BAYESIAN ESTIMATION

AND

SOCIOECONOMIC DETERMINANTS OF FAST FOOD CONSUMPTION

Thomas L. Marsh[a], Jasper Fanning[a], and Kyle Stiegert[b]

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Abstract: Fast food consumption has increased dramatically over the past three decades in U.S., accounting for nearly 35.5% of total away-from-home expenditures in 1999 (USDA/ERS). Given dramatic changes in food consumption, and heightened public concern about health and obesity, there is a considerable need to understand better the factors affecting food consumption choices and the implications of these changes for the food industry and government policymakers. We specify a random utility maximization model to analyze factors influencing an individual's food choice (food at home, fast food, and other food away from home). Bayesian analysis with Markov chain Monte Carlo methods is used to estimate a weighted extreme value logit model, which allows for sequential decision making. Data are from USDA's Continuing Survey of Food Intakes by Individuals from 1994 to 1996 and the Supplemental Children's Survey of 1998. Our results find highly significant and important (statistically and economically) interactions between the likelihood of fast food consumption and age, income, and household size.

Key Words: fast food, random utility maximization, logit, Bayesian, weighted likelihood

[a]Associate Professor and PhD Candidate, Kansas State University; [b]Associate Professor, University of Wisconsin. Contact information: Thomas L. Marsh, Department of Agricultural Economics, Kansas State University, 342 Waters Hall, Manhattan, KS 66506-4011; Phone: 785-532-4913; Email: tlmarsh@agecon.ksu.edu. We acknowledge financial support for this research by the Food Systems Research Group, University of Wisconsin-Madison.

1.0 Introduction

Fast food home is a large and growing component of U.S. food expenditure. Eating and drinking purchases have dominated food away from home expenditures over the last three decades (Putnam and Allshouse). As a share of disposable personal income, food away from home expenditure has risen from 3.6% in 1970 to 4.1% in 1997, while food at home has decreased from 10.2% in 1970 to 6.6% in 1997 (Putnam and Allshouse). In 1967, fast food accounted for 14.3% of total away-from-home expenditures and by 1999 it alone reached 35.5% (U.S. Department of Agriculture/Economic Research Service). Given this dramatic change in food consumption, as well as public concern about health and obesity (Jekanowski, Schlosser), there is a considerable need to identify those factors affecting fast food consumption and the implications of these changes for consumers, the food industry, and government policymakers. In this study, we specify a random utility maximization model to analyze factors influencing an individual's food choice (food at home, fast food, and other food away from home). Bayesian analysis with Markov chain Monte Carlo methods is used to estimate a nested multinomial logit model using USDA's Continuing Survey of Food Intakes by Individuals from 1994 to 1996 and the Supplemental Children's Survey of 1998.

There is an abundance of literature illustrating the importance of food away from home (Byrne, Capps, and Saha; Sexauer), but limited research on fast food itself. McCracken and Brandt examined the factors influencing expenditures on food away from home, at restaurants, fast food establishments, and other commercial facilities using USDA's 1977-1978 Nationwide Food Consumption Survey. They found household income, time value, size, and composition are important factors. Jekanowski, Binkley, and Eales examined the effect of price, income, and demographic characteristics on fast food. Using aggregated fast food measures at the Metropolitan Statistical Area level, they suggested that growth in the fast food consumption is related to an increasing supply of convenience. In other words, consumers have increased consumption of fast food because it provides the incentives to do so with respect to price, time, and taste. Jekanowski suggested that the limited menu aspect of most major chains means that their growth can have a potentially large impact on a selected segment of the agricultural marketing system. Moreover, any menu changes by a major firm can have enormous and almost immediate effects on particular agricultural industries. Lin, Lucier, Allhouse, and Kantor examined the influence of fast food growth on frozen potato consumption. They report that on any given day that 13% of consumers eat french fries with fast food establishments accounting for 67% of the french fry market. They also report that french fry consumption varies by age, region, urbanization, race, and ethnicity, but independent of income. Given dramatic changes in food consumption, and heightened public concern about health and obesity, our focus is to understand better the factors affecting food choices and the implications of these changes for the food industry and government policymakers.

There is also an abundance of literature linking random utility maximization to logistic regression models (e.g., McFadden 1974, 1981; McFadden and Train 2000; Lahiri and Gao 2002). McFadden (1974) proved the multinomial logit model (MNL) is derived from utility maximization if and only if the residuals are distributed independently with an extreme-value distribution. McFadden (1981) extended the MNL model to the nested multinomial logit model (NMNL) by assuming the residuals were distributed as a Type B extreme-value distribution. As an alternative to NMNL models, Cardell and Dunbar (1980) and McFadden and Train (2000) have examined the use of mixed logit models that can approximate any random utility model. The mixed logit overcomes three limitations of standard logit by allowing for random taste variation, unrestricted substitution patterns, and correlation in unobserved factors over time (McFadden and Train 2000; Train 2003).

The main objectives of our paper are to: (1) identify and quantify an empirical relationship between an individual consumer's socioeconomic and demographic characteristics and their likelihood to consume food at home, fast food, and other food away from home; and (2) construct a Bayesian estimator of the nested multinomial logit model and compare it to the maximum likelihood estimator. The remainder of the paper proceeds in the following manner. The first section specifies a random utility model for a consumer making choices among multiple foods. The next section describes the Bayesian econometric estimation with Markov chain Monte Carlo methods used in the empirical analysis. Then the data used in the analysis are discussed. Results of the empirical model is presented and then concluding comments are provided.

2.0 Random Utility Maximization

Suppose that a consumer faces multiple choices such as food at home, fast food, and other food away from home. The random utility function for each choice can be represented as

$$U_{ijr} = V_{ijr} + \varepsilon_{ijr} \tag{1}$$

where V_{ijr} is a deterministic utility function, ε_{ijr} is an unobserved random variable, the subscript i (i=1,…,N) represents the individual, the subscript r (r=1,…, R_i) represents replications by individual i, and the subscript j (j=1,…,J) represents the food of choice among the J foods. The deterministic part of the utility function is often defined as $V_{ijr} = X_{ijr}(\beta)$, where X_{ijr} is a $(1 \times K)$ matrix of characteristics of the jth alternative and the ith individual at the rth replication and β is the $(K \times 1)$ vector of unknown parameters to be estimated. The consumer's choice problem is to define U_{ij}^* (dispensing with some subscript notation), the maximum from among the J utilities, or

$$U_{ij}^* = \max\left\{U_{i1},\ldots,U_{iJ}\right\}.$$

Under the random utility framework, the decision maker has a higher likelihood of choosing food choice j over all other food types if and only if the $\Pr ob\left[U_{ij} > U_{ik}\right] \forall k \neq j$. Choice probabilities that satisfy nonnegativity, $\mathrm{P}_j\left[V\right] \geq 0$, $\sum_{j=1}^{J} \mathrm{P}_j\left[V\right] = 1$; translation invariance, $\mathrm{P}_j\left[V\right] = \mathrm{P}_j\left[V + c\right]$ for $c \in R$; nonnegative density, $\partial \mathrm{P}_j\left[V\right] / \partial V_k \geq 0$, and symmetry, $\partial \mathrm{P}_j\left[V\right] / \partial V_k = \partial \mathrm{P}_k\left[V\right] / \partial V_j$ are necessary and sufficient for locally compatible with additive RUM (see Borsh-Supan 1990; Koning and Ridder 1993).

McFadden (1974) proved the multinomial logit model (MNL) is derived from utility maximization if and only if the residuals are distributed independently with an extreme-value distribution. However, the independence assumption implies that the alternatives are dissimilar and that ratios of relative probabilities between two alternatives are invariant to the total number of choices (i.e., Irrelevance of Independent Alternatives, or IIA). McFadden (1981) extended the MNL model by assuming the residuals were distributed as a Type B extreme-value distribution

$$f\left(\varepsilon_1,\ldots,\varepsilon_J\right)=\exp\left\{-\sum_{k\in E_\omega} b_k\left(\sum_{s\in F_k} a_s\left(\sum_{j\in G_s}\exp\left(-\varepsilon_j/\rho_s\right)\right)^{\rho_s/\rho_k}\right)^{\rho_k/\rho_\omega}\right\}$$

where $\rho_s, \rho_k, \rho_\omega$ are the coefficients of the inclusive values and satisfy $0<\rho_s,\rho_k,\rho_\omega<1$ for global compatibility with RUM and overcoming the IIA property. This leads to the nested multinomial logit model, where the MNL model arises when $\rho_i=1$. Exact measures of welfare are estimable given changes of prices or characteristics (cf. Hanemann; Herriges and Kling).

Figure 1 presents a nonnested structure of food consumption. The nonnested structure is among food at home, fast food, and other food away from home, which leads to the MNL model. Figure 2 presents a nested structure of food consumption. The two-level nested structure consists of choosing between food at home and food away from home and then between fast food and other food away from home, which yields a NMNL model. For present purposes other food away from home remains aggregated, but it is recognized that disaggregating (e.g., restaurants or vending machines) it may be beneficial to understanding better individuals food choices.

3.0 Econometric Estimation

3.1 Weighted Generalized Extreme Value Likelihood Function

Consider the likelihood function weighted by the ith individual

$$L(\theta)=\prod_{\mathrm{i=1}}^{\mathrm{N}}\left(\prod_{\mathrm{r,i,j}}\left(p_{\mathrm{ijr}}(\theta)\right)^{y_{ijr}}\right)^{w_i} \qquad (2)$$

where θ is a $(K\times 1)$ parameter vector, the $p_{ijr}(\theta)$ are the probability at replication *r* of individual *i* choosing alternative *j* and $y_{ijr}=1$ if at replication *r* individual *i* chooses alternative j, otherwise 0. In (2), the vector of weights $\mathbf{w} = (w_1, \ldots, w_N)'$ are assumed to be predetermined by individual. This weighting formulation fits the sample design for the USDA data used in the empirical section of this paper. Dupuis and Morgenthaler (2002) previously examined a robust weighted likelihood estimator with an application to bivariate extreme value problems.

3.2 Bayesian Estimation

The Bayesian procedure with Markov chain Monte Carlo (MCMC) methods avoids several difficulties associated with classical estimation procedures. Bayesian approaches can overcome convergence problems of numerical optimization routines (e.g., irregular surfaces of the likelihood function or local versus global maxima), issues of econometric consistency and efficiency brought about by restrictive assumptions, and use of inappropriate ad hoc economic restrictions (Train 2003). In this paper we follow closely the MCMC Bayesian nested logit analysis discussed in Lahiri and Gao (2002).

Let $h(\theta)$ be the prior distribution. Then, based on Bayes' Theorem, the posterior distribution $G(\theta | Y)$ is proportional to the likelihood function times the prior density or

$$G(\theta | Y) \propto L(Y | \theta) h(\theta)$$

Hence, the probability that is assigned to a given value for the parameters after observing the sample is the probability that is ascribed to before seeing the sample times the probability that those parameter values would result in the observed choices. In the analysis below, the prior is defined as $h(\theta) = h_1(\beta) h_2(\rho)$ where

$$h_1(\beta | G, R) = \prod_{\mathrm{i}} \left(\prod_{\mathrm{j}} \prod_{\mathrm{r}} \left(P_{\mathrm{ijr}}(\beta | G, R) \right)^{y_{ijr}} \right)^{w_i} \tag{3}$$

is the natural conjugate prior of MNL (Koop and Poirier 1993; Poirier 1996) and

$$h_2(\rho) = \begin{cases} 0 & \text{if } \rho \le 0 \\ s\rho^{s-1}\exp(-\rho^s) & \text{if } \rho > 0 \end{cases} \qquad (4)$$

is a generalized exponential prior (Lahiri and Gao 2002). In (3) G and R are vectors of prior hyperparameters such that if G=**0** a neutral case arises, leading to equal probabilities for all alternatives when evaluated at the prior model with $\rho = 1$. The strength of the priors can be controlled with different values of R with larger values indicating stronger priors, while the prior becomes the uniform distribution as the values of R approach the zero vector. As alternatives to (4), Lahiri and Gao (2002) suggest *Gamma* or *Beta* prior densities for ρ. Indeed, other densities can be used to represent the prior distribution with the explicit choice depending on the subjective view of the researcher and data at hand.

3.2.1 Markov Chain Monte Carlo

The basic Metropolis-Hasting (MH) algorithm proceeds in several steps. Start with an initial value β_t^0, draw K independent values labeled as β^z, and then create a candidate value $\beta_t^c = \beta_t^0 + \varphi\, \Omega^* \beta^z$ where φ is a predetermined tuning constant and Ω^* is the Cholesky decomposition of a covariance matrix Ω from the proposal density $\phi\left(\beta_t^j \mid b, \Omega\right)$. Next, draw a standard uniform variable μ and calculate the ratio

$$\alpha = \frac{L\left(\beta_t^c\right)\phi\left(\beta_t^c \mid b, \Omega\right)}{L\left(\beta_t^0\right)\phi\left(\beta_t^0 \mid b, \Omega\right)}$$

If $\mu \le \alpha$, accept the candidate parameter β_t^c and let $\beta_t^1 = \beta_t^c$, else reject it and let $\beta_t^1 = \beta_t^0$. Repeat this process until convergence is reached at T*. Convergence criteria of the MCMC method for the nested and mixed logit estimators are discussed by Train (2003), Lahiri and Gao (2002), and others. If appropriately structured this MC algorithm is computationally efficient and robust. The algorithm does not numerically optimize, but rather simulates a distribution of parameter values to obtain parameter estimates and standard errors of the parameters. This last point is important because despite the popularity of the NMNL model difficulties arise in numerically maximizing its likelihood function.

4.0 Data

The data used in this study are from the Continuing Survey of Food Intakes by Individuals (CSFII) of 1994-96 and the Supplemental Children's Survey (SCS) of 1998. This survey conducted by the USDA measures individual food consumption. The goal of the 1994-1996 survey is to "obtain a nationally representative sample of noninstitutionalized persons residing in households in the United States." The goal of the Supplemental Children's Survey of 1998 was to "obtain nationally representative samples of noninstitutionalized persons 9 years of age or younger residing in the United States." In both surveys individuals were interviewed on two nonconsecutive days during which they were asked to recall their food intake in the previous 24 hours. Along with the dietary information, specific demographic information was collected such as age, income, race, and gender. Observations recorded food intake amounts per individual for day 1 or day 2. In other words, each individual food item consumed on day 1 or 2 of the survey was recorded as a separate observation.

Table 1 presents variable definitions and descriptive statistics of the weighted data on a daily basis for day 1 records. The average household surveyed included 3.43 members with an average age of 34.6 years and a mean income of $42,228.24. Of the individuals surveyed, 78.0% were classified as white, 12.8% as black, 3.0% as Asian/Pacific Islander, and 1.0% Native American or Alaskan with 89.4% being of non-Spanish or non-Hispanic origin. Over 47.2% were living in a Metropolitan Statistical Area (MSA) outside of a central city and 21.3% living in Non-MSA areas. The South, Midwest, West, and Northeast (regions defined in footnote of Table 1) had 34.9, 23.5, 22.0, and 19.6% of the weighted sample. In all, 26.9% (0.048%) of the individuals consumed a fast food item per day (per eating occasion).

5.0 Empirical Results

This illustrative model examines the likelihood of consuming food at home, fast food, or other food away from home in a two level structure (Figure 2) on *a given eating occasion* using nested multinomial logit regression. We specify an empirical model to test relationships between the likelihood of consuming and household size, income, age, gender, location, and eating occasion. Both maximum likelihood and Bayesian coefficient estimates are reported in Table 2 and were estimated using GAUSS. For the empirical analysis the CSFII and SCS data were randomly subsampled to obtain a database of 10,000 observations, which reduced the computational time to estimate the NMNL models and simplified the intertemporal structure (i.e., replications or time dependencies for individuals) of the data. To obtain the MCMC estimates, we used a burn in period of 30,000 iterations with a total simulation length of T^*=100,000. A multivariate normal was used as the proposal density. Under maximum likelihood, the likelihood value was 7026.53 with numerical optimization of the likelihood using Newton-Raphson. Under Bayesian estimation using MCMC, the likelihood decreased to 7074.80. Further comparing across the two estimators, we find that signs of several parameters were different across estimators (e.g., variables Age, Age*Age, and West for the other food away from home equation). These results demonstrate the apparent unreliability of numerical solvers for maximum likelihood estimation of the NMNL model with the current functional specification and data set. Finally the estimate of the inclusive value ρ is positive and significantly different from either zero or one for the Bayesian model (while positive and much larger in magnitude for maximum likelihood), rejecting the MNL structure in Figure 1.

To summarize information for the probability of consuming fast food, response curves across household size, income, and age are presented in Figures 3-5. For example, to generate the probability response curve across household size in Figure 3, income and age are set to their mean values and discrete shift variables are set to zero. Inspecting the probability response curves, it is evident that the likelihood of fast food consumption predominately decreases as household size increases. Alternatively, the likelihood of fast food consumption minimizes at an income level of about $50,000. However, the response to income changes is very inelastic in comparison to household size. Relative to either household size or income, age exhibits larger responses in probability. The likelihood of fast food consumption per eating occasion is maximized at 20-30 years of age and decreases thereafter. Further investigation of results from Table 2 indicates that males have higher probability of consuming fast food, there is a higher probability of consuming fast food at lunch relative to other eating occasions, and the likelihood of fast food consumption is highest in the South and Midwest.

It is interesting to compare the findings reported above to previous research. For example, our results indicated that the West region has a lower likelihood of fast food consumption. This is consistent with findings reported in Jekanowski, Binkley, and Eales. Meanwhile, Lin, Lucier, Allhouse, and Kantor reported that on average the South (followed by the Midwest region) had the highest french fry consumption on any given day. Lin, Lucier, Allhouse, and Kantor also reported that french fry consumption varies by age, region, urbanization, race, and ethnicity, but it was independent of income. Also, using the 1977-78 Nationwide Food Consumption Survey, McCracken and Brandt also reported no significant impact of income on fast food expenditures. We found that the likelihood of fast food consumption was statistically influenced by all of these variables (including income). However, while income was statistically significant in our illustrative fast food model, the probability response curves were very inelastic.

6.0 Conclusion

We specified a random utility maximization model and analyzed the likelihood that an individual consumed food at home, fast food, or other food away from home using nested multinomial logit model. Data used in the study were from the Continuing Survey of Food Intakes by Individuals of 1994-96 and the Supplemental Children's Survey of 1998. This survey was conducted by the United States Department of Agriculture (USDA) and measures individual food consumption. Descriptive results of the analysis indicate that 26.9 (4.1) percent of individuals consumed fast food on a per day (meal) basis.

Several important empirical issues were investigated in an illustrative example. First, we specified an empirical model to test relationships between the likelihood of consuming fast food and household size, income, age, gender, location, and eating occasion. Next, maximum likelihood and Bayesian (using Markov Chain Monte Carlo) results were obtained and compared for the nested multinomial logit model. In effect, the

Bayesian results were more reliable and rejected the multinomial logit model in favor of the nested multinomial logit model.

Important regional and socio-demographic factors emerged. Consumers in the South and Midwest were most likely to consume fast food. In terms of gender, males were more likely to consume fast food than were females. Individuals were more likely to consume fast food until they reached 20-30 years of age at which point the likelihood that they consume fast food decreases throughout their life. Larger households (especially those with more than four persons) were less likely to consume fast food. Although the impact of income on the likelihood of consuming fast food was statistically significant, it was very inelastic. The likelihood of consuming fast food was much more sensitive to age relative to household size and least sensitive to income.

Over all, this preliminary information should help researchers and policy makers concerned with health and obesity to better understand the socioeconomic and demographic factors that influence fast food consumption and tradeoffs with other food away from home and food at home. This information is also relevant to retailers and wholesalers in the food industry that respond directly to primary consumption. Finally, the results should be helpful to those structuring government programs that directly or indirectly influence consumer behavior or agricultural markets in general.

Preliminary results of this study highlight some important limitations. First, numerical optimization of likelihood functions may be unreliable in some circumstances. Second, we need to reconsider the current categorization of aggregating into one group "other food away from home". It is plausible that consumers behave differently to restaurant food relative to, say, vending machine consumption. Third, investigation of the sensitivity of these results to different functional specifications should be investigated. Notwithstanding the empirical issues yet to be rectified, the preliminary results from this study provide important insight into the demographic and socioeconomic determinants that influence fast food consumption.

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Table 1. Variable definitions and descriptive statistics from CSFII and SCS.

Variable	Definition	Mean	Minimum	Maximum
Fast Food	1 if consumed fast food, else 0 (/day)	0.269	0	1
	1 if consumed fast food, else 0 (/eating occasion)	0.048	0	1
Household Size	Count of household members	3.428	1	16
Income	Approximate household income	42228.24	0	100000
Age	Age of household member	34.645	0	90
Region1	1 if Northeast, else 0	0.196	0	1
Region2	1 if Midwest, else 0	0.235	0	1
Region3	1 if South, else 0	0.349	0	1
Region4	1 if West, else 0	0.220	0	1
Urban1	1 if MSA/Central City, else 0	0.315	0	1
Urban2	1 if MSA/Outside Central, else 0	0.472	0	1
Urban3	1 if Non-MSA, else 0	0.213	0	1
Female	1 if Female, else 0	0.511	0	1
Race1	1 if White, else 0	0.780	0	1
Race2	1 if Black, else 0	0.128	0	1
Race3	1 if Asian/Pacific Islander, else 0	0.030	0	1
Race4	1 if American Indian/Alaskan Native, else 0	0.006	0	1
Race5	1 if Other, else 0	0.056	0	1
Origin1	1 if Mexican/Mexican American/Chicano, else 0	0.049	0	1
Origin2	1 if Puerto Rican, else 0	0.010	0	1
Origin3	1 if Cuban, else 0	0.003	0	1
Origin4	1 if Other Spanish/Hispanic, else 0	0.043	0	1
Origin5	1 if None of the above, else 0	0.894	0	1
Year1	1 if 1994, else 0	0.312	0	1
Year2	1 if 1995, else 0	0.312	0	1
Year3	1 if 1996, else 0	0.311	0	1
Year4	1 if 1997, else 0	0.065	0	1
Wt	Sample weight for individual intake	12090.170	340	226692

Notes:

a) Descriptive statistics are for day 1 records.

b) Metropolitan Statistical Area (MSA)-A geographic area consisting of a large population nucleus together with adjacent communities that have a high degree of economic and social integration with that nucleus; defined by the Federal Office of Management and Budget for use in the presentation of statistics by agencies of the Federal government.

c) Regions as defined by the 1990 Census of Population: Northeast-Connecticut, Maine, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, Vermont; Midwest-Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, Wisconsin; South- Alabama, Arkansas, Delaware, District of Columbia, Florida, Georgia, Kentucky, Louisiana, Maryland, Mississippi, North Carolina, Oklahoma, South Carolina, Tennessee, Texas, Virginia, West Virginia; West- Alaska, Arizona, California, Colorado, Hawaii, Idaho, Montana, Nevada, New Mexico, Oregon, Utah, Washington, Wyoming.

Table 2. NMNL Maximum Likelihood and Bayesian Estimates.

	NMNL	Bayesian		
Fast Food	Coefficients	Coefficients	StdErr	T-val
Intercept	-1.342075	-1.885553	0.124087	-15.20
Household Size	0.083870	0.105813	0.053793	1.97
Household Size * Household Size	-0.006035	-0.007764	0.006682	-1.16
Income	-0.068878	-0.141009	0.042838	-3.29
Income* Income	0.006908	0.013477	0.003745	3.60
Age	0.009458	0.037634	0.003869	9.73
Age* Age	-0.000203	-0.000721	0.000064	-11.33
Sex	0.023354	0.183990	0.047785	3.85
Northeast	-0.019269	-0.117297	0.059315	-1.98
South	0.145151	0.199829	0.049422	4.04
West	-0.064480	-0.194201	0.056847	-3.42
Lunch	0.108823	0.534198	0.041291	12.94
Other Food Away From Home				
Intercept	-0.406656	-0.786899	0.087468	-9.00
Household Size	-0.046607	-0.100935	0.026411	-3.82
Household Size * Household Size	0.003221	0.006886	0.003455	1.99
Income	0.038095	0.104117	0.025768	4.04
Income* Income	-0.003568	-0.008236	0.002259	-3.65
Age	-0.000833	0.006466	0.002753	2.35
Age* Age	0.000039	-0.000036	0.000034	-1.06
Sex	-0.008858	-0.071837	0.026053	-2.76
Northeast	-0.001733	-0.021289	0.028886	-0.74
South	-0.070951	-0.090283	0.029911	-3.02
West	0.009093	-0.053062	0.029663	-1.79
Dinner	0.025660	0.108598	0.015670	6.93
ρ	31.130251	4.393893	0.265053	16.58
LL	7026.53	7074.80		

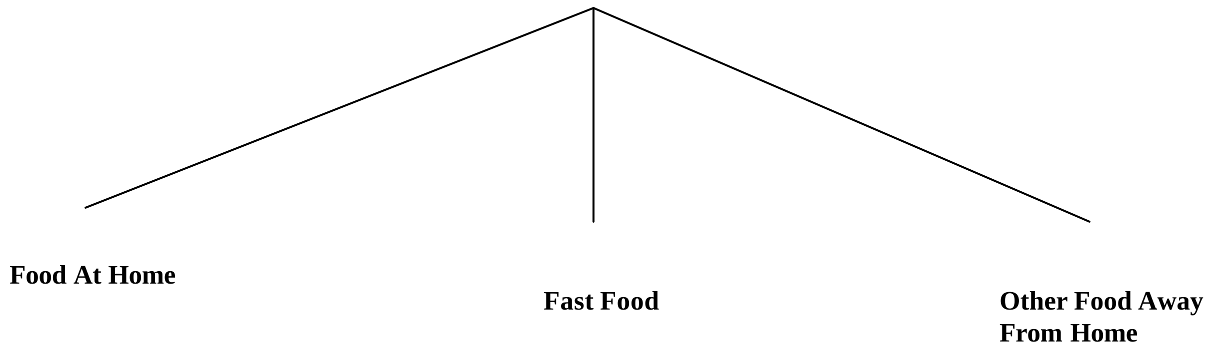

Figure 1. Nonnested Structure with MNL

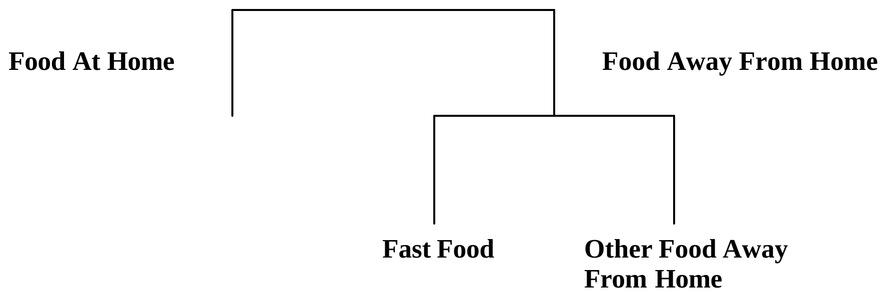

Figure 2. Nested Structure with NMNL

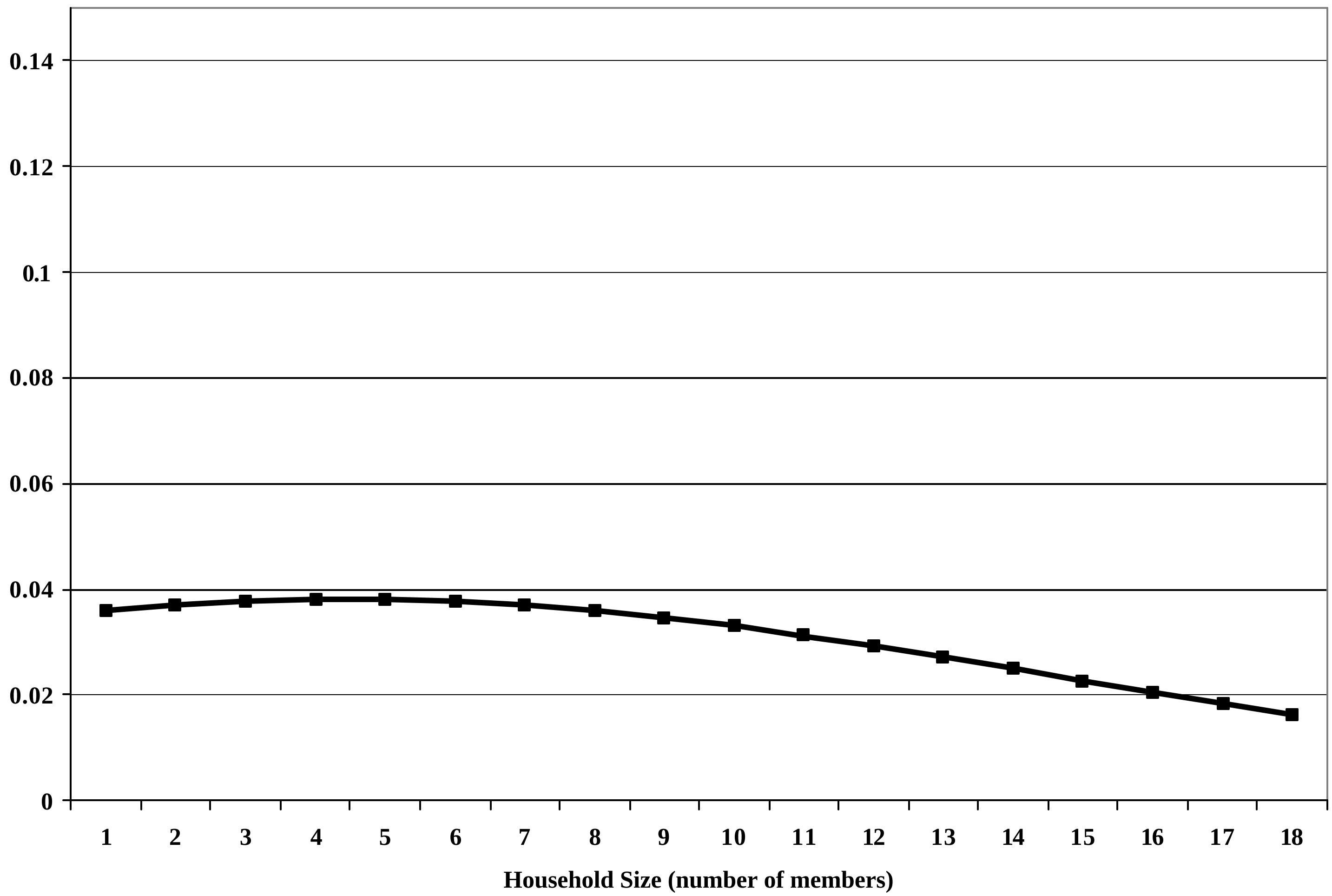

Figure 3. Probability of fast food consumption (per eating occasion) across household size (number of members).

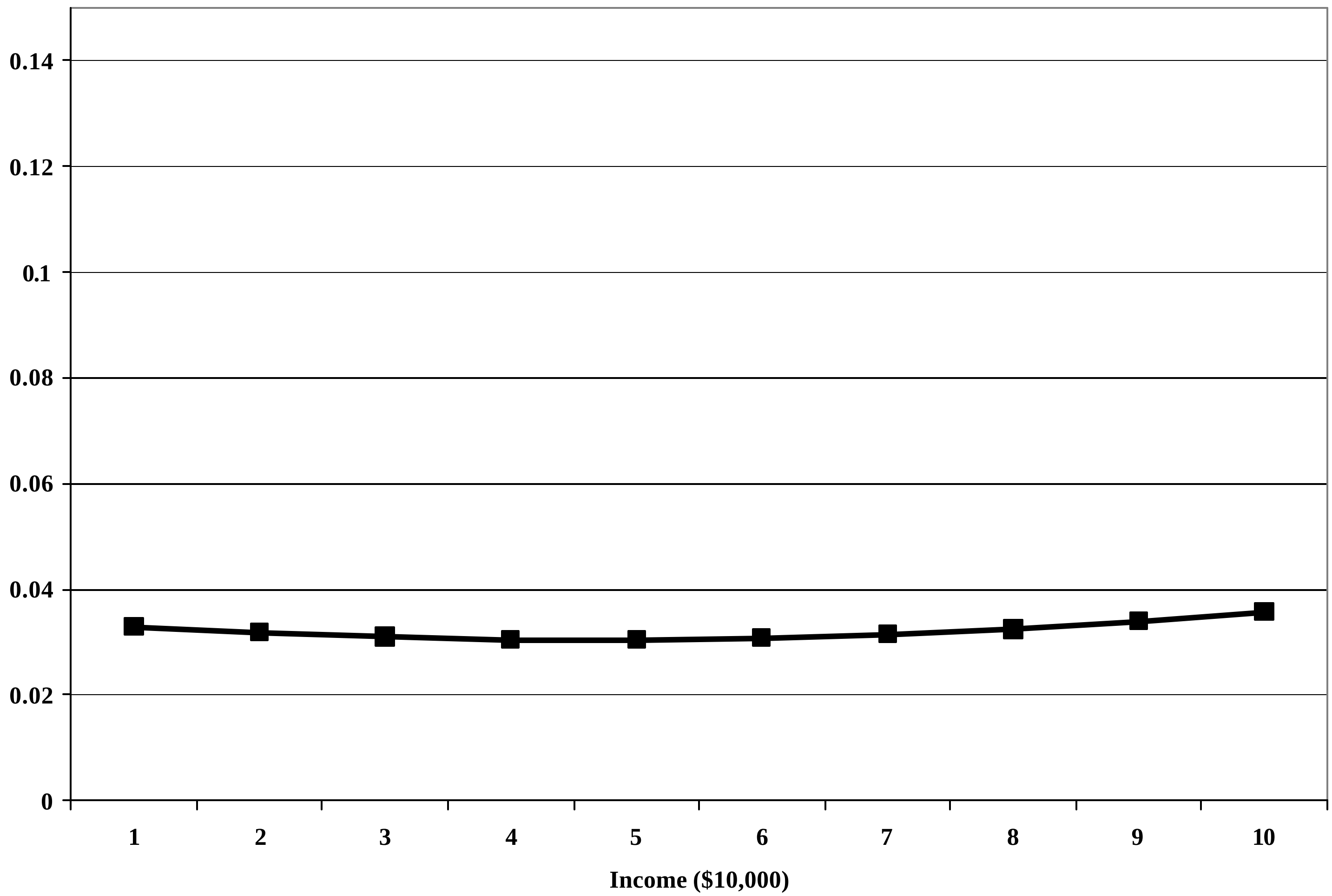

Figure 4. Probability of fast food consumption (per eating occasion) across income ($10,000).

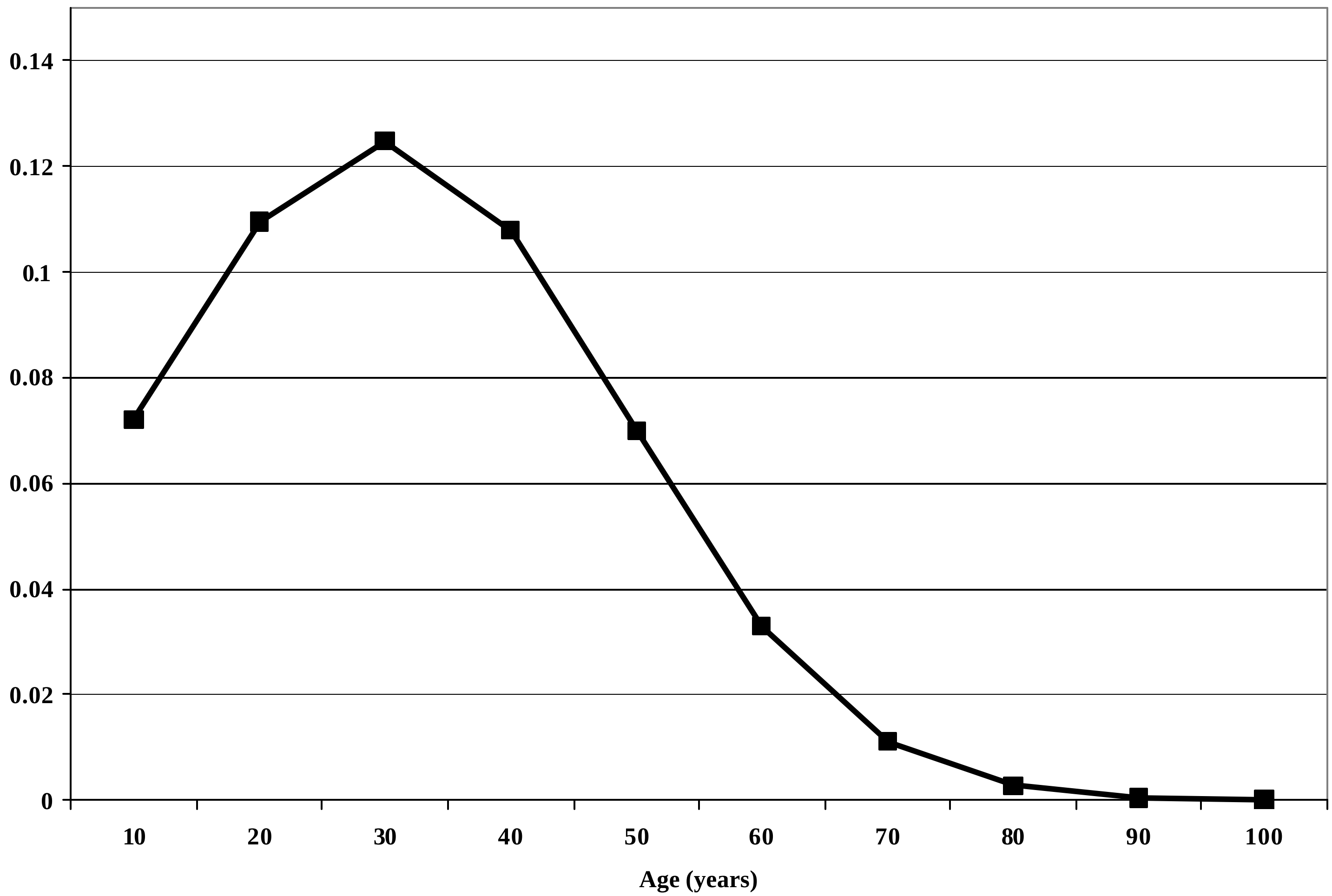

Figure 5. Probability of fast food consumption (per eating occasion) across age (years).