u_{it-1})}{\sqrt{Var(u_{it})\cdot Var(u_{it-1})}}$$
$$=\frac{\sigma_\alpha^2+\rho\sigma_\varepsilon^2}{\sqrt{\sigma_\varepsilon^2+\sigma_\alpha^2}} \tag{20}$$
$$\doteq 0.33$$

The serial correlation due to household heterogeneity $\left(\text{i.e., } \sigma_\alpha^2/\sqrt{\sigma_\varepsilon^2+\sigma_\alpha^2}\right)$ becomes positive and equal to 0.45. This outcome indicates that if we compare any two households $\left(\text{e.g., } hhid_4 \text{ and } hhid_{100}\right)$ and q_{it-1} for $hhid_{100}$ is greater to q_{it-1} for $hhid_4$, then it would be expected to observe the same purchase pattern at time period t, given that the coefficient is positive. Regarding habit persistence effects (state dependence), the coefficient of q_{it-1} (γ) is negative and highly significant, implying that lagged purchases are negatively related to current purchases.

Table 4.4 shows demand elasticities at week 30 for the probability of purchasing, conditional expected purchase given a purchase occasion at week 30, and unconditional expected fiber purchase at week 30, using equations (8)-(12). Tables 4.5 and 4.6 report demand elasticities at week 30, conditional on the previous time (week 29) purchases, based on equations (11)-(18). Table 4.5 is conditional on a zero purchased previous week while table 4.6 is conditional on a positive purchase previous week. Notice that elasticity outcomes displayed in column 3 (tables 4.4-4.6) are the sum of those elasticities reported in column 1 and column 2. The first two rows of these three tables contain predicted and actual values calculated from the model and from the data, respectively, for the probability of purchasing and conditional and unconditional expectations. These values are for the natural logarithm of the quantities.

Several findings can be derived from tables 4.4-4.6. First, it is evident that the effects on fiber purchases of one-percent changes in the covariates are different in magnitude, but the directional effects are the same. These results indicate that elasticities of current purchases vary depending on: 1) whether purchases are conditioned on previous purchases and 2) whether a previous purchase occurred or not. In looking at the purchase probability elasticity results, conditional on the purchase incidence (purchase or no-purchase), we see that in general demand for fiber is inelastic, behaving more elastic when it is conditioned to a non-purchase occasion at time period t-1 (see table 4.5). In particular for the price effect, a 1% decrease in price leads to a fraction of 0.265% increase in the probability of purchasing fiber. It is also evident, as expected, that when conditioning the probability of purchasing on a non-purchase occasion at time t-1, the household's purchase timing becomes shorter relative to the case in which the purchase probability is conditioned to a purchase occasion at time t-1.

Second, the only covariates that are not integral determinants of fiber purchases are the employment level of the female head, household participation in the WIC program, the age and presence of children between 13 and 17, and not being Hispanic. Contrary to Nayga (1996)'s results in the at-home food market, household size, household income, age, Hispanic ethnicity, and being African American have opposed signs, except residing in the west, where this variable has a positive effect on dietary fiber purchases. However, "west" is insignificant in Nayga (1996)'s study and strongly significant in our study.

Third, the lag purchase variable is highly significant indicating that state dependence has a strong effect on current purchase decisions for dietary fiber and, therefore, it is present. Indeed, a 1% increase in purchases of products with fiber content at time period t-1 decreases fiber purchases at time t by 0.02%. The fact of being negative implies that households purchasing at time period t-1 would buy less products containing fiber at time t.

Fourth, fiber demand is (relatively) inelastic with an own-price elasticity of -0.6 indicating that, on average, fiber quantity demanded declines approximately 0.6% given a one percent increase in prices of products containing fiber. From table 4.5, this elasticity outcome counts as -0.190% (33%) from the change of purchase probability and -0.406% (67%) from the change of conditional purchases. Coupons have a positive effect on fiber purchases, which implies that when the use of coupons increases, the U.S. fiber demand (grams) rises. Even though the increment is relatively small, this outcome suggests that coupons and its role in food marketing should be discussed more often. Indeed, Berning and Zheng (2011) conclude that the use of retail grocery coupons by households has an impact on household purchases for breakfast cereal with higher nutritional quality. Regarding dietary fiber purchase responsiveness to household income, the age and presence of children between 0 and 12, Hispanic, being African American, winter season, and living in the Central region of the U.S., I found that fiber elasticity estimates are small. For example, a 1% increase in household income, being African American, and living in the Central U.S., increases fiber quantity purchased by just 0.022%, 0.011%, and 0.023%, respectively (see table 4.5). On the other hand, and as expected, a 1% increase in being Hispanic reduces fiber purchases by 0.0167%. Regarding seasonal effects, the results show that relative to spring, all the other three seasons purchased less fiber while summer is the least fiber purchase season. However, the seasonal effects are small as I showed in figure 4.3 above. The results also show that regional effects on fiber household purchases are statistically significant. Indeed, a 1% increase of the household population in the East, increases fiber purchases, relative to the South, by 0.064%, while in the West region this value reduces to 0.031%.

What is striking from these results is that the education level of the female head has a negative impact on fiber purchases, whereas the variable "age" has the reverse effect. A 1%

increase in the female education level and female age, reduces and increase fiber purchase by 0.033% and 0.14%, respectively (see table 4.5). The outcome obtained for the education level effect is aligned with Blisard, Blaylock and Smallwood (1994), who concluded that meal planners that consume more fiber than average tend to be males with higher levels of education.

6. Conclusions and Future Research

Previous studies from consumption surveys have ignored the effect of price on fiber consumption and the intertemporal dependence of decisions over time. Using a unique panel dataset, this study provides a first attempt at examining household purchase dynamics for dietary fiber, supplying a more accurate representation of the purchase decision-making process and capturing simultaneously state dependence, unobserved households heterogeneity preferences, and serial correlation caused by a stationary first-order choice process.

By controlling for data censoring, accounting for the temporal correlations between current and previous purchases caused by state dependence and household preference heterogeneity over time, overcoming the multidimensional integration nature of the dynamic censored likelihood function through the use of the GHK recursive probability simulator, and allowing for the effect of price and dynamics on fiber demand, the dynamic Tobit model provides differential effects of socio-economic and demographic household and marketing characteristics on fiber purchase decisions. An important caveat is that household purchase decisions are characterized by significant unobserved heterogeneity, statistically significant positive serial correlation, and negative and significant state dependence. In addition, dietary fiber purchase responsiveness to household income, the age and presence of children between 0 and 12, Hispanic, being African American, season, and region is small. Furthermore, the education level of the female head has a negative impact on fiber purchases, whereas coupons have the opposite effect. On the other hand, the only covariates that are not integral determinants of fiber purchases are the employment level of the female head, household participation in the WIC program, the age and presence of children between 13 and 17, and not being Hispanic. Fiber demand is (relatively) inelastic with an own-price elasticity of -0.6, on average.

Regarding dynamic effects, I found that elasticities of current fiber purchases vary depending on whether a previous fiber purchase occurred or not.

Considering that new WIC food packages include whole grain since October 2009 in most states, an avenue of future research would be to expand the current sample to 2010-11 Homescan datasets to show if the new WIC program becomes an integral determinant of fiber choices.

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Table 4.1. Variables Used in the Analyses

Variable Name	Description
TqF	Total quantity of fiber (grams)
Texp	Total expenditure of fiber ($)
Coupon	Value of coupons ($)
Price	Fiber price ($/gram)
HHSize	Household size
mpAgeF	Age of the female head (years)
mpHHInc	Household income ($)
WIC	= 1 if the household participates in the federal assistance program Women with Infants and Children (WIC); = 0 otherwise
House	= 1 if the type of residence is at most a two family house living in a house, condominium, or cooperative housing project (co-op); = 0 otherwise
Hispanic	= 1 if Hispanic; = 0 otherwise
feduc	= 1 if the education level of the female head is some college, graduate college, or post college grad
femploy	= 1 if the number of hours per week the female head is employed is greater than or equal to 30 hours; = 0 otherwise
c06	= 1 if the age and presence of children is under 6; = 0 otherwise
c712	= 1 if the age and presence of children is between 7 and 12; = 0 otherwise
c1317	= 1 if the age and presence of children is between 13 and 17; = 0 otherwise
white	= 1 if the race of the household is white; = 0 otherwise
black	= 1 if the race of the household is black; = 0 otherwise
others	= 1 if the race of the household is oriental and other; = 0 otherwise
east	= 1 if the region of the household is East; = 0 otherwise
central	= 1 if the region of the household is Central; = 0 otherwise
south	= 1 if the region of the household is South; = 0 otherwise
west	= 1 if the region of the household is West; = 0 otherwise
winter	= 1 if the purchase month is from November to January; = 0 otherwise
spring	= 1 if the purchase month is from February to April; = 0 otherwise
summer	= 1 if the purchase month is from May to July; = 0 otherwise
fall	= 1 if the purchase month is from August to October; = 0 otherwise

Note: Household income was converted to a continuous variable from 33 discrete categories using the mean of each category. For the highest category, $250K and above, we used $250K. Similarly, the age variable was converted to a continuous variable from the 29 discrete categories provided by A.C. Nielsen.

Table 4.2. Descriptive Statistics for Quantitative Variables

Variable Name	Mean	Std. Dev.	Minimum	Maximum
Households' characteristics				
HHSize	2.33	1.25	1	9
mpAgeF	54.4	11.65	21.5	70
mpHHInc	61,456.13	40,963.34	3,000	250,000
Purchase characteristics				
TqF	254.9	1,352.38	0	454,257.89
Texp	23.45	28.95	0	1,100.46
Coupon	0.862	3.093	0	458
Price	0.405	3.301	0	1,765.21

Table 4.3. Estimation Results for the Dynamic Panel Tobit Model

Variable Name	Estimate	Std.Error
$HHSize^{-1}$	-0.5885***	0.0225
Ln(mpHHInc)	0.0767***	0.0079
Ln(mpAgeF)	0.4759***	0.0245
feduc	-0.1132***	0.0113
femploy	-0.0081	0.0112
WIC	0.0836	0.0617
House	-0.1052***	0.0147
c06	-0.0638**	0.0303
c712	-0.0948***	0.0227
c1317	-0.0069	0.0198
Hispanic	-0.0577**	0.0247
black	0.0384**	0.0189
others	-0.0179	0.0227
summer	-0.2325***	0.0039
fall	-0.2091***	0.0037
winter	-0.0557***	0.0038
east	0.2176***	0.0147
central	0.0780***	0.0131
west	0.1075***	0.0147
Coupon	0.2068***	0.0001
Lnprice	-2.0529***	0.0008
$Ln\left(q_{it-1}\right)$	-0.0702***	0.0009
Intercept	-2.1047***	0.1305
σ_{ε}	2.2273***	0.0005
σ_{α}	1.0543***	0.0036
ρ	-0.0592***	0.0009
Log Likelihood	-4,487,520.553	

Note: The variable *HHSize*$^{-1}$ denotes the inverse of *HHSize*, while the variables *Ln(mpHHInc), Ln(mpAgeF)*, *lnprice* and $Ln\left(q_{it-1}\right)$ are the natural logarithm of *mpHHInc*, *mpAgeF*, *price* and q_{it-1}, respectively. σ_{ε} and σ_{α} denote the square root of the residual variance and square root of the household heterogeneity variance. ρ is the autocorrelation coefficient. Non-zero values for q_{it} and q_{it-1} were scaled using the natural logarithmic transformation due to the large variation in household fiber purchases and in order to avoid convergency problems.

*** indicates statistically significant at 99% confidence level, and ** indicates statistically significant at 95% confidence level.

Table 4.4. Estimated elasticities for the unconditional expected fiber purchase

Variable Name	$P(q_{it} > 0)$	$E[q_{it} \mid q_{it} > 0]$	$E[q_{it}]$
Predicted Value	0.873024	3.398682	2.967130
Actual Value	0.684883	4.841766	3.316045
$HHSize^{-1}$	0.0315***	0.0643***	0.0957***
	(0.0012)	(0.0025)	(0.0037)
Ln(mpHHInc)	0.0074***	0.0152***	0.0226***
	(0.0008)	(0.0016)	(0.0025)
Ln(mpAgeF)	0.0460***	0.0940***	0.1400***
	(0.0021)	(0.0048)	(0.0069)
feduc	-0.0108***	-0.0225***	-0.0334***
	(0.0011)	(0.0022)	(0.0033)
femploy	-0.0008	-0.0016	-0.0024
	(0.0011)	(0.0022)	(0.0033)
WIC	0.0079	0.0167	0.0247
	(0.0057)	(0.0124)	(0.0183)
House	-0.0099***	-0.0210***	-0.0311***
	(0.0014)	(0.0030)	(0.0044)
c06	-0.0062**	-0.0126**	-0.0188**
	(0.0030)	(0.0059)	(0.0089)
c712	-0.0093***	-0.0186***	-0.0278***
	(0.0023)	(0.0044)	(0.0066)
c1317	-0.0007	-0.0014	-0.0020
	(0.0019)	(0.0039)	(0.0058)
Hispanic	-0.0056**	-0.0114**	-0.0170**
	(0.0024)	(0.0049)	(0.0073)
black	0.0037**	0.0076**	0.0114**
	(0.0018)	(0.0038)	(0.0056)
others	-0.0017	-0.0035	-0.0053
	(0.0022)	(0.0045)	(0.0067)
summer	-0.0211***	-0.0470***	-0.0693***
	(0.0004)	(0.0008)	(0.0012)
fall	-0.0210***	-0.0407***	-0.0610***
	(0.0004)	(0.0007)	(0.0011)
winter	-0.0054***	-0.0110***	-0.0164***
	(0.0004)	(0.0007)	(0.0011)
east	0.0202***	0.0437***	0.0646***
	(0.0013)	(0.0030)	(0.0044)
central	0.0074***	0.0155***	0.0230***
	(0.0012)	(0.0026)	(0.0039)
west	0.0101***	0.0214***	0.0318***
	(0.0014)	(0.0030)	(0.0044)
$Ln(q_{it-1})$	-0.0068***	-0.0139***	-0.0206***
	(0.0003)	(0.0002)	(0.0004)
Lnprice	-0.1986***	-0.4054***	-0.6040***
	(0.0009)	(0.0003)	(0.0010)
Coupon	0.0132***	0.0270***	0.0402***
	(0.0004)	(0.0001)	(0.0004)

Note: Standard errors are in parenthesis. *** Statistically significant at 99% confidence level; ** statistically significant at 95% confidence level.

Table 4.5. Estimated elasticities for the conditional expected fiber purchase given no purchase in the previous period

Variable Name	$P(q_{it} > 0 \mid q_{it-1} = 0)$	$E[q_{it} \mid q_{it} > 0, q_{it-1} = 0]$	$E[q_{it} \mid q_{it-1} = 0]$
Predicted Value	0.822645	3.774065	3.104715
Actual Value	0.218962	4.858868	1.063909
$HHSize^{-1}$	0.0420***	0.0636***	0.1057***
	(0.0018)	(0.0025)	(0.0042)
Ln(mpHHInc)	0.0099***	0.0150***	0.0249***
	(0.0007)	(0.0015)	(0.0023)
Ln(mpAgeF)	0.0615***	0.0931***	0.1546***
	(0.0032)	(0.0052)	(0.0084)
feduc	-0.0144***	-0.0223***	-0.0369***
	(0.0014)	(0.0022)	(0.0037)
femploy	-0.0010	-0.0016	-0.0026
	(0.0014)	(0.0022)	(0.0036)
WIC	0.0105	0.0165	0.0237
	(0.0077)	(0.0123)	(0.0202)
House	-0.0133***	-0.0207***	-0.0343***
	(0.0018)	(0.0029)	(0.0048)
c06	-0.0083**	-0.0125**	-0.0207**
	(0.0040)	(0.0059)	(0.0098)
c712	-0.0123***	-0.0185***	-0.0307***
	(0.0030)	(0.0044)	(0.0073)
c1317	-0.0009	-0.0014	-0.0022
	(0.0025)	(0.0039)	(0.0064)
Hispanic	-0.0075**	-0.0113**	-0.0187**
	(0.0032)	(0.0048)	(0.0080)
black	0.0049**	0.0076**	0.0125**
	(0.0024)	(0.0037)	(0.0062)
others	-0.0023	-0.0035	-0.0058
	(0.0029)	(0.0044)	(0.0074)
summer	-0.0285***	-0.0464***	-0.0765***
	(0.0005)	(0.0008)	(0.0014)
fall	-0.0279***	-0.0404***	-0.0673***
	(0.0005)	(0.0007)	(0.0012)
winter	-0.0072***	-0.0109***	-0.0181***
	(0.0005)	(0.0007)	(0.0012)
east	0.0271***	0.0431***	0.0713***
	(0.0018)	(0.0030)	(0.0049)
central	0.0099***	0.0153***	0.0254***
	(0.0017)	(0.0026)	(0.0043)
west	0.0136***	0.0212***	0.0351***
	(0.0018)	(0.0029)	(0.0048)
$Ln(q_{it-1})$	-0.0091***	-0.0137***	-0.0228***
	(0.0006)	(0.0004)	(0.0006)
Lnprice	-0.2652***	-0.4014***	-0.6666***
	(0.0013)	(0.0008)	(0.0014)
Coupon	0.0176***	0.0267***	0.0444***
	(0.0003)	(0.0013)	(0.0014)

Note: Standard errors are in parenthesis. *** Statistically significant at 99% confidence level; ** statistically significant at 95% confidence level.

Table 4.6. Estimated Elasticities for the Conditional Expected Fiber Purchase given a Purchase in the Previous Period

Variable Name	$P(q_{it} > 0 \mid q_{it-1} > 0)$	$E[q_{it} \mid q_{it} > 0, q_{it-1} > 0]$	$E[q_{it} \mid q_{it-1} > 0]$
Predicted Value	0.880166	3.446655	3.033627
Actual Value	0.465921	4.833729	2.252135
$HHSize^{-1}$	0.0301***	0.0643***	0.0944***
	(0.0012)	(0.0025)	(0.0037)
Ln(mpHHInc)	0.0071***	0.0152***	0.0223***
	(0.0008)	(0.0016)	(0.0023)
Ln(mpAgeF)	0.0440***	0.0941***	0.1381***
	(0.0020)	(0.0049)	(0.0069)
feduc	-0.0103***	-0.0225***	-0.0330***
	(0.0010)	(0.0022)	(0.0033)
femploy	-0.0007	-0.0016	-0.0023
	(0.0010)	(0.0022)	(0.0033)
WIC	0.0075	0.0167	0.0244
	(0.0054)	(0.0124)	(0.0181)
House	-0.0095***	-0.0210***	-0.0307***
	(0.0013)	(0.0030)	(0.0043)
c06	-0.0059**	-0.0126**	-0.0185**
	(0.0029)	(0.0059)	(0.0088)
c712	-0.0089***	-0.0187***	-0.0274***
	(0.0022)	(0.0044)	(0.0066)
c1317	-0.0006	-0.0014	-0.0020
	(0.0018)	(0.0039)	(0.0058)
Hispanic	-0.0053**	-0.0114**	-0.0167**
	(0.0023)	(0.0049)	(0.0072)
black	0.0035**	0.0076**	0.0112**
	(0.0017)	(0.0038)	(0.0055)
others	-0.0016	-0.0035	-0.0052
	(0.0021)	(0.0045)	(0.0066)
summer	-0.0201***	-0.0471***	-0.0683***
	(0.0004)	(0.0008)	(0.0012)
fall	-0.0201***	-0.0407***	-0.0602***
	(0.0004)	(0.0007)	(0.0011)
winter	-0.0052***	-0.0110***	-0.0161***
	(0.0004)	(0.0007)	(0.0011)
east	0.0192***	0.0437***	0.0636***
	(0.0013)	(0.0030)	(0.0044)
central	0.0071***	0.0155***	0.0227***
	(0.0012)	(0.0026)	(0.0038)
west	0.0097***	0.0214***	0.0313***
	(0.0013)	(0.0030)	(0.0043)
$Ln(q_{it-1})$	-0.0065***	-0.0139***	-0.0204***
	(0.0003)	(0.0002)	(0.0004)
Lnprice	-0.1898***	-0.4058***	-0.5956***
	(0.0009)	(0.0003)	(0.0010)
Coupon	0.0126***	0.0270***	0.0396***
	(0.0002)	(0.0001)	(0.0002)

Note: Standard errors are in parenthesis. *** Statistically significant at 99% confidence level; ** statistically significant at 95% confidence level.

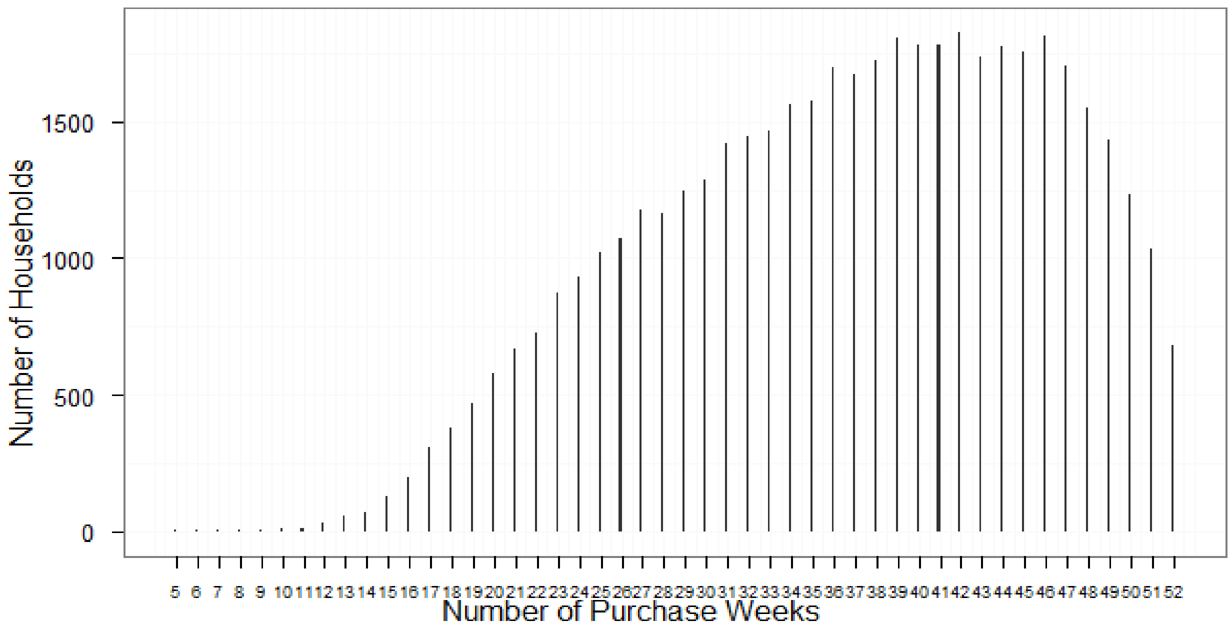


Figure 4.1. Fiber Purchase Frequency across Households

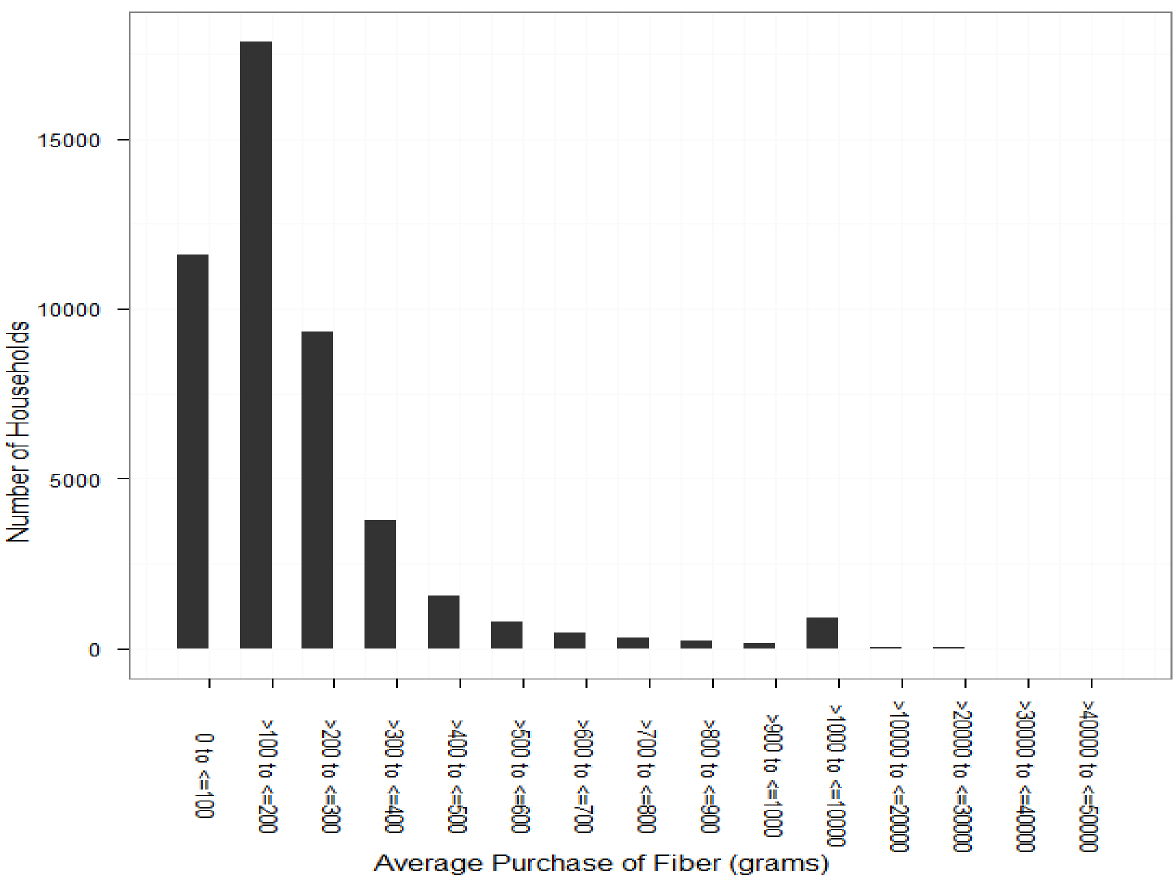


Figure 4.2. Frequency of Fiber Purchase Quantity across Households and Weeks

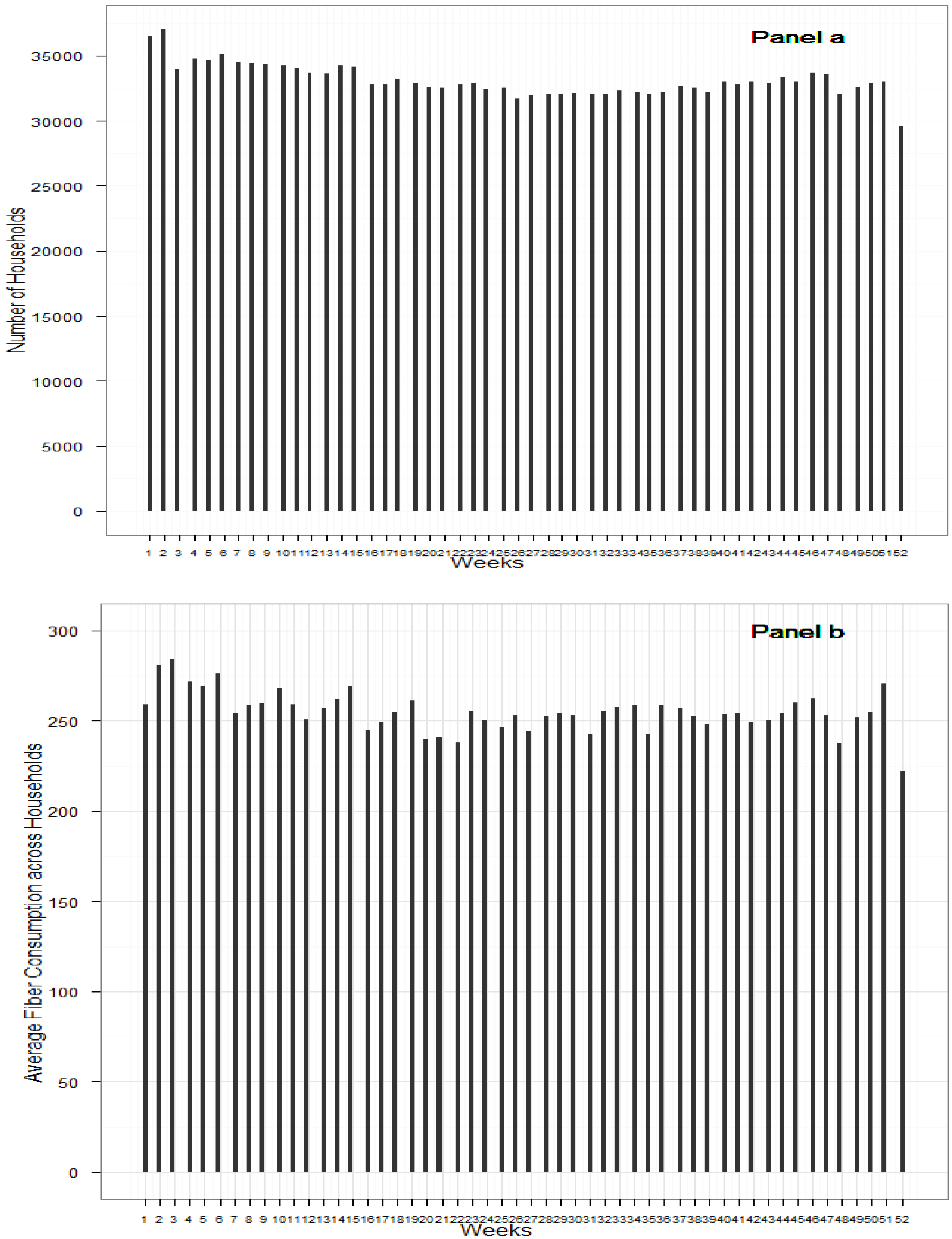


Figure 4.3. Purchase Frequency over Time

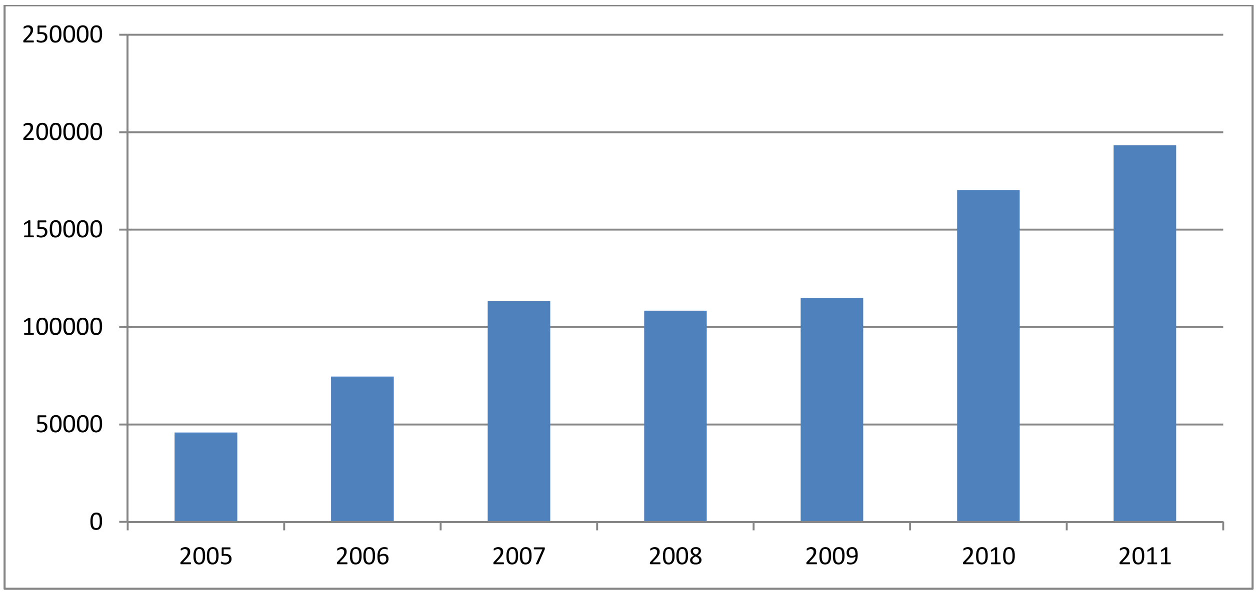
Appendix

A. Merging Nielsen Homescan and Gladson Databases

The merge process consists of three steps (direct match, heuristic match, and imputation), although its implementation was performed in one computational step using STATA.

<u>Data preparation</u>

Gladson data: As shown in the following figure, seven Gladson data sets were available for the merge.



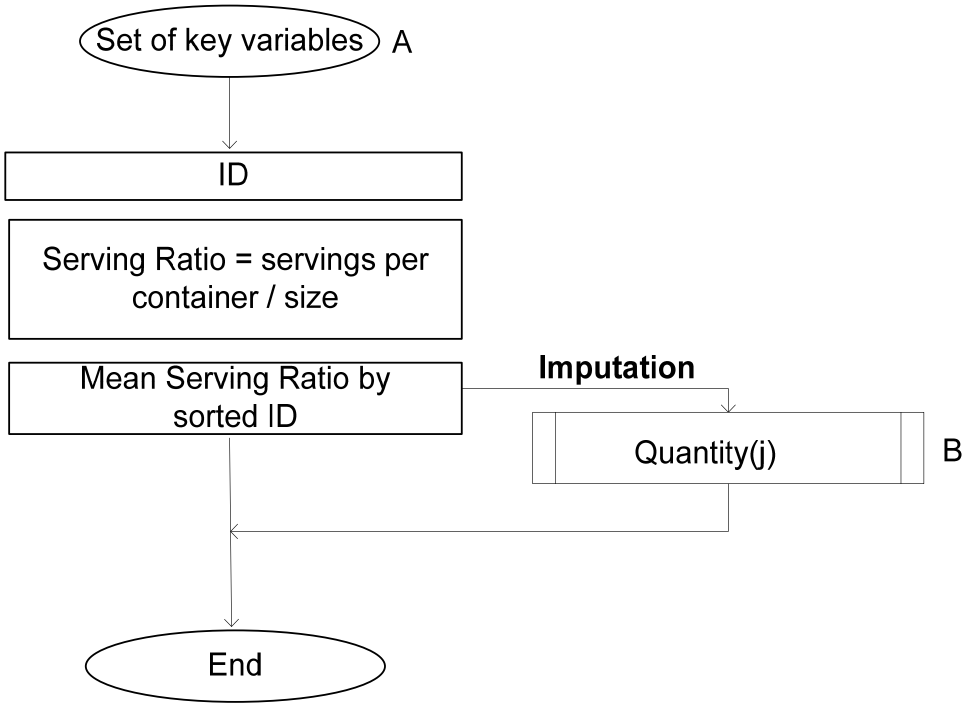
Distribution of the observations in the 2005-2011 Gladson database
Source: Henry and Rahkovsky (2011).

Since some producers recycle their UPCs (approximately 5,000) when they discontinue the old products and becauseitems are captured by Gladson year after year, 413,000 out of 821,000 UPCs are unique. By merging the seven datasets illustrated in the previous figure, based on unique and closest UPCs to the date of interest (in this case 2009), a unified 2005-2011 Gladson dataset for the year 2009 was created. In order to keep only numbers in each individual UPC, the letters on each UPC were eliminated using the STATA function *regexm*. Next, duplicates of UPCs were dropped, and since the standard length of each UPC is 13 digits, all the remaining UPCs were made 13 digits.

Nielsen Homescan data: This data is organized into four categories (Dairy products; Frozen foods, produce, and meat; Random weight products; and Dry goods), each of which as a separate dataset. Therefore, they were appended into a single dataset. Next, duplicates of UPCs were dropped, and since UPCs in Nielsen have 12 or fewer digits, zeros were added in front of each UPC in order to make them 13 digit UPCs. Finally, product, brand, and store name information was merged to the dataset as needed for the heuristic matching process.

<u>Merge Process</u>

This process started by merging directly the unified 2005-2011 Gladson dataset with the previous Homescan dataset, based on the UPCs. Then, the unmatched portion from the previous merge (i.e. unmatched observations from both Nielsen and Gladson) was heuristically matched by brand and product descriptions. Brand was changed for store and used as a match criterion for the private label products. The heuristic matching criterion was to accept a product in Nielsen to be equivalent to a product in Gladson if: 1) they are from the same firm and 2) the brand and product name combined match over 80%. The heuristic matching code searches by firm through all products in Nielsen and matches it to the Gladson product with the highest match. This part of the process contains a lengthy loop that requires approximately 20 hours of running time on a 64-bit machine. Following the heuristic match, quality control checks were conducted. Heuristically matched observations were appended to the directly match sample and then this output was merged with the Gladson nutritional data and Nielsen product information. Then, unmatched Gladson observations were dropped and five sequential imputations of missing nutritional information, based on multiple criteria and on a selected set of nutrients (Calories, Cholesterol, Fiber, Protein, Saturated Fat, Sodium, Total Fat, Sugar, Trans Fat, and Unsaturated Fat.), were conducted as follows:



Imputation process

For notational purposes the oval is used to indicate the beginning or end, rectangles imply a computation, and the double lined rectangle represents a loop. As shown in this figure, missing nutrient quantities were replaced by the mean value of the serving ratio (servings per container / product size number) by the ID number. It is worth pointing out that an additional imputation was conducted following an imputation procedure slightly different than the one illustrated in the previous figure. Once imputation four was finished, this output was merged with a dataset that was manually prepared by the USDA Nutrient Data Laboratory (2010), based on the variable "Product Module" (PM). This was done for the unmatched Gladson PM items with nutritive importance. After imputation six was done, a merged output was available for research purposes.