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

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

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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 habit formation over beverage demand. However, they do not focus censoring issue in the demand estimation.

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

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

where $y_{ith}$ 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 $z_{ith}$, the lags of the dependent variable $y_{ith-1}$ 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, $u_{ith}$, are i.i.d. normally distributed conditional on

$$(y_{ith0}^*, \{z_{ith}\}_{t=1}^T, c_{ih})$$

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 \( z_{ith} \). In other words, the possible dynamic feedback from realizations \( z_{ith} \) 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:

\[
y^*_i = z_{ith}y + y^*_{i,h-1} + c_{ih} + u_{ith}
\]  

(2)

where \( y^*_i \) represents the latent quantities of product \( i \) purchased by household \( h \) in \( t^{th} \) month, \( y^*_{i,h-1} \) is the lagged latent quantities of product \( i \) purchased by household \( h \) in \((t-1)^{th} \) month and \( z_{ith} \) 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 \( z_{ith} \) 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
\[ E[c_{ih} \mid y_{ih,0}, z_{ih}] = a + h(y_{ih,0}, z_{ih})\delta \]  

(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 \( \delta \) 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 \( z_{ih} \) 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

\[ c_{ih} = y_{ih,0}\delta_1 + z_{ih}\delta_2 + \varepsilon_{ih}, \quad \varepsilon_{ih} \mid y_{ih0}, z_{ih} \sim^{iid} \text{Normal} (0, \sigma_i^2) \]  

(4)

where \( \varepsilon_{ih} \) 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.

\[ \textbf{2. Estimation} \]

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

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

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

\( \text{\footnotesize \footnote{\textsuperscript{4} For the estimation of the model, we assume that } y_{ih0}^* = y_{ih0}, \text{ initial values of dependent variable to be uncensored following Hu (2002). } } } \)
\[ y_{sr}^* = x_{shr} \beta + c_{ih} + u_{shr} \quad (\text{or } Y^* = X\beta + C^* + u) \]

where \( x_{shr} = (z_{shr}, y_{shr,t-1}^*) \), \( \beta = (\gamma', \rho') \) and \( u_{shr} | y_{shr,t-1}, ..., y_{shr,0}, z_{shr}, c_{ih} \sim ^{iid} \text{ Normal}(0, \sigma_{uhr}^2) \)

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

where \( r_{ih} = (y_{ih0}, z_{ih}, 1) \), \( \delta = (\delta_1', \delta_2') \) and \( \varepsilon_{ih} | y_{ih0}, z_{ih} \sim ^{iid} \text{ Normal}(0, \sigma_i^2) \)

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 \( \{y_{ih}^*\}_{i=1}^T \) 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 \( u_{ih} \) 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:

\[ C^* = (c_{11}^{(i=1)}, ..., c_{11}^{(i=T)}, ..., c_{d1}^{(i=1)}, ..., c_{d1}^{(i=T)})' \]
\[
\begin{align*}
\hat{f}(y_{ih1}, y_{ih2}, \ldots, y_{ihT}) &\sim \prod_{t=1}^{T} \{1(y_{ih,t} > 0)I(y_{ih,t} = y_{ih,t}^*) + I(y_{ih,t} = 0)I(y_{ih,t}^* \leq 0) \\
&\times \frac{1}{(2\pi\sigma_{ui}^2)^{1/2}} \exp \left( -\frac{1}{2\sigma_{ui}^2} (y_{ih,t}^* - z_{ih,t}^* + y_{ih,t-1}^* - c_{ih})^2 \right) 
\end{align*}
\]

Before we discuss how the model can be fit using the MCMC, we introduce the following specifications on priors:

\[ \beta \sim (\gamma, \rho)^T \sim \text{improper flat prior}^6 \]

\[ \frac{1}{\sigma_{iu}^2} \sim \text{gamma}\left(\frac{N_1}{2}, \frac{R_{iu}}{2}\right) \text{ or } \frac{1}{\sigma_{iu}^2} \propto \left(\frac{1}{\sigma_{iu}^2}\right)^{N_1/2} e^{-R_{iu}/\sigma_{iu}^2} \]

**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 \( \beta, \delta \) and \( \sigma_{iu}^2 \), 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.”

Step 1: For each $h = 1, \ldots, H$ and $t = 1, \ldots, T$ such that $y_{ih} = 0$, generate $y_{ih}^*$ from the truncated normal distribution on the interval $[-\infty, 0]$ with mean $x_{ih} \beta + r_{ih} \delta$ and variance $\sigma_{iu}^2 + \sigma_i^2$ conditional on $y_{ih}, x_{ih}, r_{ih}, \beta, \delta, \sigma_i^2$ and $\sigma_{iu}^2$.

Step 2: Update $\sigma_{iu}^2$ and $\beta$ by drawing from the joint posterior distribution of $\frac{1}{\sigma_{iu}^2}$ and $\beta$ conditional on data and other parameters and marginalized over each other.

\[
\frac{1}{\sigma_{iu}^2} \sim \text{gamma} \left( N_i + nT, \frac{R_i + (Y^* - X \hat{\beta} - C^*)'(Y^* - X \hat{\beta} - C^*)}{2} \right)
\]

\[
\beta \sim \text{Normal} \left( \hat{\beta}, \left( \frac{X'X}{\sigma_{iu}^2} \right)^{-1} \right) \quad \text{where} \quad \hat{\beta} = (X'X)^{-1}(X'(Y^* - C^*))
\]

Step 3: For each $h = 1, \ldots, H$, update $c_{ih}$ from the normal distribution with mean

\[
c_{ih}^* = \left( \frac{T}{\sigma_{iu}^2 + \sigma_i^2} \right)^{-1} \left( \sigma_{iu}^2 \sum_{t=1}^{T} (y_{ih}^* - x_{ih} \beta) + \frac{r_{ih} \delta}{\sigma_i^2} \right)\text{ and variance} \left( \frac{T}{\sigma_{iu}^2 + \sigma_i^2} \right)^{-1}.
\]

Step 4: Update $\delta$ by drawing from the posterior distribution conditional on $r_{ih}, c_{ih}$ and $\sigma_i^2$.

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

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. 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

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 and 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 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. 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. In addition, the food expenditure  

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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 evidence 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 uncensored 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


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Table 1. The Dairy Product Categories and Distribution for Sampled Households\textsuperscript{a}

<table>
<thead>
<tr>
<th>Product Category/Product Group Description</th>
<th># of HHs</th>
<th>% of Zero Purchases*</th>
</tr>
</thead>
<tbody>
<tr>
<td>MILK</td>
<td>3565</td>
<td>17.7%</td>
</tr>
<tr>
<td>CHEESE</td>
<td>3595</td>
<td>29.1%</td>
</tr>
<tr>
<td>EGGS</td>
<td>3491</td>
<td>40.9%</td>
</tr>
<tr>
<td>OTHER</td>
<td></td>
<td></td>
</tr>
<tr>
<td>BUTTER AND MARGARINE</td>
<td></td>
<td></td>
</tr>
<tr>
<td>COT CHEESE, SOUR CREAM, TOPPINGS</td>
<td></td>
<td></td>
</tr>
<tr>
<td>DOUGH PRODUCTS</td>
<td>3613</td>
<td>19.5%</td>
</tr>
<tr>
<td>PUDDING, DESSERTS-DAIRY</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SNACKS, SPREADS, DIPS-DAIRY</td>
<td></td>
<td></td>
</tr>
<tr>
<td>YEAST</td>
<td></td>
<td></td>
</tr>
<tr>
<td>YOGURT</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Total Dairy 3626

\textsuperscript{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\textsuperscript{a}

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

\textsuperscript{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

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Mean</th>
<th>Std.Dev</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Household income</td>
<td></td>
<td>59976</td>
<td>38795</td>
<td>5000</td>
<td>200000</td>
</tr>
<tr>
<td>Sum_expd</td>
<td>Monthly total food expenditure</td>
<td>155.73</td>
<td>189.24</td>
<td>0</td>
<td>3150.25</td>
</tr>
<tr>
<td>Household age</td>
<td>Maximum age of the two household's heads</td>
<td>59.67</td>
<td>12.58</td>
<td>25</td>
<td>110</td>
</tr>
<tr>
<td><strong>Binary Variables (equal 1 if following conditions met, and 0 otherwise)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Kids</td>
<td>Household has a kid under 5 year olds</td>
<td>0.037</td>
<td>0.19</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Skids</td>
<td>Household has a kid between 5 and 11 year olds</td>
<td>0.08</td>
<td>0.27</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Bkids</td>
<td>Household has a kid between 13 and 17 year olds</td>
<td>0.07</td>
<td>0.26</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Emplf</td>
<td>Female household head is employed</td>
<td>0.56</td>
<td>0.50</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Black</td>
<td>Household’s sampled person’s race is black</td>
<td>0.08</td>
<td>0.28</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>White</td>
<td>Household’s sampled person’s race is white</td>
<td>0.86</td>
<td>0.35</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Hispanic</td>
<td>Household's sampled person’s ethnicity is Hispanic</td>
<td>0.04</td>
<td>0.20</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Summer</td>
<td>Purchasing month is in June to August</td>
<td>0.25</td>
<td>0.43</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Winter</td>
<td>Purchasing month is in November to January</td>
<td>0.25</td>
<td>0.43</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

*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

<table>
<thead>
<tr>
<th>Main Equation</th>
<th>Milk</th>
<th>Cheese</th>
<th>Other Dairy</th>
<th>Eggs</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Std</td>
<td>Prob&gt;0</td>
<td>Mean</td>
</tr>
<tr>
<td>Yt-1</td>
<td>0.538</td>
<td>0.002</td>
<td>1.000</td>
<td>0.177</td>
</tr>
<tr>
<td>log(P_milk)</td>
<td>-</td>
<td></td>
<td></td>
<td>-0.824</td>
</tr>
<tr>
<td>log(P_other)</td>
<td>12.886</td>
<td>1.296</td>
<td>0.000</td>
<td>-0.459</td>
</tr>
<tr>
<td>log(P_cheese)</td>
<td>3.556</td>
<td>1.978</td>
<td>0.966</td>
<td>-2.674</td>
</tr>
<tr>
<td>log(P_egg)</td>
<td>4.264</td>
<td>2.176</td>
<td>0.975</td>
<td>1.101</td>
</tr>
<tr>
<td>log(Sum_expd)</td>
<td>4.018</td>
<td>1.628</td>
<td>0.992</td>
<td>1.114</td>
</tr>
<tr>
<td>Kids</td>
<td>5.994</td>
<td>0.059</td>
<td>1.000</td>
<td>1.152</td>
</tr>
<tr>
<td>Skids</td>
<td>9.338</td>
<td>1.224</td>
<td>1.000</td>
<td>0.752</td>
</tr>
<tr>
<td>Bkids</td>
<td>7.357</td>
<td>0.744</td>
<td>1.000</td>
<td>0.939</td>
</tr>
<tr>
<td>Hhage</td>
<td>-0.183</td>
<td>0.016</td>
<td>0.000</td>
<td>-0.035</td>
</tr>
<tr>
<td>Emplf</td>
<td>-3.572</td>
<td>0.400</td>
<td>0.000</td>
<td>-0.116</td>
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<tr>
<td>Summer</td>
<td>0.048</td>
<td>0.462</td>
<td>0.544</td>
<td>-0.295</td>
</tr>
<tr>
<td>Winter</td>
<td>-2.800</td>
<td>0.478</td>
<td>0.000</td>
<td>-0.040</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Auxiliary Equation</th>
<th>Mean</th>
<th>Std</th>
<th>Prob&gt;0</th>
<th>Mean</th>
<th>Std</th>
<th>Prob&gt;0</th>
<th>Mean</th>
<th>Std</th>
<th>Prob&gt;0</th>
<th>Mean</th>
<th>Std</th>
<th>Prob&gt;0</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yo</td>
<td>0.071</td>
<td>0.001</td>
<td>1.000</td>
<td>0.050</td>
<td>0.006</td>
<td>1.000</td>
<td>0.148</td>
<td>0.005</td>
<td>1.000</td>
<td>0.058</td>
<td>0.003</td>
<td>1.000</td>
</tr>
<tr>
<td>mean of log(P_milk)</td>
<td>0.303</td>
<td>0.110</td>
<td>1.000</td>
<td>-0.547</td>
<td>0.314</td>
<td>0.000</td>
<td>1.363</td>
<td>0.210</td>
<td>1.000</td>
<td>-0.443</td>
<td>0.096</td>
<td>0.000</td>
</tr>
<tr>
<td>mean of log(P_other)</td>
<td>-0.955</td>
<td>0.251</td>
<td>0.000</td>
<td>-1.184</td>
<td>0.536</td>
<td>0.000</td>
<td>0.166</td>
<td>0.123</td>
<td>0.928</td>
<td>-0.278</td>
<td>0.155</td>
<td>0.045</td>
</tr>
<tr>
<td>mean of log(P_cheese)</td>
<td>0.249</td>
<td>0.234</td>
<td>0.877</td>
<td>1.328</td>
<td>0.590</td>
<td>1.000</td>
<td>1.066</td>
<td>0.197</td>
<td>1.000</td>
<td>-0.834</td>
<td>0.359</td>
<td>0.000</td>
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<tr>
<td>mean of log(P_egg)</td>
<td>0.373</td>
<td>0.247</td>
<td>0.956</td>
<td>0.787</td>
<td>0.417</td>
<td>1.000</td>
<td>-1.416</td>
<td>0.215</td>
<td>0.000</td>
<td>0.659</td>
<td>0.195</td>
<td>1.000</td>
</tr>
<tr>
<td>mean of log(Sum_expd)</td>
<td>-0.113</td>
<td>0.037</td>
<td>0.000</td>
<td>0.309</td>
<td>0.122</td>
<td>1.000</td>
<td>-0.112</td>
<td>0.024</td>
<td>0.000</td>
<td>0.286</td>
<td>0.076</td>
<td>1.000</td>
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<tr>
<td>mean of kids</td>
<td>0.275</td>
<td>0.111</td>
<td>1.000</td>
<td>-0.297</td>
<td>0.151</td>
<td>0.048</td>
<td>-0.034</td>
<td>0.086</td>
<td>0.315</td>
<td>-0.079</td>
<td>0.073</td>
<td>0.145</td>
</tr>
<tr>
<td>mean of skids</td>
<td>-0.146</td>
<td>0.053</td>
<td>0.000</td>
<td>0.087</td>
<td>0.085</td>
<td>0.904</td>
<td>-0.114</td>
<td>0.061</td>
<td>0.006</td>
<td>-0.030</td>
<td>0.055</td>
<td>0.367</td>
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<tr>
<td>mean of bkids</td>
<td>-0.008</td>
<td>0.038</td>
<td>0.391</td>
<td>-0.060</td>
<td>0.048</td>
<td>0.147</td>
<td>0.109</td>
<td>0.071</td>
<td>0.828</td>
<td>-0.156</td>
<td>0.061</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>mean of hhage</td>
<td></td>
<td></td>
<td>mean of emplf</td>
<td></td>
<td></td>
<td>Black</td>
<td></td>
<td></td>
<td>White</td>
<td></td>
<td>Hispanic</td>
</tr>
<tr>
<td>----------------</td>
<td>---------------</td>
<td>---------</td>
<td>---------</td>
<td>---------------</td>
<td>---------</td>
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<td>---------</td>
<td>---------</td>
<td>---------</td>
<td>---------</td>
<td>---------</td>
<td>---------</td>
</tr>
<tr>
<td>mean of hhage</td>
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<td>0.001</td>
<td>1.000</td>
<td>0.021</td>
<td>0.006</td>
<td>1.000</td>
<td>0.009</td>
<td>0.001</td>
<td>1.000</td>
<td>0.015</td>
<td>0.001</td>
<td>1.000</td>
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<tr>
<td>mean of emplf</td>
<td>0.071</td>
<td>0.020</td>
<td>1.000</td>
<td>0.050</td>
<td>0.031</td>
<td>0.992</td>
<td>-0.050</td>
<td>0.019</td>
<td>0.000</td>
<td>0.058</td>
<td>0.012</td>
<td>1.000</td>
</tr>
<tr>
<td>Black</td>
<td>-0.034</td>
<td>0.046</td>
<td>0.245</td>
<td>-0.333</td>
<td>0.139</td>
<td>0.000</td>
<td>-0.317</td>
<td>0.101</td>
<td>0.000</td>
<td>0.356</td>
<td>0.068</td>
<td>1.000</td>
</tr>
<tr>
<td>White</td>
<td>0.075</td>
<td>0.048</td>
<td>0.988</td>
<td>-0.051</td>
<td>0.052</td>
<td>0.191</td>
<td>-0.094</td>
<td>0.045</td>
<td>0.005</td>
<td>-0.261</td>
<td>0.080</td>
<td>0.000</td>
</tr>
<tr>
<td>Hispanic</td>
<td>0.283</td>
<td>0.082</td>
<td>1.000</td>
<td>0.228</td>
<td>0.152</td>
<td>0.925</td>
<td>0.034</td>
<td>0.069</td>
<td>0.668</td>
<td>0.432</td>
<td>0.062</td>
<td>1.000</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.064</td>
<td>0.264</td>
<td>0.520</td>
<td>-2.938</td>
<td>1.461</td>
<td>0.000</td>
<td>2.884</td>
<td>0.633</td>
<td>1.000</td>
<td>-3.401</td>
<td>0.479</td>
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</table>
Table 5. Bayesian Dynamic Tobit Estimation for Milk Demand by Different Income Groups

<table>
<thead>
<tr>
<th>Main Equation</th>
<th>Low income</th>
<th></th>
<th></th>
<th>High income</th>
<th></th>
<th></th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Std</td>
<td>Prob&gt;0</td>
<td>Mean</td>
<td>Std</td>
<td>Prob&gt;0</td>
</tr>
<tr>
<td>Yt-1</td>
<td>0.510</td>
<td>0.006</td>
<td>1.000</td>
<td>0.542</td>
<td>0.003</td>
<td>1.000</td>
</tr>
<tr>
<td>log(P_milk)</td>
<td>-15.517</td>
<td>3.219</td>
<td>0.000</td>
<td>-12.560</td>
<td>1.436</td>
<td>0.000</td>
</tr>
<tr>
<td>log(P_other)</td>
<td>10.650</td>
<td>4.894</td>
<td>0.985</td>
<td>1.946</td>
<td>2.148</td>
<td>0.821</td>
</tr>
<tr>
<td>log(P_cheese)</td>
<td>9.850</td>
<td>5.584</td>
<td>0.962</td>
<td>4.131</td>
<td>2.329</td>
<td>0.960</td>
</tr>
<tr>
<td>log(P_egg)</td>
<td>-0.550</td>
<td>4.098</td>
<td>0.450</td>
<td>4.743</td>
<td>1.774</td>
<td>0.995</td>
</tr>
<tr>
<td>log(Sum_expd)</td>
<td>6.413</td>
<td>0.141</td>
<td>1.000</td>
<td>5.935</td>
<td>0.068</td>
<td>1.000</td>
</tr>
<tr>
<td>Kids</td>
<td>7.539</td>
<td>2.809</td>
<td>0.996</td>
<td>9.994</td>
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<td>1.000</td>
</tr>
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<td>Skids</td>
<td>4.019</td>
<td>1.737</td>
<td>0.990</td>
<td>8.194</td>
<td>0.809</td>
<td>1.000</td>
</tr>
<tr>
<td>Bkids</td>
<td>5.970</td>
<td>1.616</td>
<td>1.000</td>
<td>7.172</td>
<td>0.811</td>
<td>1.000</td>
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<tr>
<td>Hhage</td>
<td>-0.140</td>
<td>0.036</td>
<td>0.000</td>
<td>-0.194</td>
<td>0.019</td>
<td>0.000</td>
</tr>
<tr>
<td>Emplf</td>
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<td>1.011</td>
<td>0.483</td>
<td>-3.992</td>
<td>0.452</td>
<td>0.000</td>
</tr>
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<td>Summer</td>
<td>-0.053</td>
<td>1.112</td>
<td>0.489</td>
<td>0.072</td>
<td>0.496</td>
<td>0.559</td>
</tr>
<tr>
<td>Winter</td>
<td>-3.300</td>
<td>1.155</td>
<td>0.002</td>
<td>-2.619</td>
<td>0.522</td>
<td>0.000</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Auxiliary Equation</th>
<th>Mean</th>
<th>Std</th>
<th>Prob&gt;0</th>
<th>Mean</th>
<th>Std</th>
<th>Prob&gt;0</th>
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</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yo</td>
<td>0.158</td>
<td>0.003</td>
<td>1.000</td>
<td>0.026</td>
<td>0.001</td>
<td>1.000</td>
</tr>
<tr>
<td>mean of log(P_milk)</td>
<td>0.303</td>
<td>1.021</td>
<td>0.621</td>
<td>-0.437</td>
<td>0.140</td>
<td>0.000</td>
</tr>
<tr>
<td>mean of log(P_other)</td>
<td>0.764</td>
<td>1.387</td>
<td>0.626</td>
<td>-1.001</td>
<td>0.182</td>
<td>0.000</td>
</tr>
<tr>
<td>mean of log(P_cheese)</td>
<td>-2.226</td>
<td>0.918</td>
<td>0.000</td>
<td>-1.173</td>
<td>0.109</td>
<td>0.000</td>
</tr>
<tr>
<td>mean of log(P_egg)</td>
<td>-0.158</td>
<td>0.667</td>
<td>0.476</td>
<td>1.208</td>
<td>0.124</td>
<td>1.000</td>
</tr>
<tr>
<td>mean of log(Sum_expd)</td>
<td>-0.706</td>
<td>0.214</td>
<td>0.000</td>
<td>-0.214</td>
<td>0.065</td>
<td>0.000</td>
</tr>
<tr>
<td>mean of kids</td>
<td>0.378</td>
<td>0.309</td>
<td>0.840</td>
<td>0.134</td>
<td>0.066</td>
<td>0.978</td>
</tr>
<tr>
<td>mean of skids</td>
<td>-0.713</td>
<td>0.173</td>
<td>0.000</td>
<td>-0.163</td>
<td>0.064</td>
<td>0.000</td>
</tr>
<tr>
<td>mean of bkids</td>
<td>1.442</td>
<td>0.361</td>
<td>1.000</td>
<td>-0.176</td>
<td>0.059</td>
<td>0.000</td>
</tr>
<tr>
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<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>---------------</td>
<td>-----</td>
<td>-----</td>
<td>-----</td>
<td>-----</td>
<td>-----</td>
<td>-----</td>
</tr>
<tr>
<td>mean of hhage</td>
<td>0.009</td>
<td>0.004</td>
<td>1.000</td>
<td>0.011</td>
<td>0.001</td>
<td>1.000</td>
</tr>
<tr>
<td>mean of emplf</td>
<td>0.158</td>
<td>0.099</td>
<td>1.000</td>
<td>-0.042</td>
<td>0.025</td>
<td>0.073</td>
</tr>
<tr>
<td>Black</td>
<td>-0.894</td>
<td>0.245</td>
<td>0.000</td>
<td>0.535</td>
<td>0.202</td>
<td>1.000</td>
</tr>
<tr>
<td>White</td>
<td>-0.747</td>
<td>0.136</td>
<td>0.000</td>
<td>0.253</td>
<td>0.160</td>
<td>0.884</td>
</tr>
<tr>
<td>Hispanic</td>
<td>3.020</td>
<td>0.414</td>
<td>1.000</td>
<td>0.061</td>
<td>0.048</td>
<td>0.960</td>
</tr>
<tr>
<td>Constant</td>
<td>1.312</td>
<td>1.401</td>
<td>0.830</td>
<td>-1.839</td>
<td>0.412</td>
<td>0.000</td>
</tr>
</tbody>
</table>
Table 6. Elasticities of Dairy Product Demand

<table>
<thead>
<tr>
<th></th>
<th>Milk</th>
<th>Cheese</th>
<th>Other Dairy</th>
<th>Eggs</th>
</tr>
</thead>
<tbody>
<tr>
<td>P_milk</td>
<td>-0.141</td>
<td>-0.089</td>
<td>-0.127</td>
<td>-0.014</td>
</tr>
<tr>
<td></td>
<td>(-0.169, -0.112)</td>
<td>(-0.148, -0.028)</td>
<td>(-0.179, -0.075)</td>
<td>(-0.070, 0.041)</td>
</tr>
<tr>
<td>P_cheese</td>
<td>0.047</td>
<td>-0.287</td>
<td>0.259</td>
<td>-0.088</td>
</tr>
<tr>
<td></td>
<td>(0.000, 0.094)</td>
<td>(-0.393, -0.179)</td>
<td>(0.173, 0.345)</td>
<td>(-0.183, -0.07)</td>
</tr>
<tr>
<td>P_other</td>
<td>0.039</td>
<td>-0.049</td>
<td>-0.129</td>
<td>0.011</td>
</tr>
<tr>
<td></td>
<td>(-0.003, 0.081)</td>
<td>(-0.136, -0.036)</td>
<td>(-0.206, -0.050)</td>
<td>(-0.071, 0.096)</td>
</tr>
<tr>
<td>P_egg</td>
<td>0.044</td>
<td>0.118</td>
<td>0.049</td>
<td>-0.002</td>
</tr>
<tr>
<td></td>
<td>(0.009, 0.079)</td>
<td>(0.037, 0.202)</td>
<td>(-0.017, 0.115)</td>
<td>(-0.070, 0.069)</td>
</tr>
<tr>
<td>Sum_expd</td>
<td>0.066</td>
<td>0.120</td>
<td>0.104</td>
<td>0.099</td>
</tr>
<tr>
<td></td>
<td>(0.065, 0.067)</td>
<td>(0.115, 0.125)</td>
<td>(0.101, 0.107)</td>
<td>(0.096, 0.102)</td>
</tr>
</tbody>
</table>

Table 7. Elasticities of Milk Demand by Different Income Groups

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