# Household food expenditures in the United States: A Bayesian MCMC approach to censored equation systems

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**Abstract**

We apply a Bayesian Markov Chain Monte Carlo (MCMC) technique, along with data augmentation to accommodate censoring in the dependent variables, to the estimation of a large expenditure system of food expenditures. Our finding of significant error covariance estimates justifies estimation of the system in improving statistical efficiency. Income, household composition, regions and other socio-demographic variables are found to play significant roles in determining household food expenditures.

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# 1. Introduction

Micro survey data have been popular means of analysis in the investigation of microeconomic relationships such as consumption and production activities. One data feature frequently encountered in such analysis with microdata is censoring (observed zero values) in the dependent variables. Statistical procedures not accounting for such censoring can produce biased and inconsistent parameter estimates as censoring, among other things, obscures the conditional means of the dependent variables. This issue of censored dependent variables is more complicated in multiple-equation than single-equation setting, due to presence of cross-equation restrictions and the need to evaluate multiple probability integrals in classical estimation procedures.

In this article we address the issues of censored dependent variables within a system framework, by investigating household food expenditures in the United States (U.S.). Analyses of consumer demand and expenditure relationships have had more than a fair share of uses of single-equation limited dependent variable models (Deaton and Irish 1984; Pudney 1988). In food demand analysis, however, the interactions among the demands for food commodities can be important due to substitution relationships among these commodities. Besides a lack of behavioral appeal, these single-equation approaches also compromise statistical efficiency because information about the error correlations is not utilized.

A number of censored-system estimation procedures have existed in the literature. These include maximum-likelihood estimators of Amemiya (1974), Wales and Woodland (1983), and Lee and Pitt (1986); the sample selection estimator of Yen and Lin (2006) and its two-step alternative (Shonkwiler and Yen 1999), and a number of additional two-step estimators (Perali and Chavas 2000; Meyerhoefer *et al.* 2005). In this paper, we estimate a large Tobit system (Amemiya 1974) of household food expenditures. Other applications of the Tobit system in food demand and agricultural economic analyses a include Chavas and Kim (2004) and Cornick *et al.* (1994). However, except the large system in Cornick *et al.* (1994), which was estimated by a simulation procedure, existing applications typically feature small equation systems, which were estimated by the maximum likelihood (ML) procedure. Our empirical application involves an unusually large system which cannot be estimated by conventional ML or simulation procedure due to the dimensionality problem. This numerical difficulty with a large system highlights the advantages of the alternative approach we consider—-the Bayesian Markov Chain Monte Carlo (MCMC) procedure, vis-à-vis a conventional ML procedure.

We begin by presenting the Bayesian MCMC procedure for a censored seemingly unrelated regression (SUR) system. The data used for the food expenditure system are then described. After presenting the estimation results, a final section concludes. Further details on implementation of the Bayesian MCMC procedure are presented in the Appendix.

# 2. Model specification

To motivate the econometric specification, consider an individual $i$ facing choice set $q_i$ with prices $p_i$, both $M$-vectors. Also, let $c_i$ be a vector of personal characteristics. Optimal levels of $q_i$ are determined by solving the constrained utility maximization problem with income $I_i$:

$$\max_{q_i}\{U(q_i, c_i)|p_i'q_i = I_i\}. \tag{1}$$

Assuming the utility function is continuous, increasing, and quasi-concave in $q_i$, optimal levels of quantities can be expressed as a function of prices, income and personal characteristics. In practice, consumption levels are also subject to nonnegativity constraints and the observed level of each good can be zero or positive. With a single cross section, prices are assumed constant and therefore absorbed into the constant terms. Using a vector $X_i$ to represent explanatory variables, a linear function to (first-order) approximate the deterministic demand functions (in expenditure forms, denoted $y_i$), and a random error vector $\varepsilon_i$ to capture the unobservable, we consider a censored seemingly unrelated regression (SUR) system (Amemiya 1974) for $M$ commodities and $N$ households, in which censoring in each observed expenditure $(y_{ij})$ is governed by the Tobit rule

$$\begin{aligned} y_{ij} &= y_{ij}^* \quad \text{if} \quad y_{ij}^* \geq 0 \\ &= 0 \quad\ \ \text{if} \quad y_{ij}^* < 0, \quad i = 1, ..., N; \ j = 1, ..., M. \end{aligned} \tag{2}$$

The structural equations for the latent expenditures $(y_{ij}^*)$ are

$$y_{ij}^* = X_{ij}\beta_j + \varepsilon_{ij}, \ \ i = 1, ..., N; \ \ j = 1, ..., M \tag{3}$$

where $X_{ij}$ are $1 \times k$ vectors of exogenous variables, and $\beta_j$ are conformable parameter vectors. The error vector $\varepsilon_i = (\varepsilon_{i1}, ..., \varepsilon_{iM})'$ is distributed as $M$-dimensioned i.i.d. normal with zero means and finite covariance matrix $\Sigma$:

$$\varepsilon_i \overset{i.i.d.}{\sim} \mathcal{N}_M(0, \Sigma) \tag{4}$$

where

$$\Sigma = \begin{bmatrix} \sigma_{11} & \cdots & \sigma_{1M} \\ \vdots & \ddots & \vdots \\ \sigma_{M1} & \cdots & \sigma_{MM} \end{bmatrix}. \tag{5}$$

Joint estimation of the SUR is typically motivated by correlations among the error terms, as specified in the distribution in equation (4). Although separate estimation of the equations in the SUR system (1) produces parameter estimates that are consistent, they are not efficient. Joint estimation of the equations produces more efficient parameter estimates. To explain the difficulty with such joint estimation by a conventional procedure such as the maximum-likelihood method, consider a sample regime in which the first $\ell$ goods are zeros and the remaining goods are positive, with observed vector $(0, ..., 0, y_{\ell+1}, ..., y_M)$. The sample likelihood contribution for this observation is

$$\begin{aligned} L &= g(\varepsilon_{i(\ell+1)}, ..., \varepsilon_{iM}) \\ &\quad \times \int_{-\infty}^{-X_{i1}\beta_1} ... \int_{-\infty}^{-X_{i\ell}\beta_\ell} h(\varepsilon_{i1}, ..., \varepsilon_{i\ell} | \varepsilon_{i(\ell+1)}, ..., \varepsilon_{iM}) d\varepsilon_{i\ell} ... d\varepsilon_{i1} \end{aligned} \tag{6}$$

where $\varepsilon_{ij} = y_{ij} - X_{ij}\beta_j$ for $j = \ell + 1, ..., M$, $g$ is the marginal probability density function (pdf) for the $(M - \ell)$-dimensioned random vector $(y_{i(\ell+1)}, ..., y_{iM})$, $h$ is the conditional pdf for $\varepsilon_{i1}, ..., \varepsilon_{i\ell}|\varepsilon_{i(\ell+1)}, ..., \varepsilon_{iM}$. As seen in equation (5), the likelihood contribution requires evaluation of $\ell$-dimensioned normal probability integrals. For a small equation system the model can be estimated with a conventional method such as maximum likelihood (Amemiya 1974; Chavas and Kim 2004; Yen and Lin 2002). For the large (fifteen-equation) system considered in the current application, with the many zeros described above, the likelihood function contains high-dimensioned probability integrals which becomes intractable by conventional numerical procedures. It is also worth noting that the Tobit parameterization and censoring mechanism specified in (2) and (3) is often claimed to be undesirable in addressing zero observations. While it is possible in principle to consider alternative specifications such as the sample selection system (Yen, 2005) with alternative behavioral motivation for the zero observations, the resulting system would constitute $2M$ equations, a $2M$-dimensioned error distribution, and require evaluations of $M$-dimensioned normal probability integrals which would be infeasible for a large sample. Importantly, the Tobit system considered here amounts to the simultaneous-equation model of Amemiya (1974) which, when prices are treated as constant as in the single cross section used in the current application, is identical to the utility-theoretic Kuhn-Tucker model (Wales and Woodland 1983; cf. Ransom 1987).

The Bayesian MCMC method offers a viable alternative to the intractable multiple probability integral for a large equation system with many zeros. To explain the Bayesian MCMC procedure, stack all equations into an $M$-vector and the latent structure (2) can be written as

$$\tilde{y}_i = \tilde{X}_i\beta + \varepsilon_i \tag{7}$$

where $\tilde{y}_i = (y^*_{i1}, ..., y^*_{iM})'$, $\tilde{X}_i = diag(X_{i1}, ..., X_{iM})$, $\beta = (\beta'_1, ..., \beta'_M)'$, and $\tilde{y}_i \sim \mathcal{N}_M(\tilde{X}_i\beta, \Sigma)$.

Monte Carlo integration involves taking random draws from the posterior distribution $p(\theta|y)$, where $\theta$ is the parameter vector and $y$ the observed data, and then averaging them to produce estimates $E[f(\theta)|y]$ where $f(\theta)$ is the function of interest. Since drawing directly from the posterior distribution is feasible only in a few special cases, Gibbs sampling is typically used when it is easy to sequentially draw from the full conditional posterior distributions $p(\theta_{(1)}|y_i, \theta_{(2)}, \theta_{(3)}, ..., \theta_{(p)})$, $p(\theta_{(2)}|y_i, \theta_{(1)}, \theta_{(3)}, ..., \theta_{(p)}), ..., p(\theta_{(p)}|y_i, \theta_{(1)},\ \theta_{(2)}, ..., \theta_{(p-1)})$, where $\theta_{(1)}, \theta_{(2)}, ..., \theta_{(p)}$ are partitions of the parameter vector $\theta$. It can be shown that the sequence of these draws converges to a sequence of draws from the joint posterior $p(\theta_{(1)}, \theta_{(2)}, ..., \theta_{(p)}|y_i)$. For latent-variable models such as the Tobit equation system, data augmentation simplifies the MCMC algorithm by including the complete (observed and latent) data in the posterior distribution (Albert and Chib 1993; Tanner and Wong 1987).

For the censored SUR model the augmented data $z_{ij}$ consist of the uncensored observations and the latent expenditures for the corresponding censored observations. That is,

$$z_{ij} = I(y_{ij} > 0)y_{ij} + I(y_{ij} = 0)y_{ij}^* \tag{8}$$

where $I(A)$ is a binary indicator function taking a value of one if event $A$ holds and zero otherwise. Let $Z_i = (z_{i1}, ..., z_{iM})'$ and denote the augmented data as $Z$. Then, the augmented posterior distribution is given by

$$\begin{aligned} p(\beta, \Sigma, Z|y) &\propto p(y|Z, \beta, \Sigma)p(Z|\beta, \Sigma)p(\beta)p(\Sigma) \\ &= \prod_{i=1}^{N} \left\{ \left[ \prod_{j=1}^{M} [I(y_{ij} = 0)I(z_{ij} \leq 0) + I(y_{ij} > 0)I(y_{ij} = z_{ij})] \right] p(Z_i|\beta, \Sigma) \right\} \\ &\quad \times p(\beta)p(\Sigma) \end{aligned} \tag{9}$$

where $p(\beta)$ is the normal prior $\beta \sim \mathcal{N}(\underline{\mu_\beta}, \underline{V_\beta})$ and $p(\Sigma)$ is the Wishart prior $\mathcal{W}(\Omega, v)$.

Coupled with data augmentation, the posterior simulator is implemented by drawing sequentially the conditional posteriors $p(Z|y, \beta, \Sigma)$, $p(\beta|z, \Sigma)$, and $p(\Sigma|Z, \beta)$. A complete MCMC algorithm with details about drawings from the full conditional distributions and choice of priors is available in a appendix upon request.

# 3. Data and sample

Our data are compiled from the diary component of the 2008 Consumer Expenditure Survey (CEX), collected for the Bureau of Labor Statistics by the U.S. Census Bureau (U.S. BLS 2009). The CEX contains Interview Survey and Diary survey microdata which contain detailed information on the buying habits of American consumers. The Diary survey collects data on weekly expenditures of frequently purchased items such as food at home, food away from home, alcoholic beverages, smoking supplies, personal care products and services and nonprescription drugs, as well as well as income, and characteristics and demographics of Consumer Units (CUs). Demographic characteristics, such as family size, refer to the CU status on the date of the interview. Income variables contain annual values, covering the 12-months prior to the date of the interview. Of the total sample of CUs, 693 reported only one diary week and were excluded from the analysis. The remaining 6,743 provided weekly information for two weeks which was averaged to weekly expenditures. There are 271 households with more than one CU in the sample. While each observation in our data refers to a CU, in the following we refer to each CU as a "household".

Household expenditures on 14 categories of foods consumed at home and a catch-all category of food consumed away from home are used as the dependent variables. Table 1 presents the sample statistics of all expenditure variables. Censoring occurs in all expenditures, with the proportions of consuming households ranging from 37% for poultry to 87% for cereals at home, and 87% for food away from home. Note that the zeros may reflect the infrequency of consumption during the two-week period. A household on average spends the largest amount ($45.15) on food away from home, followed by miscellaneous food ($13.53), cereals ($10.04) and meat ($9.94), with the smallest amount spent on eggs ($0.85). Among the consuming households, the largest amount ($55.35) is spent on food away from home and the smallest on eggs ($1.97). The proportions of consuming households range from 37% for poultry to 87% for cereals and food away from home. Only 45.35% of the sample reported zero purchases in three goods or less, with 54.65% of the sample reported four or more zeros, 35.44% reported six or more zeros, and 17.90% reported nine or more zeros which require evaluations of nine or higher-level probability integrals in estimating the censored regression system.

Table 2 presents definitions and sample statistics of all explanatory variables. Household composition variables include the number of children age $< 18$, the number of adults age 18-64, the number of elderly (age $\geq 65$), and the number of earners in the household. The other two continuous variables are the age of the reference person and annual income, defined as the after-tax household income in the past 12 months. Also included are dummy variables indicating home ownership (home owner), urbanization (urban), region (Northeast, Midwest, South, West (reference)), education ($<$ high school, high school, college, post graduate (reference)), marital status (married, divorced, widowed, single (reference)), race and ethnicity (White, Black, other (reference)), gender (male), food stamp participation status (FSP), occupation (professional, administrator, labor, sales, unemployed (reference)), and seasons (spring, summer, fall, winter (reference)) in which the survey took place. Although price information was not collected in the Diary Survey, the regional and seasonal dummies are expected to account for much of the regional and seasonal price variations and avoid potential misspecification.

## 4. Estimation results

We run our MCMC algorithm for 5,000 replications and collect every 10th replication after discarding the first 1,000 replications of the burn-in or convergence phase. The remaining 400 draws are averaged to obtain means of the posterior densities. Posterior standard deviations (similar to frequentist standard errors) are obtained by calculating standard deviations of the 900 draws. Marginal effects and predicted means and probabilities, presented below, are calculated accordingly. The estimates (posterior means and standard deviations) for parameters of the expenditure equations and the error correlations are not presented due to space consideration, and we summarize the results here. All error correlations are positive and significant at the 1% level of significance. These uniformly positive error correlations are unusual but they are confirmed with those obtained from the generalized residuals of equation-by-equation Tobit (maximum-likelihood) estimates. Importantly, the statistical significance of these error covariance estimates justifies joint estimation of the expenditure equations improve statistical efficiency.

Of the 32 explanatory variables, over half are significant, at the 10% level of significance or lower, for milk, fresh fruits, fresh vegetables, and miscellaneous foods at home; and half of the variables are significant for cereals, eggs, and sweets at home, and food away from home. The sparsest significance is seen in poultry and oil at home, with one third of the variables significant. As typical in most Tobit estimates, all error standard deviations are significant at the 1% level of significance. Nonlinear effects of age are found in 13 of the 15 equations (except processed fruits at home and food away from home), with significant and negative coefficients for the squared term of age. Such nonlinear effects are also found for income, with significant and negative coefficient for the square of income for cereals, meat, milk, processed fruits, processed vegetables, sweets, non-alcoholic beverages, miscellaneous foods at home, and food away from home. All household composition variables are positive and significant at the 1% level of significance for all equations, except age $> 64$ for food away from home, which is significant at the 5% level. Due to space limit we defer further discussion of the effects of explanatory variable to the marginal effects, which convey more detailed information on the roles of socio-demographic variables.

## 5. Marginal effects

As in other limited dependent variable models, it is useful to explore the effects of explanatory variables beyond the parameter estimates. We calculate the marginal effects on the probability, conditional levels, and unconditional levels of expenditures. Denote the univariate standard normal pdf as $\phi_1(\cdot)$, cumulative distribution function (cdf) as $\Phi_1(\cdot)$, and the error standard deviation for good $j$ as $\sigma_j = \sqrt{\sigma_{jj}}$. Then, based on the normality of the marginal of each error term, the probability of a positive outcome and the the conditional mean of $y_{ij}$ are, respectively,

$$\Pr(y_{ij} > 0) = \Phi_1(X_{ij}\beta_j/\sigma_j) \tag{10}$$

$$E(y_{ij}|y_{ij} > 0) = X_{ij}\beta_j + \sigma_j \left\{ \frac{\phi_1(X_{ij}\beta_j/\sigma_j)}{\Phi_1(X_{ij}\beta_j/\sigma_j)} \right\} \tag{11}$$

which together imply the unconditional mean of $y_{ij}$:

$$E(y_{ij}) = \Phi_1(X_{ij}\beta_j/\sigma_j)X_{ij}\beta_j + \sigma_j\phi_1(X_{ij}\beta_j/\sigma_j). \tag{12}$$

Marginal effects are calculated by differentiating equations (10), (11) and (12), and averaging over observations and over MCMC replications.

Table 3 presents the marginal effects of probabilities, conditional levels, and unconditional levels of expenditures with respect to explanatory variables. As expected, the household composition variables (age <18, age18–64, age >64) have positive effects on the expenditures of all goods, mostly at the 1% level of significance, except age 18-64 on food away from home. The marginal effects of probability, conditional level and unconditional level all differ among these variables. All else equal, an additional household member age $<$ 18 increases the probability of milk consumption by 5.6% and the expenditure on milk by \$1.14 per week, which are higher than the estimates of 4.5% and \$0.91 per week for each additional member age 18-64 and the estimates of 4.8% and \$0.97 for each additional member age $>$ 64, respectively. These differentiated effects are likely to be masked by the use of household size and highlight the importance of using separate household composition variables. Overall, according to the marginal effects on the unconditional level, expenditure on milk increases by \$1.48 for each additional household member age $<$ 18, and by slightly lower (\$1.19 and \$1.26) for each additional member age 18–64 and age $>$ 64.

Age is an important factor, having positive effects on most food products (cereals, meat, seafood, eggs, milk, fresh and processed fruits and vegetables, sweets, and oils) at home but negative effects on food away from home. These negative effects of age on food away from home reflect the possibility that the elderly prefer food at home and are relatively too weak or inactive to dine out as much as their younger cohort. Income has positive and significant effects on all goods, suggesting that these food products are normal goods. Most marginal effects with respect to income are unusually small, however, with an additional $10,000 per year increasing the probability of consumption by about 1% and the level by less than $1 per week for most food products, except food away from home, which increases the probability by 2% and conditional (unconditional) levels by $1.88 ($2.56) per week.

The role of education is remarkable. Compared with highly educated households (with a reference person holding a graduate degree), less educated households consume less meat, milk, fresh and processed fruits, fresh vegetables, miscellaneous food, and food away from home but more poultry.

Marital status is important as households with a married reference person spend more on all foods except seafood and food away from home, which are insignificant. The most notable effects of marriage are seen in cereals, fresh fruits, milk, fresh vegetables, and miscellaneous food, with effects on unconditional levels greater than $1 per week. Marriage increases the probabilities of food expenditures by between 3% and 10%.

Relative to households of other races, Black households on average consume less cereals, seafood, fresh fruits and vegetables, and food away from home, but more poultry and processed fruits. Whites consume less seafood, fresh fruits and vegetables but more milk, processed fruits and vegetables, oils, and miscellaneous food. Households with a male reference person consume less of fresh fruits and vegetables, processed vegetables, sweets, and oils, but more food away from home.

Food stamp participation plays an important role, increasing the consumption of meat, milk, processed vegetables, sweets, non-alcoholic beverages, oil, and miscellaneous food. However, it reduces expenditures on food away from home (at the

10% level of significance). Surprisingly, residing in an urban area and being below the poverty level do not affect food expenditures. The effects of poverty are likely captured, at least partially, by other “social status” variables such as education and income. Regional differences are also present, the most notable being that households residing in the West consume more fresh fruits and vegetables than households in other regions of the country. Also relative to those residing in the West, households in the South consume less eggs, milk, processed fruits and sweets, households in the Northeast spend less on eggs and more on cereals, poultry, and seafood, and households in the Midwest consume less seafood and eggs. Home ownership implies more stability and less economic hardship than renters for instance, and the its positive effects are seen in the marginal effects of probabilities and levels of cereals, milk, fresh fruits and vegetables, sweets, and food away from home.

The number of earners plays a mixed role. More earners in the household are associated with lower probabilities and levels of expenditures of seafood, eggs, fresh fruits and vegetables but more of sweets and food away from home. Occupation has in general limited effects on consumption. Relative to households with an unemployed reference person, households with a professional consume less cereals, sweets, and non alcoholic beverages. It is also interesting that those with an occupation in labor consume less food away from home than the unemployed. Households residing within an MSA area consume on average more poultry, seafood, milk, and fresh fruits and vegetables.

Finally, there are also seasonal variations in food expenditures. Not surprisingly, households surveyed in spring and summer report higher consumption of fresh fruits relative to those surveyed in winters. On the other hand, they consume fewer eggs and sweets. More non-alcoholic beverages are consumed in the summer than in other seasons.

## 6. Concluding remarks

One of the most challenging tasks in consumer demand modeling with microdata is censoring in the dependent variables caused by non-consumption. Statistical procedures not accounting for such data feature produce biased and inconsistent empirical estimates. In consumer demand analysis, interest in statistical efficiency and presence of cross-equation restrictions (though absent in the current application) call for estimation of the demand equations as a system. Due to the need to evaluate large-dimensioned probability integrals, estimation of a large equation system with censored dependent variables has remained computationally burdensome even with recent simulation techniques and modern computer technology. The Bayesian MCMC method offers a practical solution to this difficult problem. By augmenting the latent data with the Gibbs sampling technique, the problem becomes as manageable as that of a conventional SUR system without censoring. Applying the Bayesian MCMC technique, we are able to estimate an unusually large system of food expenditures. A compromise of such dis-aggregation is that the dimension of the large equation system prevents other plausible parameterization and censoring mechanisms such as sample selection and infrequency of purchases. Our finding of significant error covariance estimates justifies estimation of the system in improving statistical efficiency. We find income, household composition, regions and other socio-demographic variables play significant roles in determining household food expenditures.

Two major caveats pertain. First, while the linear Tobit system estimated here is consistent with a utility-theoretic Kuhn-Tucker model of consumer demand despite the absence of prices, there are other approaches to the censored dependent variable issues. Further studies might explore other behavioral causes of zeros such as infrequency of purchases, abstention (which motivates the double-hurdle model), and sample selection, which can be motivated with random utility theory. Such statistical models however have to be limited to a smaller system because of the obvious dimensionality issue in a large equation system, which calls for estimation of twice as many equations as (and with a dimension of probability integrals equal to) the number of commodities considered. Further, while price elasticity estimates are invaluable information in designing policy interventions and marketing strategy, the current sample does not include price information for estimation of price and expenditure elasticities. Although the censored system estimator achieves statistical efficiency relative to the single-equation Tobit estimator, the ultimate advantage of the estimator lies in the ability to accommodate cross-equation parametric restrictions. Our results with the Bayesian MCMC procedure for the linear SUR Tobit demonstrate that a nonlinear and utility-theoretic demand system is equally viable.

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**Table 1.** Sample statistics of dependent variables: household food expenditures per week.

| | % | Full sample | | Consuming sample | |
|---|---|---|---|---|---|
| Expenditure | Consuming | Mean ($) | SD ($) | Mean ($) | SD ($) |
| Cereals | 0.87 | 10.04 | 10.27 | 11.58 | 10.19 |
| Meat | 0.73 | 9.94 | 13.25 | 13.58 | 13.80 |
| Poultry | 0.37 | 3.13 | 4.95 | 6.36 | 5.41 |
| Seafood | 0.51 | 2.56 | 6.31 | 6.98 | 8.81 |
| Eggs | 0.85 | 1.00 | 1.47 | 1.97 | 1.53 |
| Milk | 0.71 | 8.45 | 8.33 | 9.94 | 8.18 |
| Fresh fruits | 0.72 | 4.47 | 6.26 | 6.29 | 6.60 |
| Fresh vegetables | 0.59 | 4.24 | 5.92 | 5.87 | 6.24 |
| Processed fruits | 0.60 | 2.33 | 3.47 | 3.93 | 3.75 |
| Processed vegetables | 0.60 | 2.09 | 3.10 | 3.52 | 3.34 |
| Sweets | 0.76 | 2.56 | 4.27 | 4.23 | 4.80 |
| Non-alcoholic bev. | 0.54 | 6.74 | 8.14 | 8.85 | 8.26 |
| Oils | 0.84 | 2.06 | 3.23 | 3.83 | 3.54 |
| Misc. food | 0.82 | 13.53 | 15.06 | 16.10 | 15.12 |
| Food away | 0.87 | 45.15 | 56.41 | 55.35 | 57.76 |

**Table 2.** Definitions and sample statistics of explanatory variables.

| Variable | Definitions | Mean | SD |
|---|---|---|---|
| Continuous explanatory variables | | | |
| Household characteristics | | | |
| Age < 18 | Number of children age < 18 in household | 0.62 | 1.05 |
| Age 18–64 | Number of adults age 18–64 | 1.54 | 0.99 |
| Age > 64 | Number of adults age > 64 | 0.32 | 0.62 |
| Earners | Number of earners in household | 1.30 | 0.93 |
| Income | Amount of household after-tax income in past 12 months (imputed mean, unit = $1,000) | 66.24 | 68.04 |
| Reference person characteristics | | | |
| Age | Age in years | 49.47 | 16.97 |
| Dummy variables (1 = yes; no = 0) | | | |
| Household characteristics | | | |
| Home owner | Owns a home | 0.69 | |
| FSP | Any household members received food stamps during past year | 0.06 | |
| Poverty | Income below current year's poverty threshold | 0.11 | |
| Urban | Resides in an urban area (reference = rural area) | 0.94 | |
| MSA | Resides in metropolitan statistical area (MSA) | 0.87 | |
| Northeast | Resides in the Northeast | 0.18 | |
| Midwest | Resides in the Midwest | 0.26 | |
| South | Resides in the South | 0.34 | |
| West | Resides in the West (reference) | 0.21 | |
| Spring | Diary (survey) date occurred during spring | 0.26 | |
| Summer | Diary date during summer | 0.24 | |
| Fall | Diary date during fall | 0.25 | |
| Winter | Diary date during winter (ref.) | 0.24 | |
| Reference person characteristics | | | |
| White | Race is White | 0.84 | |
| Black | Race is Black | 0.10 | |
| Others | Race is of other race (ref.) | 0.06 | |
| Male | Gender is male | 0.47 | |
| < High school | Has less than high school | 0.13 | |

| | | |
|---|---|---|
| High school | High school graduate | 0.26 |
| College | Has a bachelor degree or some college | 0.50 |
| Graduate | Has a graduate degree (ref.) | 0.11 |
| Married | Marital status is married | 0.54 |
| Widowed | Widowed | 0.10 |
| Divorced | Divorced or separated | 0.16 |
| Single | Never married (ref.) | 0.20 |
| Professional | Occupation is dminstrator, manager, teacher, or professional | 0.27 |
| Admin. | Administrative support including clerical, or armed forces | 0.07 |
| Labor | Machine operator, assembler, inspector, transportation operator, handler, helper, laborer, mechanic, repairer, precision production, construction, mining, farming, forestry, fishing, grounds keeping | 0.12 |
| Sales | Sales (retail, business goods and services), technician, protective service, private household service, other service | 0.23 |
| Unemployed | No occupation (ref.) | 0.32 |

**Table 3.** Marginal effects of explanatory variables on probabilities, conditional levels and unconditional levels.

| | Cereals | | | Meat | | | Poultry | | |
|---|---|---|---|---|---|---|---|---|---|
| Variable | Prob. | Level (C) | Level (U) | Prob. | Level (C) | Level (U) | Prob. | Level (C) | Level (U) |
| Continuous Explanatory Variables | | | | | | | | | |
| Age < 18 | 0.061*** | 1.488*** | 1.941*** | 0.053*** | 1.171*** | 1.619*** | 0.043*** | 0.313*** | 0.426*** |
| Age 18–64 | 0.054*** | 1.317*** | 1.720*** | 0.084*** | 1.843*** | 2.548*** | 0.085*** | 0.622*** | 0.846*** |
| Age > 64 | 0.064*** | 1.564*** | 2.041*** | 0.069*** | 1.512*** | 2.090*** | 0.081*** | 0.587*** | 0.799*** |
| Earners | 0.001 | 0.035 | 0.046 | –0.007 | –0.144 | –0.199 | –0.012 | –0.084 | –0.115 |
| Age | 0.001*** | 0.029*** | 0.038*** | 0.002*** | 0.038*** | 0.052*** | 0.000 | –0.001 | –0.001 |
| Income | 0.008*** | 0.178*** | 0.235*** | 0.006*** | 0.127*** | 0.175*** | 0.004** | 0.027** | 0.036** |
| Binary Explanatory Variables | | | | | | | | | |
| Urban | 0.006 | 0.120 | 0.159 | 0.017 | 0.344 | 0.477 | 0.034 | 0.239 | 0.323 |
| Home owner | 0.025*** | 0.584*** | 0.766*** | 0.014 | 0.298 | 0.413 | 0.004 | 0.027 | 0.037 |
| Northeast | 0.037*** | 0.968*** | 1.254*** | 0.019 | 0.416 | 0.575 | 0.055*** | 0.412*** | 0.566*** |
| Midwest | 0.008 | 0.192 | 0.251 | 0.014 | 0.294 | 0.406 | –0.018 | –0.126 | –0.170 |
| South | –0.010 | –0.243 | –0.319 | 0.014 | 0.310 | 0.429 | 0.002 | 0.017 | 0.023 |
| MSA | 0.019 | 0.435* | 0.570* | 0.000 | –0.014 | –0.019 | 0.039** | 0.272** | 0.368** |
| Poverty | 0.003 | 0.089 | 0.116 | –0.025 | –0.535 | –0.741 | 0.003 | 0.021 | 0.030 |
| < High school | –0.044*** | –1.065*** | –1.392*** | 0.078*** | 1.637*** | 2.266*** | 0.021 | 0.155 | 0.211 |
| High school | –0.028** | –0.714** | –0.930** | 0.067*** | 1.390*** | 1.924*** | 0.013 | 0.094 | 0.128 |
| College | –0.013 | –0.336 | –0.435 | 0.057*** | 1.157*** | 1.604*** | 0.011 | 0.078 | 0.106 |
| Married | 0.040*** | 0.966*** | 1.270*** | 0.034** | 0.734** | 1.019** | 0.048*** | 0.340*** | 0.462*** |
| Widowed | 0.000 | 0.012 | 0.015 | –0.024 | –0.482 | –0.671 | 0.024 | 0.171 | 0.232 |
| Divorced | –0.002 | –0.036 | –0.047 | 0.014 | 0.306 | 0.425 | 0.010 | 0.071 | 0.096 |
| White | 0.001 | 0.014 | 0.020 | 0.028 | 0.595 | 0.824 | –0.007 | –0.053 | –0.073 |
| Black | –0.041** | –0.919** | –1.210** | 0.020 | 0.427 | 0.591 | 0.086*** | 0.670*** | 0.923*** |
| Male | –0.011* | –0.262* | –0.342* | 0.003 | 0.057 | 0.079 | –0.011 | –0.081 | –0.110 |
| FSP | 0.008 | 0.200 | 0.258 | 0.040** | 0.952** | 1.311** | 0.023 | 0.171 | 0.234 |
| Professional | –0.027** | –0.658** | –0.858** | –0.012 | –0.258 | –0.356 | 0.010 | 0.072 | 0.098 |
| Admin. | 0.009 | 0.245 | 0.316 | 0.013 | 0.311 | 0.429 | 0.030 | 0.220 | 0.301 |
| Labor | –0.020 | –0.486 | –0.634 | 0.006 | 0.130 | 0.180 | 0.035 | 0.259 | 0.353 |
| Sales | –0.016 | –0.409 | –0.533 | –0.015 | –0.338 | –0.467 | 0.014 | 0.099 | 0.135 |
| Fall | 0.011 | 0.282 | 0.367 | –0.008 | –0.176 | –0.243 | 0.038*** | 0.279*** | 0.382*** |
| Spring | 0.003 | 0.060 | 0.079 | –0.008 | –0.170 | –0.235 | –0.018 | –0.125 | –0.170 |
| Summer | –0.003 | –0.067 | –0.088 | –0.007 | –0.144 | –0.200 | –0.001 | –0.009 | –0.013 |

**Table 3.** Continued

| Variable | Seafood Prob. | Seafood Level (C) | Seafood Level (U) | Eggs Prob. | Eggs Level (C) | Eggs Level (U) | Milk Prob. | Milk Level (C) | Milk Level (U) |
|---|---|---|---|---|---|---|---|---|---|
| Continuous Explanatory Variables | | | | | | | | | |
| Age < 18 | 0.029*** | 0.273*** | 0.330*** | 0.054*** | 0.124*** | 0.168*** | 0.056*** | 1.136*** | 1.478*** |
| Age 18–64 | 0.060*** | 0.567*** | 0.685*** | 0.095*** | 0.217*** | 0.295*** | 0.045*** | 0.912*** | 1.186*** |
| Age > 64 | 0.049*** | 0.466*** | 0.562*** | 0.085*** | 0.194*** | 0.264*** | 0.048*** | 0.969*** | 1.261*** |
| Earners | –0.023** | –0.218** | –0.264** | –0.034*** | –0.077*** | –0.105*** | –0.006 | –0.115 | –0.149 |
| Age | 0.001* | 0.010* | 0.012* | 0.002*** | 0.005*** | 0.006*** | 0.001** | 0.017*** | 0.021** |
| Income | 0.005*** | 0.049*** | 0.059*** | 0.003** | 0.007** | 0.009** | 0.008*** | 0.144*** | 0.190*** |
| Binary Explanatory Variables | | | | | | | | | |
| Urban | 0.012 | 0.113 | 0.131 | –0.012 | –0.030 | –0.041 | –0.026* | –0.583 | –0.752 |
| Home owner | 0.008 | 0.079 | 0.094 | 0.011 | 0.025 | 0.033 | 0.030*** | 0.587*** | 0.768*** |
| Northeast | 0.044*** | 0.426*** | 0.532*** | –0.043** | –0.099** | –0.135** | 0.002 | 0.040 | 0.051 |
| Midwest | –0.029** | –0.276** | –0.330** | –0.045*** | –0.104*** | –0.142*** | –0.011 | –0.230 | –0.298 |
| South | –0.021 | –0.195 | –0.235 | –0.035** | –0.083** | –0.113** | –0.035*** | –0.693*** | –0.903*** |
| MSA | 0.032* | 0.303* | 0.359* | 0.013 | 0.028 | 0.038 | 0.022** | 0.434** | 0.567** |
| Poverty | –0.030 | –0.283 | –0.335 | –0.009 | –0.019 | –0.026 | 0.002 | 0.055 | 0.070 |
| < High school | –0.039* | –0.369* | –0.441* | 0.027 | 0.064 | 0.087 | –0.052*** | –1.063*** | –1.384*** |
| High school | –0.015 | –0.141 | –0.172 | 0.010 | 0.023 | 0.030 | –0.040*** | –0.837*** | –1.087*** |
| College | –0.002 | –0.021 | –0.027 | –0.008 | –0.017 | –0.024 | –0.015 | –0.344 | –0.444 |
| Married | –0.004 | –0.042 | –0.052 | 0.030* | 0.068* | 0.093* | 0.063*** | 1.237*** | 1.627*** |
| Widowed | –0.012 | –0.117 | –0.140 | –0.009 | –0.021 | –0.028 | 0.007 | 0.133 | 0.176 |
| Divorced | –0.023 | –0.213 | –0.257 | 0.010 | 0.022 | 0.029 | 0.006 | 0.108 | 0.144 |
| White | –0.124*** | –1.230*** | –1.565*** | 0.000 | –0.002 | –0.003 | 0.085*** | 1.514*** | 1.999*** |
| Black | –0.072** | –0.726** | –0.946** | 0.001 | 0.002 | 0.003 | –0.018 | –0.268 | –0.360 |
| Male | 0.004 | 0.040 | 0.048 | –0.012 | –0.028 | –0.038 | –0.020*** | –0.397*** | –0.517*** |
| FSP | –0.013 | –0.123 | –0.144 | 0.033 | 0.078 | 0.107 | 0.027** | 0.592* | 0.763* |
| Professional | –0.012 | –0.119 | –0.145 | 0.008 | 0.019 | 0.025 | –0.003 | –0.068 | –0.089 |
| Admin. | –0.025 | –0.240 | –0.288 | 0.062** | 0.145** | 0.198** | –0.002 | –0.028 | –0.036 |
| Labor | 0.002 | 0.019 | 0.023 | 0.048** | 0.110** | 0.150** | –0.018 | –0.364 | –0.475 |
| Sales | –0.029 | –0.272 | –0.327 | 0.030 | 0.069 | 0.093 | –0.013 | –0.264 | –0.344 |
| Fall | –0.030* | –0.284* | –0.340* | –0.029** | –0.068** | –0.093** | 0.006 | 0.129 | 0.167 |
| Spring | 0.009 | 0.088 | 0.108 | –0.045*** | –0.105*** | –0.143*** | 0.004 | 0.074 | 0.096 |
| Summer | –0.004 | –0.040 | –0.049 | –0.056*** | –0.129*** | –0.175*** | 0.005 | 0.102 | 0.132 |

**Table 3.** Continued

| Variable | Fresh fruits Prob. | Fresh fruits Level (C) | Fresh fruits Level (U) | Fresh vegetables Prob. | Fresh vegetables Level (C) | Fresh vegetables Level (U) | Processed fruits Prob. | Processed fruits Level (C) | Processed fruits Level (U) |
|---|---|---|---|---|---|---|---|---|---|
| Continuous Explanatory Variables | | | | | | | | | |
| Age < 18 | 0.038*** | 0.381*** | 0.525*** | 0.024*** | 0.228*** | 0.314*** | 0.062*** | 0.322*** | 0.445*** |
| Age 18–64 | 0.058*** | 0.578*** | 0.797*** | 0.078*** | 0.740*** | 1.020*** | 0.064*** | 0.333*** | 0.460*** |
| Age > 64 | 0.062*** | 0.623*** | 0.860*** | 0.069*** | 0.654*** | 0.903*** | 0.068*** | 0.356*** | 0.492*** |
| Earners | –0.026** | –0.259** | –0.358** | –0.020** | –0.194** | –0.268** | –0.011 | –0.059 | –0.081 |
| Age | 0.001*** | 0.013*** | 0.018*** | 0.002*** | 0.018*** | 0.025*** | 0.001*** | 0.008*** | 0.011*** |
| Income | 0.006*** | 0.062*** | 0.086*** | 0.006*** | 0.055*** | 0.076*** | 0.009*** | 0.046*** | 0.063*** |
| Binary Explanatory Variables | | | | | | | | | |
| Urban | –0.009 | –0.100 | –0.138 | –0.009 | –0.095 | –0.131 | 0.006 | 0.027 | 0.037 |
| Home owner | 0.034*** | 0.335*** | 0.463*** | 0.019* | 0.173* | 0.240* | 0.018 | 0.091 | 0.126 |
| Northeast | –0.037*** | –0.403*** | –0.555*** | –0.026** | –0.281** | –0.387** | 0.026* | 0.147* | 0.204* |
| Midwest | –0.056*** | –0.599*** | –0.826*** | –0.088*** | –0.860*** | –1.190*** | –0.019 | –0.103 | –0.142 |
| South | –0.085*** | –0.865*** | –1.194*** | –0.087*** | –0.854*** | –1.180*** | –0.057*** | –0.293*** | –0.405*** |
| MSA | 0.056*** | 0.530*** | 0.733*** | 0.048*** | 0.429*** | 0.593*** | 0.027 | 0.137 | 0.189 |
| Poverty | –0.008 | –0.078 | –0.108 | 0.015 | 0.143 | 0.197 | 0.001 | 0.006 | 0.009 |
| < High school | –0.081*** | –0.840*** | –1.159*** | –0.058*** | –0.560*** | –0.773*** | –0.078*** | –0.401*** | –0.554*** |
| High school | –0.089*** | –0.908*** | –1.254*** | –0.056*** | –0.546*** | –0.753*** | –0.054*** | –0.283*** | –0.392*** |
| College | –0.038*** | –0.418*** | –0.576*** | –0.031** | –0.311** | –0.429** | –0.013 | –0.070 | –0.098 |
| Married | 0.096*** | 0.917*** | 1.277*** | 0.083*** | 0.755*** | 1.050*** | 0.039** | 0.200** | 0.277** |
| Widowed | 0.027 | 0.233 | 0.325 | 0.014 | 0.123 | 0.171 | 0.019 | 0.095 | 0.132 |
| Divorced | 0.020 | 0.171 | 0.239 | 0.001 | 0.007 | 0.010 | 0.000 | 0.002 | 0.003 |
| White | –0.040** | –0.433** | –0.596** | –0.077*** | –0.822*** | –1.130*** | 0.062*** | 0.304*** | 0.416*** |
| Black | –0.106*** | –1.046*** | –1.443*** | –0.143*** | –1.396*** | –1.924*** | 0.079*** | 0.398*** | 0.546*** |
| Male | –0.031*** | –0.314*** | –0.432*** | –0.041*** | –0.385*** | –0.531*** | 0.000 | 0.003 | 0.004 |
| FSP | –0.010 | –0.091 | –0.125 | 0.003 | 0.036 | 0.050 | 0.018 | 0.097 | 0.135 |
| Professional | 0.006 | 0.055 | 0.076 | 0.024 | 0.224 | 0.309 | 0.006 | 0.031 | 0.043 |
| Admin. | –0.024 | –0.227 | –0.313 | –0.007 | –0.062 | –0.086 | –0.003 | –0.016 | –0.022 |
| Labor | 0.012 | 0.126 | 0.174 | 0.030* | 0.287* | 0.396* | –0.023 | –0.120 | –0.166 |
| Sales | 0.007 | 0.074 | 0.102 | 0.018 | 0.167 | 0.231 | –0.012 | –0.061 | –0.084 |
| Fall | 0.008 | 0.074 | 0.102 | –0.013 | –0.119 | –0.164 | 0.011 | 0.060 | 0.083 |
| Spring | 0.045*** | 0.441*** | 0.609*** | –0.010 | –0.097 | –0.133 | –0.007 | –0.036 | –0.050 |
| Summer | 0.063*** | 0.638*** | 0.880*** | –0.004 | –0.040 | –0.055 | –0.009 | –0.045 | –0.063 |

**Table 3.** Continued

| Variable | Processed vegetables | | | Sweets | | | Non-alcoholic beverage | | |
|---|---|---|---|---|---|---|---|---|---|
| | Prob. | Level (C) | Level (U) | Prob. | Level (C) | Level (U) | Prob. | Level (C) | Level (U) |
| Continuous Explanatory Variables | | | | | | | | | |
| Age < 18 | 0.052*** | 0.242*** | 0.336*** | 0.050*** | 0.306*** | 0.421*** | 0.039*** | 0.565*** | 0.778*** |
| Age 18–64 | 0.078*** | 0.364*** | 0.504*** | 0.027** | 0.169** | 0.233** | 0.066*** | 0.963*** | 1.326*** |
| Age > 64 | 0.089*** | 0.416*** | 0.576*** | 0.048*** | 0.298*** | 0.409*** | 0.067*** | 0.983*** | 1.353*** |
| Earners | –0.017 | –0.079 | –0.110 | 0.027** | 0.167** | 0.229** | 0.015 | 0.226 | 0.311 |
| Age | 0.001** | 0.006** | 0.008** | 0.002*** | 0.010*** | 0.014*** | 0.000 | 0.002 | 0.003 |
| Income | 0.005*** | 0.024*** | 0.033*** | 0.005*** | 0.032*** | 0.044*** | 0.008*** | 0.107*** | 0.147*** |
| Binary Explanatory Variables | | | | | | | | | |
| Urban | –0.022 | –0.111 | –0.154 | –0.016 | –0.101 | –0.139 | 0.013 | 0.178 | 0.245 |
| Home owner | 0.012 | 0.058 | 0.080 | 0.048*** | 0.290*** | 0.399*** | 0.000 | –0.003 | –0.004 |
| Northeast | –0.002 | –0.008 | –0.011 | –0.015 | –0.094 | –0.130 | –0.004 | –0.066 | –0.091 |
| Midwest | 0.004 | 0.019 | 0.026 | 0.011 | 0.068 | 0.095 | –0.012 | –0.172 | –0.237 |
| South | –0.011 | –0.052 | –0.072 | –0.049*** | –0.298*** | –0.409*** | –0.014 | –0.208 | –0.286 |
| MSA | –0.010 | –0.047 | –0.065 | 0.023 | 0.138 | 0.189 | 0.015 | 0.219 | 0.302 |
| Poverty | –0.018 | –0.083 | –0.115 | –0.016 | –0.098 | –0.134 | –0.009 | –0.124 | –0.171 |
| < High school | –0.033 | –0.157 | –0.218 | –0.027 | –0.163 | –0.224 | 0.005 | 0.068 | 0.094 |
| High school | –0.012 | –0.057 | –0.079 | –0.021 | –0.131 | –0.181 | 0.009 | 0.127 | 0.175 |
| College | –0.029* | –0.138* | –0.192* | –0.002 | –0.011 | –0.015 | 0.013 | 0.192 | 0.265 |
| Married | 0.033** | 0.155** | 0.216** | 0.045*** | 0.271*** | 0.374*** | 0.038** | 0.540*** | 0.747*** |
| Widowed | –0.023 | –0.101 | –0.140 | 0.010 | 0.060 | 0.083 | 0.000 | 0.003 | 0.004 |
| Divorced | –0.029 | –0.129 | –0.178 | –0.020 | –0.118 | –0.160 | 0.027* | 0.375* | 0.519* |
| White | 0.048** | 0.217** | 0.299** | 0.033 | 0.198 | 0.271 | 0.035* | 0.485* | 0.669* |
| Black | 0.037 | 0.165 | 0.227 | –0.018 | –0.105 | –0.143 | –0.021 | –0.275 | –0.381 |
| Male | –0.022** | –0.103** | –0.142** | –0.025** | –0.155** | –0.213** | –0.011 | –0.153 | –0.211 |
| FSP | 0.049** | 0.241** | 0.335** | 0.083*** | 0.553*** | 0.766*** | 0.061*** | 0.988*** | 1.349*** |
| Professional | –0.003 | –0.015 | –0.021 | –0.036** | –0.218** | –0.299** | –0.040*** | –0.590*** | –0.811*** |
| Admin. | 0.047* | 0.230* | 0.320* | 0.013 | 0.082 | 0.113 | –0.028 | –0.421 | –0.578 |
| Labor | 0.016 | 0.077 | 0.107 | –0.027 | –0.166 | –0.228 | –0.016 | –0.235 | –0.322 |
| Sales | –0.003 | –0.013 | –0.018 | –0.005 | –0.034 | –0.046 | –0.022 | –0.327 | –0.449 |
| Fall | 0.005 | 0.024 | 0.033 | –0.015 | –0.098 | –0.136 | 0.015 | 0.218 | 0.301 |
| Spring | –0.025* | –0.119* | –0.166* | –0.038*** | –0.239*** | –0.330*** | 0.021* | 0.305* | 0.420* |
| Summer | –0.046*** | –0.214*** | –0.296*** | –0.067*** | –0.408*** | –0.561*** | 0.027** | 0.385** | 0.530** |

**Table 3.** Continued

| Variable | Oils Prob. | Oils Level (C) | Oils Level (U) | Miscellaneous food Prob. | Miscellaneous food Level (C) | Miscellaneous food Level (U) | Food away from home Prob. | Food away from home Level (C) | Food away from home Level (U) |
|---|---|---|---|---|---|---|---|---|---|
| Continuous Explanatory Variables | | | | | | | | | |
| Age < 18 | 0.037*** | 0.182*** | 0.247*** | 0.055*** | 1.672*** | 2.252*** | 0.016*** | 1.593*** | 2.147*** |
| Age 18–64 | 0.066*** | 0.325*** | 0.442*** | 0.040*** | 1.202*** | 1.619*** | 0.009 | 0.935 | 1.261 |
| Age > 64 | 0.088*** | 0.428*** | 0.583*** | 0.049*** | 1.498*** | 2.018*** | 0.027** | 2.775** | 3.740** |
| Earners | 0.005 | 0.025 | 0.034 | 0.012 | 0.372 | 0.501 | 0.044*** | 4.480*** | 6.039*** |
| Age | 0.001** | 0.006** | 0.008** | 0.000 | 0.000 | –0.001 | –0.002*** | –0.202*** | –0.272*** |
| Income | 0.003** | 0.016** | 0.021** | 0.010*** | 0.272*** | 0.370*** | 0.020*** | 1.876*** | 2.562*** |
| Binary Explanatory Variables | | | | | | | | | |
| Urban | –0.040 | –0.207 | –0.284 | –0.003 | –0.109 | –0.144 | –0.002 | –0.221 | –0.292 |
| Home owner | 0.013 | 0.064 | 0.087 | 0.036*** | 1.050*** | 1.421*** | 0.020** | 1.968** | 2.659** |
| Northeast | 0.013 | 0.065 | 0.088 | –0.029** | –0.907** | –1.221** | 0.007 | 0.675 | 0.910 |
| Midwest | 0.006 | 0.028 | 0.039 | –0.001 | –0.046 | –0.061 | –0.020* | –1.965* | –2.654* |
| South | –0.019 | –0.091 | –0.124 | –0.041*** | –1.235*** | –1.665*** | 0.010 | 1.068 | 1.438 |
| MSA | 0.028 | 0.135 | 0.182 | 0.027** | 0.777** | 1.051** | 0.028* | 2.730** | 3.692** |
| Poverty | –0.021 | –0.100 | –0.135 | –0.015 | –0.431 | –0.583 | 0.004 | 0.413 | 0.553 |
| < High school | 0.038* | 0.184* | 0.250* | –0.098*** | –2.914*** | –3.936*** | –0.063*** | –6.187*** | –8.381*** |
| High school | 0.031 | 0.150 | 0.203 | –0.056*** | –1.795*** | –2.410*** | –0.032** | –3.305** | –4.463** |
| College | 0.029 | 0.137* | 0.186* | –0.031*** | –1.060*** | –1.416*** | –0.010 | –1.079 | –1.453 |
| Married | 0.067*** | 0.318*** | 0.434*** | 0.036*** | 1.056*** | 1.431*** | 0.001 | 0.066 | 0.091 |
| Widowed | –0.005 | –0.022 | –0.030 | 0.015 | 0.434 | 0.589 | –0.004 | –0.348 | –0.472 |
| Divorced | 0.027 | 0.124 | 0.168 | 0.015 | 0.420 | 0.571 | 0.008 | 0.870 | 1.172 |
| White | 0.051** | 0.240** | 0.324** | 0.052*** | 1.465*** | 1.986*** | 0.001 | 0.102 | 0.139 |
| Black | 0.016 | 0.071 | 0.095 | –0.024 | –0.610 | –0.833 | –0.058*** | –5.531*** | –7.495*** |
| Male | –0.028*** | –0.134*** | –0.183*** | –0.008 | –0.251 | –0.338 | 0.030*** | 3.108*** | 4.193*** |
| FSP | 0.102*** | 0.543*** | 0.750*** | 0.059*** | 2.022*** | 2.691*** | –0.035* | –3.311* | –4.483* |
| Professional | –0.017 | –0.082 | –0.112 | –0.031** | –0.965** | –1.296** | –0.005 | –0.505 | –0.677 |
| Admin. | 0.016 | 0.084 | 0.115 | 0.005 | 0.172 | 0.229 | 0.014 | 1.560 | 2.094 |
| Labor | –0.030 | –0.148 | –0.201 | –0.046*** | –1.372*** | –1.847*** | –0.041** | –4.035*** | –5.449*** |
| Sales | –0.029 | –0.139 | –0.190 | –0.023* | –0.731* | –0.980* | –0.010 | –0.985 | –1.325 |
| Fall | 0.021 | 0.103 | 0.140 | 0.017 | 0.518 | 0.696 | 0.002 | 0.166 | 0.225 |
| Spring | 0.008 | 0.040 | 0.054 | –0.012 | –0.365 | –0.493 | 0.022** | 2.271** | 3.060** |
| Summer | 0.016 | 0.076 | 0.103 | 0.002 | 0.059 | 0.079 | 0.002 | 0.164 | 0.222 |

Posterior standard deviations in parentheses. * $p < 0.10$, ** $p < 0.05$,*** $p < 0.01$.