Dynamic food demand and habit forming behaviors: Bayesian approach to a Dynamic Tobit panel data model with unobserved heterogeneity

Miyoung Oh and Helen H. Jensen

Iowa State University

Contact information:

Miyoung Oh, Department of Economics, Iowa State University, 75 Heady Hall, Ames, IA 50011, USA. E-mail: my153@iastate.edu

Selected Paper prepared for presentation at the Agricultural & Applied Economics Association's

2013 AAEA & CAES Joint Annual Meeting, Washington, DC, August 4-6, 2013.

Dynamic food demand and habit forming behaviors: Bayesian approach to a Dynamic Tobit panel data model with unobserved heterogeneity

Miyoung Oh and Helen H. Jensen[1]
Iowa State University

June 3, 2013

Abstract

Incorporating dynamics such as habit formation in analysis of demand can make estimation more reliable and help to explain the "stickiness" in consumer demand behavior when consumers receive new information about products, such as a food safety event or recall. Scanner data allow many repeated observations of the same household so are ideal for analyzing the impact of habit on demand. In addition to that, scanner data allow us to easily observe the presence of zero purchases. The presence of zero purchases is an important econometric issue in empirical modeling on food demand in the sense that ignoring the censoring issue could lead to biased estimation results. This paper investigates the impact of state dependence on food demand using Nielsen 2009 and 2010 HomeScan data. In this paper, we take into account the censored nature of food expenditure data and employ a Bayesian procedure to estimate the dynamic demand models on dairy products. By controlling the individual heterogeneity in the model the source of endogeneity for the lagged dependent variable is removed.

---

[1] Please do not circulate or cite without permission of the authors. We thank USDA and Sandy Hoffmann, Economic Research Service, for collaborating with us on this research under a Third Party Agreement with Nielsen, and Ellen Goddard, University of Alberta, for discussions about the research and application. The judgments and conclusions herein are those of the authors and do not necessarily reflect those of the U.S. Department of Agriculture. The authors are responsible for all errors.

Introduction

Habit formation

Eating behaviors and habits contribute to health outcomes and thus understanding factors associated with eating choices is important to efforts to protect and improve health status. Food habits are also important in explaining observed “stickiness” in food demand when consumers are provided new information about food safety and risk. Food choices can be explained, in part, by investigating market demand for food. The empirical evidence of habitual behaviors in demand provides support for considering a model with dynamics in a study of the food demand. Following Pollack (1970), habit forming goods are defined as goods associated with preferences for which current consumption behavior relies on the past consumption experience. Therefore, lagged dependent variables are used to show how habit formation influences the demand.

A number of empirical studies in food demand have analyzed habit formation using macro and micro level panel data. Habit forming behaviors are found in various categories of food products including products such as beverages, meats, cereal, cheese, ketchup and snacks, as well as food at home, food away from home and aggregate food (Zhen et al, 2010; Wohlgenant and Zhen, 2006; Thunström, 2009; Arnade et al., 2008; Seetharaman, 2004; Richards et al., 2007; Heien and Durham, 1991; Naik and Moore, 1996). Although food demand models generally exhibit habit formation, the evidence of habit formation varies over empirical methods used (Daunfeldt et al., 2011). For example, Naik and Moore (1996) use a single demand functions model and show habit formation in individual food consumption using aggregated food consumption of household panel data. In contrast, Dynan (2000) uses a life-cycle consumption model and finds no evidence of habit formation using the same data set. And, Browning and Collado (2007) find habit formation for consumption of ‘food outside the home’ while there is no state dependence for ‘food at home’. Other important example is found in studies of non-alcoholic beverages. Zhen et al. (2011) examine state dependence over beverage demand and find strong evidence for habit formation.

As an alternative to traditional state dependence approach, the recent work of Adamowicz and Swait (2012) evaluates a conceptual framework of decision strategy which would minimize cognitive effort using panel data. Significant evidence of the habitual decision strategy was shown particularly in the case of catsup which has a relatively longer inter-purchase period while there is evidence of variety-seeking preference in the case of yogurt.

Controlling for the unobserved individual heterogeneity is one distinct issue that arises when estimating the effect of habit. Often, the literature on habit formation is concerned with possible sources of persistence in consumer’s behavior and addresses whether the association between current and past consumption reflects state dependence or individual heterogeneity (Naik and Moore, 1996; Carrasco et al., 2005: Browning and Collado, 2007). Failure to control for unobserved heterogeneity in micro data may lead to overestimation of the underlying habit formation. In order to distinguish between heterogeneity among individuals and the effect of habit, researchers have estimated models that include fixed effects to explain the time invariant unobserved heterogeneity across households and provide a strong tool for testing the habit formation hypothesis. Naik and Moore (1996) conclude that controlling for heterogeneity reduces estimated habit effects; the importance of accounting for time invariant unobserved individual effects has been shown in Carrasco et al. (2005).

Most of the literature referenced above on habit formation employs dynamic linear panel data models to estimate dynamic demand. In the linear models with unobserved individual effects, the unobserved effects can be eliminated by using an appropriate transformation such as differencing; instrumental variables (IV) can be implemented to estimate the transformed model in a generalized method of moments (GMM) framework. To date, significant progress has been achieved in estimating unbiased and consistent estimators and improving the efficiency of the estimators (Anderson and Hsiao, 1982; Arellano and Bond, 1991; Arellano and Bover, 1995; Baltagi, 1995; Bond and Hahn, 1999; Arellano and Honore, 2001; Hsiao, 2003).

Empirical challenges: Censoring

Generally, households do not purchase or consume all goods available in the market in the time period observed. It is a well-known econometric issue in microdata based on surveys of household expenditures that households do not purchase all goods available but only some of them in the observed time period. This leads to censoring of the dependent variable in the estimation of demand or consumption equations. While this zero consumption issue can be represented as a corner solution in the utility maximization (Perali and Chavas, 2000), we could also find various reasons for the household's decision to purchase none of the good (zero purchases). For example, people may simply avoid certain products or, if they do make purchases, do so infrequently according to their lifestyles. Alternatively, the decision related to infrequent purchases which are observed as zero purchases in a given period of time, may be related to the capacity of storing products and use of inventories. Other non-purchase decisions may be related to factors related to information about the safety of products or the dietary environment. This type of response would occur as a change in behavior from the previous responses. With any possible reasons, if there is a significant fraction of the zero observations in the dependent variable, the analysis with a conventional regression approach may cause inappropriate biased and inconsistent estimators.

In order to deal with censored data, several approaches to demand systems have been taken in the econometric literature such as The Kuhn-Tucker model, Amemiya-Tobin model, Heckman's two-step method and Bayesian approach (Wales and Woodland, 1983; Lee and Pitt, 1986; Tobin, 1958; Amemiya, 1974; Heien and Wessells, 1990; Shonkwiler and Yen, 1999; Tiffin and Arnoult, 2010; Ishdorj and Jensen, 2010; Kasteridis et al., 2011).

For estimating dynamic food demand, this paper uses the dynamic Tobit panel model with unobserved individual heterogeneity. The non-linear nature of treating censored panel data makes the estimation even more difficult along with some complexity that arises from the two main features of the dynamic panel data model: the individual specific effects and lagged dependent variables. The literature on the nonlinear panel models, particularly in the case of censored regression, have been developed to overcome the difficulties of differencing away the unobserved effects and dealing with initial conditions (Honore, 1993; Hu, 2002, Hsiao, 2003; Honore and Hu, 2004; Wooldridge, 2005; Li and Zheng, 2008).

In this paper, we apply the Bayesian approach to estimate a dynamic censored dairy food demand. We selected the dairy and eggs food group because some of these products are purchased by most households and it is a sector of interest in food and health programs. In micro panel data, the pairs of observations corresponding to a given individual are likely to be correlated and individual specific effect are introduced in models to account for this fact. The form of the correctly specified likelihood function might be complex and this leads to computational difficulties. Bayesian approach – inference from the parameters' posterior distribution conditioned on the observations - is our alternative to maximum likelihood estimation having computational convenience through the simulation methods. One of the standard Markov Chain Monte Carlo (MCMC) algorithms that can be easily applied to high dimensional problems is the Gibbs sampler. This method is used in the iteration procedure for sampling the parameters from the conditional posterior distributions.

1. The Model

The dynamic single demand equations are estimated as a dynamic Tobit panel data model. The literature considers a dynamic unobserved effects Tobit model in the form

$$y_{iht} = \max[\,0, z_{iht}\gamma + g(y_{ih,t-1})\rho + c_{ih} + u_{iht}\,], \qquad i = 1,..., n,\ \ h = 1,..., H,\ \ t = 1,..., T \quad (1)$$

$$u_{iht} \,\big|\, y_{ih,t-1},..., y_{ih,0}, z_{ih}, c_{ih} \ \overset{iid}{\sim} \ \text{Normal}(0,\ \sigma^2_{iu})$$

where y_{iht} is the censored response variable of interest on the i^{th} good by the h^{th} household in time period t which depends on the explanatory variables z_{iht}, the lags of the dependent variable y_{iht-1} and the unobserved individual heterogeneity c_{ih} (Hu, 2002; Wooldridge, 2005; Li and Zheng, 2008). As Heckman (1981) notes, in order to interpret observed persistence in consumption as the habit effect corresponding to the case of true state dependence, we allow the intercept in equation (1) to vary across households to control for omitted factors.

We assume that the error terms, u_{iht}, are i.i.d. normally distributed conditional on $(y^*_{ih0},\ \{z_{iht}\}_{t=1}^{T},\ c_{ih})$ and not serially correlated in the model. As we account for the unobserved individual effects and the assumptions on error terms, the model exhibits the strict exogeneity on z_{iht}. In other words, the possible dynamic feedback from realizations z_{ih} on past and future time periods to the current realizations of the dependent variables is removed in the model so that the dynamic nature of the model is only from the presence of the lagged dependent variables (Hu, 2002).

The model in equation (1) is well suited to corner solution applications however, the model with lagged censored dependent variable is not applicable for data censoring applications (Wooldridge, 2002; 2005). As we are to account for a data censoring case, the lagged latent dependent variable will be placed in the function $g(\cdot)$ as same as in Hu (2002) and the model in this paper is specified as follows:

$$y^*_{iht} = z_{iht}\gamma + y^*_{ih,t-1}\rho + c_{ih} + u_{iht} \qquad (2)$$

where y^*_{iht} represents the latent quantities of product i purchased by household h in t^{th} month, $y^*_{ih,t-1}$ is the lagged latent quantities of product i purchased by household h in $(t-1)^{th}$ month and z_{iht} represents the covariates vector of interest: set of own and cross prices, set of demographic variables with total expenditures over all food categories(food at home) and seasonal effects.

As the unobserved individual heterogeneity c_{ih} is a nuisance parameter, specifying the distribution of c_{ih} and its relationship with z_{iht} is needed to complete the model setup. We follow the specification of the relationship between the individual effects and the initial conditions in Li and Zheng (2008). Li and Zheng make an assumption of the following conditional mean dependence of the c_{ih} on the initial conditions and observed strictly exogenous variables

$$E[c_{ih} | y_{ih,0}, z_{ih}] = a + h(y_{ih,0}, z_{ih})\delta \tag{3}$$

where a is a constant, $h(\cdot)$ is a function of the vector of initial values of the dependent variable y_{ih0} and a matrix of time-invariant covariates z_{ih} which only vary over different households and δ is a vector of corresponding parameters.[2] Independent relationship between $y_{ih,0}$ and z_{ih} is assumed. We set $z_{ih} = \bar{z}_{ih}$ where $\bar{z}_{ih}$ is the average of z_{iht} over entire time path as in Chib and Jeliazkov(2006).[3] Following the specification of $h(y_{ih0}, z_{ih}) = y_{ih0}\delta_1 + z_{ih}\delta_2$ in Li and Zheng (2008), we rewrite (3) as

$$c_{ih} = y_{ih,0}\delta_1 + z_{ih}\delta_2 + \varepsilon_{ih}\ , \qquad \varepsilon_{ih} | y_{ih0}, z_{ih} \sim^{iid} \text{Normal } (0,\ \sigma_i^2) \tag{4}$$

where ε_{ih} is an error term in the auxiliary equation.[4] This specification of the unobserved individual heterogeneity allows its linear correlation with the initial observations of the dependent variable and the set of exogenous explanatory variables.

2. Estimation

We fit the following dynamic Tobit model with the unobserved individual heterogeneity

---

[2] Alternatively, z_{ih} can be the set of all explanatory variables in all time periods, $z_{ih} = (z_{ih1}, \ldots, z_{ihT})$ with multidimensional z_{ih} as in Wooldridge (2005).

[3] Time-invariant variables such as race or ethnicity cannot be in both z_{iht} and $\bar{z}_{ih}$ for the identification purpose. (Li and Zheng; 2008)

[4] For the estimation of the model, we assume that $y^*_{ih0} = y_{ih0}$, initial values of dependent variable to be uncensored following Hu (2002).

$$y^*_{iht} = x_{iht}\beta + c_{ih} + u_{iht} \quad (\text{or } Y^* = X\beta + C^e + u)$$

where $x_{iht} = (z_{iht}, y^*_{ih,t-1})$, $\beta = (\gamma', \rho')'$ and $u_{iht} \left| y_{ih,t-1},..., y_{ih,0}, z_{ih}, c_{ih} \right. \sim^{iid}$ Normal $(0, \sigma^2_{iu})$

$$c_{ih} = r_{ih}\delta + \varepsilon_{ih} \quad (\text{or } C = R\delta + \varepsilon)$$

where $r_{ih} = (y_{ih0,} z_{ih}, 1)$, $\delta = (\delta_1', \delta_2')'$ and $\varepsilon_{ih} \left| y_{ih0}, z_{ih} \right. \sim^{iid}$ Normal $(0, \sigma^2_i)$

using a Bayesian approach by drawing samples from the posterior distribution of the parameters in the model.[5] One thing we are concerned about is that our latent variables $\{y^*_{ih}\}^T_{t=1}$ and c_{ih} are not completely observable. So, we need to employ data augmentation suggested by Albert and Chib (1993) to replace the zero observations with fitted values for latent dependent variables and update nuisance parameters c_{ih} through the Bayesian Markov Chain Monte Carlo algorithm (MCMC) iterations. We will discuss about the data augmentation in the Gibbs sampling algorithm.

Sampling density and priors

Recall that the distribution of u_{iht} and equation (2) give us the sampling density of the dependent variables conditioned on the latent variables. In addition to other variables, we write the model as follows:

---

[5] $C^e = (c_{i1}^{(t=1)},..., c_{i1}^{(t=T)},..., c_{iH}^{(t=1)},..., c_{iH}^{(t=T)})'$

$$f(y_{ih1}, y_{ih2}, \ldots, y_{ihT} \left| y^*_{ih1}, y^*_{ih2}, \ldots, y^*_{ihT}, y_{ih,0}, z_{ih}, c_{ih}, \gamma, \rho \right)$$

$$= \prod_{t=1}^{T} \{1(y_{iht} > 0)1(y_{iht} = y^*_{iht}) + 1(y_{iht} = 0)1(y^*_{iht} \le 0\} \quad (5)$$

$$* \frac{1}{\left(2\pi\sigma^2_{ui}\right)^{-\frac{1}{2}}} \exp\left(-\frac{1}{2\sigma^2_{ui}} (y^*_{iht} - z_{iht}\gamma - y^*_{ih,t-1}\rho - c_{ih})^2 \right)$$

Before we discuss how the model can be fit using the MCMC, we introduce the specifications on priors following Li and Zheng (2008):

$\beta = (\gamma', \rho')'$ ~ improper flat prior [6]

$$\frac{1}{\sigma^2_{iu}} \sim \text{gamma}\left(\frac{N_1}{2}, \frac{R_1}{2}\right) \text{ or } \frac{1}{\sigma^2_{iu}} \propto \left(1/\sigma^2_{iu} \right)^{\frac{N1}{2}-1} e^{-R_1\left(1/\sigma^2_{iu}\right)} \quad (6)$$

Gibbs sampling from the posterior

Combining the model given in (2) and the prior information in (6), we can figure out what the posterior conditional distributions of the parameters look like. We use one simple and effective sampler in the MCMC algorithms called the Gibbs sampler to generate samples from the posterior. As we set initial values for β, δ and σ^2_{iu}, the Gibbs iteration algorithm proceeds in the following steps:

[6] "For example, a uniform prior distribution on the real line, $\pi(\theta) \propto 1$, for $-\infty < \theta < \infty$, is an improper prior. Improper priors are often used in Bayesian inference since they usually yield noninformative priors and proper posterior distributions." (SAS/STAT(R) 9.2 User's Guide, Second edition)(http://support.sas.com/documentation/cdl/en/statug/63033/HTML/default/viewer.htm#statug_introbayes_sect004.htm

Step1: For each $h=1,\ldots,H$ and $t=1,\ldots,T$ such that $y_{iht}=0,$ generate y^{*}_{iht} from the truncated normal distribution on the interval [-∞, 0] with mean $x_{iht}\beta + r_{ih}\delta$ and variance $\sigma^2_{iu}+\sigma^2_i$ conditional on $y_{iht}, x_{iht}, r_{ih}, \beta, \delta, \sigma^2_i$ and σ^2_{iu}.

Step2: Update σ^2_{iu} and β by drawing from the joint posterior distribution of $\frac{1}{\sigma^2_{iu}}$ and β conditional on data and other parameters and marginalized over each other.

$$\frac{1}{\sigma^2_{iu}} \quad \sim \quad \text{gamma}\left(\frac{N_1+nT}{2}, \frac{R_1+(Y^*-X\hat{\beta}-C^e)'(Y^*-X\hat{\beta}-C^e)}{2}\right)$$

$$\beta \quad \sim \quad \text{Normal}\left(\hat{\beta}, \left(\frac{X'X}{\sigma^2_{iu}}\right)^{-1}\right) \text{ where } \hat{\beta}=\left(X'X\right)^{-1}(X'(Y^*-C^e))$$

Step3: For each $h=1,\ldots,H$, update c_{ih} from the normal distribution with mean

$$c^*_{ih}=\left(\frac{T}{\sigma^2_{iu}}+\frac{1}{\sigma^2_i}\right)^{-1}\times\left(\frac{1}{\sigma^2_{iu}}\sum_{t=1}^{T}(y^*_{iht}-x_{iht}\beta)+\frac{r_{ih}\delta}{\sigma^2_i}\right) \text{and variance} \left(\frac{T}{\sigma^2_{iu}}+\frac{1}{\sigma^2_i}\right)^{-1}.$$

Step4: Update δ by drawing from the posterior distribution conditional on r_{ih}, c_{ih} and σ^2_i.

$$\delta \quad \sim \quad \text{Normal}\left(\hat{\delta}, \left(\frac{R'R}{\sigma^2_i}\right)^{-1}\right) \text{ where } \hat{\delta}=\left(\frac{R'R}{\sigma^2_i}\right)^{-1}\left(\frac{R'C}{\sigma^2_i}\right).$$

3. Data description

The dynamic food demand is estimated by using the Nielsen HomeScan data for the period 2009 and 2010. The data are based on a representative sample of U.S. households that report on all food purchase for each shopping trip. The food items are recorded by the unique Uniform Product Code (UPC) using a scanning device and the information is collected on weekly basis. The initial dataset consists of dry grocery purchases, dairy products purchases, UPC-produce, meat and frozen products purchases, and random weight purchase data. “Household expenditures on food at home” are generated by using the aggregated expenditures on dairy, dry grocery, frozen and random weight products purchase data. The data files also contain information on household socio-economic and demographic characteristics and purchase information by purchase date, product module, UPC number, size, quantity, multipack, use of coupon and price paid. The demographic characteristics matched with the household purchases data include household income, age, education and employment of household head, race and ethnicity, marital status, and presence of children.

The total number of households reporting any food purchase in the 2009 and 2010 scanner data is over 60,000 households. Of those, more than 59,000 households report some food purchases at least 10 months of a year. Among those households, 36,256 households report dairy products both in 2009 and 2010. This was our sample of interest. The dairy file includes both dairy products and shell eggs. We refer to this as the “dairy” products group. In order to have a sample size that would simplify the estimation process we took a random sample of 3,626 households for our analytic sample, which is approximately 10% of 36,256 households.

In Table 1, the dairy products are categorized into four groups of products – milk, cheese, egg and other dairy products. Table 1 provides the number of households who purchase each group of products and the percentages of zero purchases of each group. The majority of the households who reported any grocery purchase information for at least 10 months have purchased each group of products at least once in 2009 and 2010. As we consider a month as a time unit out of 24 months' time period based on the expected average shelf life of dairy products; the number of observations is the number of households times 24.[7] Of our final sample, 40 percent of observations on egg purchases and 29 percent of observations on cheese purchases had no expenditures on the respective products while 17 percent of observations of milk data were zero purchases. As we see some households that have zero purchase of each category of products, it is a reasonable concern to account for censoring in the estimation.

Table 2 provides information on the distribution of average quantities and imputed prices (unit values) for the four product groups. We calculated regional prices as the households' prices after we accounted for the reported product units: ounces, fluid ounces and count measures. The price of each group of products for each region is imputed as the unit value defined as the sum of households' expenditure ($) in each region for the group of products divided by quantity purchased in ounces. In Table 2, monthly average quantities purchased of each category and prices are reported. As shown in the table, cheese and other dairy products are more expensive than milk and eggs on a per ounce basis.

Table 3 presents the descriptions of variables and provides the calculated means and standard deviations of the final sample. Demographic variables include the household's income, total food (at home) expenditures, household's age, presence of children (kids), employment status of female household head and race and ethnicity. The race and ethnicity are collected from the sample person, and may not reflect the race and ethnicity of all members of the household when

[7] Note that the shelf life of cheese might last longer than any other dairy products in the freezer. This may influence the result of estimation on cheese demand.

race and ethnicity are mixed. The household's income is recorded as a categorical variable. In our estimation we use the household's monthly expenditure calculated over all food groceries as an explanatory variable, instead of reported income (Benson et al., 2002). In doing this, similar to Benson et al. (2002), the estimation results of the demand equations solve the second stage of a two-stage budgeting problem based upon weak separability over households' preferences. Households allocate the total food expenditures monthly among purchases of dairy products and non-dairy food products after the first allocation of income among purchases of food at home and other goods or services. Using total food expenditure also reduces possible endogeneity posed from use of the dairy group expenditure as a measure of total expenditures or income. We use the information of household's income to compare the demand of low income households to the demand of high income households. The presence of children, race and ethnicity, and the employment status of female household head were considered as binary variables.

The main contribution of this paper is to estimate a dynamic demand model by using a Bayesian approach, accounting for censored data. We are applying the estimation procedures to the dairy group, a group that has relatively well defined products. Gibbs sampling is conducted to deal with the censored data. The estimation proceeded as follows: the numbers of observations on each data file were iterated 10,000 times; the first 5,000 iterations were set to be burn-in periods.

4. Results

Table 4 presents the results from the estimation of the dynamic Tobit model with individual heterogeneity on purchases of dairy products reporting the posterior means and standard deviations of parameters for the prices and demographic variables. The probabilities of being positive that is loosely comparable to the notion of "significance" are also reported for each set of parameters estimated for the demand model. The parameter estimates from the main equation and auxiliary equation are shown in Table 4. The effect of the habit persistence is seen in the parameter value of Yt-1. We find strong evidences that past purchases of each dairy category play an important role in current purchases of each group of products, as the estimates of all four demand equations present similar positive impacts for the lagged dependent variable with probability of being positive 1.0. Even though we controlled for the effect of unobserved heterogeneity, we observe the presence of habit formation in the purchases of dairy products. In particular, the milk demand exhibits the strongest strength of habit forming behavior while we find less impact of lagged dependent variable on cheese demand.[8]

As shown in Table 4, the estimates of the own price responses for all dairy demands are negative signed; most of the own price response have probability of being positive near 0 except for eggs. Estimated response to total food expenditures is positive for all products as we expected, and with probability of being positive 1.0. The presence of children in all age ranges and total food expenditures have substantial positive impacts on milk demand. The effect of having kids on milk consumption is particularly large in the households that have children under 5 years of age.

Some interesting result from the estimates for the auxiliary equation is that there is a positive correlation between the unobserved heterogeneity and Hispanic ethnicity in all dairy demands.

---

[8] When it comes to estimating habit effects of food demand, perishability and storage motives together with the length of lags may also matter to state dependence. As the length of lags was to be set consistent with the length of shelf life for dairy products except cheese products, we are not overly concerned about controlling storage behaviors from state dependence. The weakest impact of lagged variable for cheese demand among dairy demands may relate to longer length of self life. So, there might be possible storage behaviors in cheese purchases and habit formation factor may possibly be underestimated.

In order to avoid possible correlation expected between total expenditure and income, we conducted an additional analysis by separating the sample into two income groups of households and ran the same estimation process on milk products only. We convert midpoints of categorical income ranges into estimated income and compute poverty-income ratios. Low income household is defined if having income less than 200% of the poverty income level and high income household has income more than the cut-off level.[9] The results in Table 5 show that the price and total food expenditure responses of low income households are more responsive than those of high income households. Also, the effect of the presence of children is larger among the low income households.

Uncompensated price and total food expenditure elasticities were calculated from the posterior parameters on prices and food expenditures and are provided in Table 6. Point estimates provided in the each cell are the means of the Gibbs samples and the 95% credible intervals are given in parentheses. Corresponding to the probabilities of being positive in Table 4, most of the own-price elasticities and all the food expenditure elasticities are considered to be "significant" as 95% credible sets exclude zero. The own-price elasticities of each group are negative and inelastic which means that dairy products are necessary goods, as we expect. Demand for cheese is relatively more price responsive than the other products. In the case of egg demand, there is little evidence that most of the price elasticities are "significant" as the 95% credible sets include zero. Complementarity was found among the dairy products.[10] In addition, the food expenditure

[9] The official cut-off applied in some nutrition programs (e.g., WIC) is 185%. We use 200% to include "potentially" eligible households.

[10] Note that as we estimate single demand equations, no restrictions such adding-up, symmetry and homogeneity were imposed.

elasticity estimates for each group are positive. We find some evidences of larger food expenditure elasticities for cheese and other dairy products than milk and eggs. Higher and low income households both have similar inelastic milk demand patterns (see Table 7). Low income households exhibit more elastic price and expenditure responses for milk demand compared to the responses of the higher income households.

5. Conclusions

This paper investigates the impact of state dependence on dairy demand using Nielsen 2009 and 2010 HomeScan data. The results of the estimation show that habit forming behaviors exist for these products and are conditional on unobserved individual heterogeneity. As expected in estimating demand for particular product categories, problems of censoring appear in the micro-data. In this paper, we take into account the censored nature of food expenditure data and employ a Bayesian procedure to estimate the dynamic demand models on dairy products. By controlling the individual heterogeneity in the model, the source of endogeneity for the lagged dependent variable has been removed. The Bayesian estimation approach used reduces the burdens of having complicated computations through the simulation methods.

This research provides a unique contribution to a dynamic censored demand on food applying Bayesian method. We examined the dairy foods group and find that most of the dairy products exhibit habit formation. These findings suggest that consumers of these products will be slower to adjust their purchase behavior. Subsequent analysis will expand the time period covered and examine responses to specific food safety recalls and product information. Additional product groups will be considered as well, including meats. Another area for extension of this work is to account for some correlation among the single equations estimating demand as a demand system.

Reference

Adamowicz, W.L. and J.D.Swait. 2012. "Are Food Choices Really Habitual? Integrating Habits, Variety-seeking and Compensatory Choice in a Utility-maximizing Framework." *American Journal of Agricultural Economics* 95(1): 17-41.

Albert, J. and S. Chib. 1993. "Bayesian Analysis of Binary and Polychotomous Response Data." *Journal of the American Statistical Association* 88:669-679.

Amemiya, T. 1974. "Multivariate regression and simultaneous equation models when the dependent variables are truncated normal." *Econometrica* 42: 999-1012.

Arnade, C., M. Gopinath and D.Pick. 2008. "Brand inertia in U.S. household cheese consumption." *American Journal of Agricultural Economics* 90: 813-326.

Benson, J.T., Breidt, F.J. and Schroeter, J.R. 2002. "Television Adevertising and Beef Demand: Bayesian Inference in a Random Effects Tobit Model." *Canadian Journal of Agricultural Economics* 50:201-219.

Browning, Martin and M. D. Collado. 2007. "Habits and heterogeneity in demands: a panel data analysis." *Journal of Applied Econometrics* 22:625-640.

Blanciforti and Green. 1983. "An Almost Ideal Demand System Incorporating Habits: An Analysis of Expenditures on Food and Aggregate Community Groups." *Review of Economics and Statistics* 65:511-515.

Carrasco, R., Labeaga, J. M. and Lopez-Salido, J. D, 2005. "Consumption and habits: evidence from panel data." *The economic Journal* 115:144-165.

Chib, S. and I. Jeliazkov 2006. "Inference in semiparametric dynamic models for binary longitudinal data." *Journal of the American Statistical Association* 101:685-700.

Daunfeldt, S. O., Nordström, J. and Thunström, L. 2011. "Habit formation in food consumption." *The Oxford Handbook of the economics of food consumption and policy* 770-790.

Dynan, Karen. 2000. "Habit Formation in Consumer Preferences: Evidence from Panel Data." *The American Economic Review* 90(3): 391-406.

Griffiths, E., C.J. O'Donnell and A.T. Cruz. 2000. "Imposing regularity conditions on a system of cost and factor share equations." *The Australian Journal of Agricultural and Resource Economics* 44:101-127.

Heien, D. and C.R. Wessells. 1990. "Demand systems estimation with microdata – a censored regression approach." *Journal of Business and Economic Statistics* 8: 365–371.

Heien, Dale and C. Durham. 1991. "A test of the habit formation hypothesis using household data." *The Review of Economics and Statistics* 73(2):189-199.

Heckman, J.J. 1981. "Heterogeneity and state dependence." *Studies in Labor Markets* (Chicago: NBER).

Hoff, P. 2009. "A First Course in Bayesian Statistical Methods." Springer Texts in Statistics.

Honor´e B. 1993. "Orthogonality conditions for Tobit models with fixed effects." *Journal of Econometrics* 59: 35–61.

Honor´e B, Hu L. 2004. "Estimation of cross sectional and panel data censored regression models with endogeneity." *Journal of Econometrics* 122: 293–316.

Hsiao C. 2003. "*Analysis of Panel Data* (2nd edn)." Cambridge University Press: Cambridge, UK.

Hu, L. 2002. "Estimation of a Censored Dynamic Panel Data Model." *Econometrica* 70:

2499-2517.
Huang, C.J., F.A. Sloan and K.W. Adamache. 1987. “Estimation of seemingly unrelated Tobit regressions via the EM algorithm.” *Journal of Business and Economic Statistics* 5:425-430.
Ishdorj, A. and H.H. Jensen. 2010. “Demand for breakfast cereals: whole grains guidance and food choice.” Selected Paper at the 1st Joint EAAE/AAEA Seminar “The Economics of Food, Food Choice and Health” Freising, Germany, September 15-17, 2010.
Kasteridis, P., S.T. Yen and C. Fang. 2011. " Bayesian estimation of a censored Linear Almost Ideal Demand System: food demand in Pakistan.” *American Journal of Agricultural Economics* 93(5): 1374–1390.
Lee, L.F. and M. Pitt. 1986. “Microeconometric demand systems with binding nonnegativity constraints: A dual approach.” *Econometrica* 55:1237-42.
Li, Tong. and Xiaoyong Zheng 2008. “Semiparametric Bayesian Inference for Dynamic Tobit Panel Data Models with Unobserved Heterogeneity.” *Journal of Applied Econometrics* 23:699-728.
Naik, N. Y. and M. J. Moore. 1996. “Habit formation and intertemporal substitution in individual food consumption.” The *Review of Economics and Statistics* 78(2):321-328.
Pollack, R. 1970. “Habit Formation and Dynamic Demand Functions.” *Journal of Political Economy* 78:745-763.
Paseka, A. and George Theocharides.2010. “Predictability in Consumption Growth and Equity Returns: A Bayesian Investigation.” *The Financial Review* 45:167-203.
Richards, T. J., P.M. Patterson and A. Tegene. 2007 “Obesity and nutrient consumption: a rational addiction?” *Contemporary economic policy*, 25(3), 309-324.
Shonkwiler, J. S. and S. T. Yen. 1999. “Two-step estimation of a censored system of equations.” *American Journal of Agricultural Economics* 81: 972–982.
Seetharaman, P. B. 2004. “Modeling multiple sources of state dependence in random utility models: A distributed lag approach.” *Marketing Science* 23: 263−271.
Tiffin, R. and M. Arnoult. 2010. “The demand for a healthy diet: estimating the almost ideal demand system with infrequency of purchase.” *European Review of Agricultural Economics* 37: 501-521.
Tobin, J. 1958. Estimation of relationships for limited dependent variables. *Econometrica* 26:24-36.
Thunström, L. 2010. “Preference Heterogeneity and Habit Persistence: The Case of Breakfast Cereal Consumption” *Journal of Agricultural Economics*, 61(1), 76-96.
Wales, T.J. and A.D. Woodland. 1983. “Estimation of consumer demand system with binding non-negativity constraints.” *Journal of Econometrics* 21: 263-85.
Wooldridge, J.M. 2002. “Econometric Analysis of Cross Section and Panel Data.” Cambridge, MA: MIT Press.
Wooldridge, J.M. 2005. “Simple Solutions to the Initial Conditions Problem in Dynamic, Nonlinear Panel Data Models with Unobserved Heterogeneity.” *Journal of Applied Econometrics* 20:39-54.
Wohlgenant, M.K. and C. Zhen. 2006. “Meat Demand under Rational Habit Persistence.” *Canadian Journal of Agricultural Economics* 54(4): 477–495.
Zhen, C., M.K. Wohlgenant, S. Karns and P. Kaufman. 2011. “Habit formation and demand for sugar-sweetened beverages.” *American Journal of Agricultural Economics* 93:175-193.

Table 1. The Dairy Product Categories and Distribution for Sampled Households[a]

Product Category/Product Group Description	# of HHs	% of Zero Purchases*
MILK	3565	17.7%
CHEESE	3595	29.1%
EGGS	3491	40.9%
OTHER		
BUTTER AND MARGARINE		
COT CHEESE, SOUR CREAM, TOPPINGS		
DOUGH PRODUCTS	3613	19.5%
PUDDING, DESSERTS-DAIRY		
SNACKS, SPREADS, DIPS-DAIRY		
YEAST		
YOGURT		
Total Dairy	3626	

[a] Note: Percentage of observed month with zero purchases over all households purchasing each category of product. Data are reported on the 10% randomly drawn sample of reporting households.

Table 2. Distributions of Monthly Average Quantities and Prices for Sampled Households[a]

Variable	Unit	Mean	Std.	Min.	Max.
Milk	Ounce	94.20	77.24	0.00	1382.40
Cheese	Ounce	10.46	10.83	0.00	320.00
Egg	Ounce	17.18	18.82	0.00	761.92
Other dairy	Ounce	13.52	14.77	0.00	288.00
P_milk	$/oz	0.03	0.01	0.02	0.06
P_cheese	$/oz	0.28	0.03	0.20	0.45
P_egg	$/oz	0.07	0.01	0.04	0.12
P_other	$/oz	0.12	0.02	0.08	0.22

[a] Note: Data are reported on the 10% randomly drawn sample of reporting households.

Table 3. Definitions and Statistics on the Variables for Sampled Households[a]

Variable		Mean	Std.Dev	Minimum	Maximum
Household income		59976	38795	5000	200000
Sum_expd	Monthly total food expenditure	155.73	189.24	0	3150.25
Household age	Maximum age of the two household's heads	59.67	12.58	25	110
Binary Variables (equal 1 if following conditions met, and 0 otherwise)					
Kids	Household has a kid under 5 year olds	0.037	0.19	0	1
Skids	Household has a kid between 5 and 11 year olds	0.08	0.27	0	1
Bkids	Household has a kid between13 and 17 year olds	0.07	0.26	0	1
Emplf	Female household head is employed	0.56	0.50	0.00	1.00
Black	Household's sampled person's race is black	0.08	0.28	0	1
White	Household's sampled person's race is white	0.86	0.35	0	1
Hispanic	Household's sampled person's ethnicity is Hispanic	0.04	0.20	0	1
Summer	Purchasing month is in June to August	0.25	0.43	0	1
Winter	Purchasing month is in November to January	0.25	0.43	0	1

[a] Note: Data are reported on the 10% randomly drawn sample of reporting households.

Table 4. Bayesian Dynamic Tobit Estimation Results for each Dairy Group's Demand

	Milk			Cheese			Other Dairy			Eggs		
Main Equation	**Mean**	**Std**	**Prob>0**	**Mean**	**Std**	**Prob>0**	**Mean**	**Std**	**Prob>0**	**Mean**	**Std**	**Prob>0**
Yt-1	0.538	0.002	1.000	0.177	0.005	1.000	0.284	0.003	1.000	0.246	0.003	1.000
log(P_milk)	-12.886	1.296	0.000	-0.824	0.286	0.002	-1.593	0.333	0.000	-0.222	0.445	0.307
log(P_other)	3.556	1.978	0.966	-0.459	0.411	0.134	-1.618	0.500	0.001	0.173	0.676	0.593
log(P_cheese)	4.264	2.176	0.975	-2.674	0.512	0.000	3.251	0.557	1.000	-1.399	0.763	0.034
log(P_egg)	4.018	1.628	0.992	1.101	0.390	0.997	0.612	0.423	0.929	-0.039	0.573	0.474
log(Sum_expd)	5.994	0.059	1.000	1.114	0.026	1.000	1.306	0.019	1.000	1.572	0.027	1.000
Kids	9.338	1.224	1.000	1.152	0.262	1.000	0.719	0.305	0.991	0.288	0.405	0.755
Skids	7.357	0.744	1.000	0.752	0.184	1.000	0.943	0.193	1.000	1.714	0.250	1.000
Bkids	7.084	0.722	1.000	0.939	0.149	1.000	0.390	0.198	0.977	1.277	0.248	1.000
Hhage	-0.183	0.016	0.000	-0.035	0.005	0.000	-0.015	0.004	0.000	0.038	0.006	1.000
Emplf	-3.572	0.400	0.000	-0.116	0.083	0.080	0.268	0.101	0.995	-1.016	0.138	0.000
Summer	0.048	0.462	0.544	-0.295	0.095	0.001	0.014	0.114	0.551	-0.576	0.156	0.000
Winter	-2.800	0.478	0.000	-0.040	0.097	0.345	-0.743	0.122	0.000	0.592	0.163	1.000
Auxiliary Equation	**Mean**	**Std**	**Prob>0**	**Mean**	**Std**	**Prob>0**	**Mean**	**Std**	**Prob>0**	**Mean**	**Std**	**Prob>0**
Yo	0.071	0.001	1.000	0.050	0.006	1.000	0.148	0.005	1.000	0.058	0.003	1.000
mean of log(P_milk)	0.303	0.110	1.000	-0.547	0.314	0.000	1.363	0.210	1.000	-0.443	0.096	0.000
mean of log(P_other)	-0.955	0.251	0.000	-1.184	0.536	0.000	0.166	0.123	0.928	-0.278	0.155	0.045
mean of log(P_cheese)	0.249	0.234	0.877	1.328	0.590	1.000	1.066	0.197	1.000	-0.834	0.359	0.000
mean of log(P_egg)	0.373	0.247	0.956	0.787	0.417	1.000	-1.416	0.215	0.000	0.659	0.195	1.000
mean of log(Sum_expd)	-0.113	0.037	0.000	0.309	0.122	1.000	-0.112	0.024	0.000	0.286	0.076	1.000
mean of kids	0.275	0.111	1.000	-0.297	0.151	0.048	-0.034	0.086	0.315	-0.079	0.073	0.145
mean of skids	-0.146	0.053	0.000	0.087	0.085	0.904	-0.114	0.061	0.006	-0.030	0.055	0.367
mean of bkids	-0.008	0.038	0.391	-0.060	0.048	0.147	0.109	0.071	0.828	-0.156	0.061	0.000
mean of hhage	0.016	0.001	1.000	0.021	0.006	1.000	0.009	0.001	1.000	0.015	0.001	1.000

mean of emplf	0.071	0.020	1.000	0.050	0.031	0.992	-0.050	0.019	0.000	0.058	0.012	1.000
Black	-0.034	0.046	0.245	-0.333	0.139	0.000	-0.317	0.101	0.000	0.356	0.068	1.000
White	0.075	0.048	0.988	-0.051	0.052	0.191	-0.094	0.045	0.005	-0.261	0.080	0.000
Hispanic	0.283	0.082	1.000	0.228	0.152	0.925	0.034	0.069	0.668	0.432	0.062	1.000
Constant	-0.064	0.264	0.520	-2.938	1.461	0.000	2.884	0.633	1.000	-3.401	0.479	0.000

Table 5. Bayesian Dynamic Tobit Estimation for Milk Demand by Different Income Groups

	Low income			High income		
Main Equation	**Mean**	**Std**	**Prob>0**	**Mean**	**Std**	**Prob>0**
Yt-1	0.510	0.006	1.000	0.542	0.003	1.000
log(P_milk)	-15.517	3.219	0.000	-12.560	1.436	0.000
log(P_other)	10.650	4.894	0.985	1.946	2.148	0.821
log(P_cheese)	9.850	5.584	0.962	4.131	2.329	0.960
log(P_egg)	-0.550	4.098	0.450	4.743	1.774	0.995
log(Sum_expd)	6.413	0.141	1.000	5.935	0.068	1.000
Kids	7.539	2.809	0.996	9.994	1.320	1.000
Skids	4.019	1.737	0.990	8.194	0.809	1.000
Bkids	5.970	1.616	1.000	7.172	0.811	1.000
Hhage	-0.140	0.036	0.000	-0.194	0.019	0.000
Emplf	-0.050	1.011	0.483	-3.992	0.452	0.000
Summer	-0.053	1.112	0.489	0.072	0.496	0.559
Winter	-3.300	1.155	0.002	-2.619	0.522	0.000
Auxiliary Equation	**Mean**	**Std**	**Prob>0**	**Mean**	**Std**	**Prob>0**
Yo	0.158	0.003	1.000	0.026	0.001	1.000
mean of log(P_milk)	0.303	1.021	0.621	-0.437	0.140	0.000
mean of log(P_other)	0.764	1.387	0.626	-1.001	0.182	0.000
mean of log(P_cheese)	-2.226	0.918	0.000	-1.173	0.109	0.000
mean of log(P_egg)	-0.158	0.667	0.476	1.208	0.124	1.000
mean of log(Sum_expd)	-0.706	0.214	0.000	-0.214	0.065	0.000
mean of kids	0.378	0.309	0.840	0.134	0.066	0.978
mean of skids	-0.713	0.173	0.000	-0.163	0.064	0.000
mean of bkids	1.442	0.361	1.000	-0.176	0.059	0.000

mean of hhage	0.009	0.004	1.000	0.011	0.001	1.000
mean of emplf	0.158	0.099	1.000	-0.042	0.025	0.073
Black	-0.894	0.245	0.000	0.535	0.202	1.000
White	-0.747	0.136	0.000	0.253	0.160	0.884
Hispanic	3.020	0.414	1.000	0.061	0.048	0.960
Constant	1.312	1.401	0.830	-1.839	0.412	0.000

Table 6. Elasticities of Dairy Product Demand

	Milk	Cheese	Other Dairy	Eggs
P_milk	-0.141	-0.089	-0.127	-0.014
	(-0.169, -0.112)	(-0.148, -0.028)	(-0.179, -0.075)	(-0.070, 0.041)
P_cheese	0.047	-0.287	0.259	-0.088
	(0.000, 0.094)	(-0.393, -0.179)	(0.173, 0.345)	(-0183, -0.07)
P_other	0.039	-0.049	-0.129	0.011
	(-0.003, 0.081)	(-0.136, -0.036)	(-0.206, -0.050)	(-0.071, 0.096)
P_egg	0.044	0.118	0.049	-0.002
	(0.009, 0.079)	(0.037, 0.202)	(-0.017, 0.115)	(-0.070, 0.069)
Sum_expd	0.066	0.120	0.104	0.099
	(0.065, 0.067)	(0.115, 0.125)	(0.101, 0.107)	(0.096, 0.102)

Table 7. Elasticities of Milk Demand by Different Income Groups

	Low income	High income
P_milk	-0.172	-0.138
	(-0.242, -0.102)	(-0.168, -0.106)
P_cheese	0.109	0.045
	(-0.012, 0.231)	(-0.005, 0.095)
P_other	0.118	0.021
	(0.012, 0.222)	(-0.024, 0.067)
P_egg	-0.006	0.054
	(-0.095, 0.008)	(0.014, 0.09)
Sum_expd	0.071	0.065
	(0.068, 0.074)	(0.063, 0.066)