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Cross-Sectional Estimation of U.S. Demand for Beef Products: A Censored System Approach

Steven T. Yen and Chung L. Huang

Demands for beef products are investigated using the U.S. Department of Agriculture's 1987–88 Nationwide Food Consumption Survey data. The censored translog demand system is estimated with full-information and simulated maximum-likelihood procedures. These procedures represent different approaches to evaluation of multiple probability integrals in the likelihood function, but produce very similar parameter and elasticity estimates. Findings suggest sociodemographic variables play important roles in the demand for beef, and that demand for different cuts of beef should be treated differently.

Key words: demand elasticities, GHK simulator, limited dependent variables, translog demand system

Introduction

Red meat consumption in the United States has decreased significantly in the past few decades following a steady downward trend started in the late 1970s. Per capita consumption of beef, accounting for approximately 60% of total red meat, reached an all-time high of 88.8 pounds in 1976. It dropped about 19% to 72.1 pounds in 1980, remained relatively flat in the early 1980s, and then steadily declined from 74.6 pounds in 1985 to 56.1 pounds in 1998.

Considerable interest and concern have focused on the trend of declining red meat consumption, with special attention given to beef consumption. Smallwood, Haidacher, and Blaylock provide a review of the literature on meat demand with a broad perspective on significant economic and demographic factors affecting the demand for meat. Chavas (1989) suggested that changes in meat consumption could be explained mainly by changing meat prices and lifestyles of American consumers.

Numerous time-series studies have focused on price effects in the demand for meat (e.g., Chavas 1983; Dahlgran; Moschini and Meilke; Wohlgenant). Few analyses, however, have incorporated the use of cross-sectional microdata to examine the effects of changing lifestyles, tastes, and preferences on meat demand. Manchester suggests demand analyses based on aggregate time-series data are unsatisfactory because aggregate data usually mask many changes in the groups that comprise the whole. Furthermore, analyses based on aggregate economic measures provide price and income elasticities but not shifters for the demand function related to changes in socioeconomic and demographic characteristics of the population.

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Another source of data available for food demand analysis is the consumer panel data collected by private firms such as ACNielsen. However, these panel data are often more expensive to obtain and not as readily available as public data sources such as the U.S. Department of Agriculture's (USDA's) Nationwide Food Consumption Survey (NFCS) used in the present study.

With the increasing availability of microdata, more recent studies have focused on the effects of demographic characteristics (Capps and Havlicek; Gao and Spreen; Heien and Pompelli; Nayga; Park et al.) and taste change (Gao, Wailes, and Cramer) on demand for disaggregated meat products. Demand studies based on microdata provide better insights on how different groups within the population behave. Taking individual households at the micro level, microeconomic models enable better estimation of demand parameters and improvement of forecasts over those assuming average effects for all members of the population based on aggregate data (Manchester). Accurate forecast of future demands is particularly important to decision makers in the beef industry, as well as government officials, in formulating sound marketing strategies and public policies.

The analysis of microdata, however, is often hindered by the problem of zeros in the dependent variables. Earlier meat demand studies did not address such issues of censored dependent variables (Capps and Havlicek; Heien and Pompelli).[1] It is well known that estimation procedures not accounting for the censored dependent variables produce biased and inconsistent parameter estimates. A number of censored demand system estimators have appeared in the literature (Lee and Pitt 1986, 1987; Wales and Woodland 1983), and early empirical applications of these estimators include analyses by Yen and Roe, and Gould.

More recent studies of meat demand have addressed the issue of censoring in demand systems (Gao and Spreen; Gao, Wailes, and Cramer; Nayga; Park et al.). These studies have typically applied a two-step estimation procedure developed by Heien and Wessells for demand systems with censored dependent variables. The Heien and Wessells procedure involves estimation of a set of probit equations in the first step, and a system of equations augmented by the inverse Mills' ratios (calculated from the probit estimates) in the second step, typically estimated by seemingly unrelated regression (SUR). Shonkwiler and Yen found this procedure to be inconsistent.

Two alternative multi-step estimation procedures have been proposed recently. Shonkwiler and Yen introduce an estimator based on the unconditional means of the censored dependent variables, which also involves probit in the first step and SUR in the second step. The estimator is shown to perform better than the Heien and Wessells estimator in a Monte Carlo experiment. The procedure of Perali and Chavas involves estimating separate unrestricted equations in the first step, estimating error correlation in the second step, and then recovering restricted demand parameters by minimum distance estimation. These multi-step procedures generally produce inefficient parameter estimates relative to the full-information maximum-likelihood (FIML) estimator, but can be useful for large demand systems with many zeros.[2]

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[1] The sample proportions of zeros range from under 20% in Heien and Pompelli to between 20% and 50% in Capps and Havlicek.

[2] Inefficiency (relative to maximum-likelihood estimators) of two-step single-equation estimators similar to those considered in the censored system literature was proved by Hartley and demonstrated in a Monte Carlo investigation by Wales and Woodland (1980). Inefficiency of two-step system estimators is implied by these single-equation results, and we are not aware of any empirical inquiry into the efficiency of censored system estimators, due to the obvious numerical complexity.

This study proposes alternative estimation procedures for estimating a translog demand system for disaggregated beef products. The FIML and simulated maximum-likelihood (SML) estimation procedures applicable to a censored demand system are considered. Given the structural parameter estimates, conditional and unconditional demand elasticities with respect to prices and income are computed. These procedures are applied to estimate U.S. household consumption of four major beef products (steak, roast, ground beef, and other beef) and other meat based on sample data collected from the USDA's 1987–88 NFCS. Although the data set is dated, the present study illustrates the use of the FIML and SML procedures in the absence of more recent survey data.

The Translog Demand System

The focus of this analysis is on the demand for meat products, so these products are assumed to be weakly separable from all other goods. We consider the translog demand system, derived from the translog indirect utility function (Christensen, Jorgenson, and Lau):

$$\log V(p_1, p_2, \ldots, p_n, m) = \alpha_0 + \sum_{i=1}^{n} \alpha_i \log(p_i/m) + \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \beta_{ij}\log(p_i/m)\log(p_j/m), \quad (1)$$

where $V(\cdot)$ is indirect utility; $m = \Sigma_{i=1}^{m} p_i q_i$ is total meat expenditure; q_i are quantities with corresponding prices p_i; and α_0, α_i, and β_{ij} are unknown parameters. Applying Roy's identity to equation (1) yields the translog demand system in expenditure-share form:

$$w_i = \frac{\alpha_i + \Sigma_{j=1}^{n} \beta_{ij}\log(p_j/m)}{\Sigma_{j=1}^{n} \alpha_j + \Sigma_{k=1}^{n}\Sigma_{j=1}^{n} \beta_{kj}\log(p_j/m)}, \quad i = 1, 2, \ldots, n, \quad (2)$$

where w_i is the expenditure share for good i. Homogeneity is implicit in equations (1) and (2) by use of normalized prices p_j/m for all j. The translog demand system is known to be flexible in that it is a second-order approximation to any functional form (Christensen, Jorgenson, and Lau).

To incorporate demographic variables in the demand system (2), let

$$\alpha_i = \sum_{k} \alpha_{ik} z_k, \quad (3)$$

where z_1 is unity. While demographic variables can be incorporated many other ways (Pollak and Wales), the specification (3) is also common (e.g., Lee and Pitt 1987). Parametric symmetry and "adding-up" restrictions are imposed in estimating the system:

$$\beta_{ij} = \beta_{ji} \quad \forall i, j; \quad (4)$$

$$\sum_{i=1}^{n} \alpha_{i1} = -1, \quad \sum_{i=1}^{n} \alpha_{ik} = 0 \quad \text{for } k \geq 2. \quad (5)$$

However, the restrictions specified in equation (5) guarantee adding-up only in the absence of censoring. The adding-up issue in a censored demand system is discussed in the next section.

FIML and SML Estimation of a Censored System

Denote the deterministic component of the demand share equation for good i as $f_i(\theta)$, where θ is a vector of all demand parameters. Consider the system of censored equations (Amemiya), such as:

(6) $$w_i = \begin{cases} f_i(\theta) + \varepsilon_i & \text{if } f_i(\theta) + \varepsilon_i > 0 \\ 0 & \text{otherwise} \end{cases} \qquad i = 1, 2, ..., n,$$

where $\varepsilon_1, \varepsilon_2, ..., \varepsilon_n$ are random errors. For convenience, subscripts on cross-sectional observations are suppressed. Note that in the presence of censoring, the right-hand side of system (6) no longer adds up to unity, even if $\Sigma_{i=1}^{n} \varepsilon_i = 0$.

To address this adding-up issue, we follow the recommendation of Pudney in estimating the first $n - 1$ equations in a system and treating the nth equation as a residual demand. Consider, without loss of generality, a demand regime in which the first ℓ goods are consumed, with observed $(n - 1)$th vector $\mathbf{w} = [w_1, w_2, ..., w_\ell; 0, 0, ..., 0]'$. Adding-up is guaranteed by specifying the nth equation as:

(7) $$w_n = 1 - \sum_{k=1}^{\ell} \left[f_k(\theta) + \varepsilon_k \right] = f_n(\theta) + \varepsilon_n,$$

where $f_n(\theta) = 1 - \Sigma_{k=1}^{\ell} f_k(\theta)$, and $\varepsilon_n = -\Sigma_{k=1}^{\ell} \varepsilon_k$. It is easily seen from (6) and (7) that the first ℓ equations and equation n now add up to unity, as do the error terms $\varepsilon_1, \varepsilon_2, ..., \varepsilon_\ell$, and ε_n to zero. Therefore, the likelihood function can be constructed exclusively from the first $(n - 1)$ equations. Elasticities for the nth good can be calculated using the adding-up restriction. Note that FIML estimates are not invariant to the equation excluded. However, given our interest in beef demand, our empirical strategy is to estimate $n - 1$ component beef demand equations and treat the demand for all other meat as the residual demand.

To construct the likelihood function, assume the random error vector $\mathbf{e} \equiv [\varepsilon_1, \varepsilon_2, ..., \varepsilon_\ell | \varepsilon_{\ell+1}, \varepsilon_{\ell+2}, ..., \varepsilon_{n-1}]' \equiv [\mathbf{e}_1', \mathbf{e}_2']'$ is distributed as $(n - 1)$-variate normal with zero mean vector and covariance matrix

$$\Sigma = \begin{bmatrix} \Sigma_{11} & \\ \Sigma_{21} & \Sigma_{22} \end{bmatrix},$$

which has entries $\sigma_{ij} = \rho_{ij}\sigma_i\sigma_j$, where σ_i are error standard deviations and ρ_{ij} are correlation coefficients. Then, the likelihood contribution of this regime is specified as:

(8) $$L_c(\mathbf{w}) = g(\mathbf{e}_1) \int_{\{\mathbf{e}_2 : \mathbf{e}_2 \leq \mathbf{u}; \Sigma_{22\cdot1}\}} h(\mathbf{e}_2 | \mathbf{e}_1)\, d\mathbf{e}_2,$$

where $\mathbf{u} = -[s_{\ell+1}(\theta), s_{\ell+2}(\theta), ..., s_{n-1}(\theta)]'$, $g(\mathbf{e}_1)$ is the marginal distribution of $\mathbf{e}_1$ with mean zero and variance Σ_{11}, and $h(\mathbf{e}_2 | \mathbf{e}_1)$ is the conditional distribution of $\mathbf{e}_2$ given $\mathbf{e}_1$ with mean $\boldsymbol{\mu}_{2\cdot1} = \Sigma_{21}\Sigma_{11}^{-1}\mathbf{e}_1$ and variance $\Sigma_{22\cdot1} = \Sigma_{22} - \Sigma_{21}\Sigma_{11}^{-1}\Sigma_{21}'$ (Kotz, Balakrishnan, and Johnson).

Define for observation t a dichotomous indicator such that $I_t(c) = 1$ if observed consumption vector $\mathbf{w}_t$ lies in the demand regime c, and $I_t(c) = 0$ otherwise. Then, denoting the likelihood contribution (8) for observation t as $L_{ct}(\theta)$, the likelihood function for the entire sample is:

(9) $$L = \prod_t \prod_c \left[L_{ct}(\mathbf{w}_t) \right]^{I_t(c)}.$$

Heteroskedasticity of the error terms is accommodated by allowing each error standard deviation to vary across observations. Specifically, for observation t,

(10) $$\sigma_{it} = \exp(\mathbf{h}_{it}'\gamma_i),$$

where $\mathbf{h}_{it}$ is a vector of exogenous variables and γ_i is a conformable parameter vector.

Estimation requires evaluation of the multiple probability integrals in (8). With a system of five equations which requires evaluation of four-level normal probability integrals, we compare results from FIML estimation in which all integrals are evaluated numerically,[3] and SML estimation in which four-level integrals are evaluated by the Geweke-Hajivassiliou-Keane (GHK) simulator (e.g., Hajivassiliou). Because of the computational burden, the SML procedure is convenient to use in lieu of the FIML estimator when the level of integrals is greater than three. The GHK probability simulator, in the context of lower-tailed probability integrals used in the present study, is described briefly in appendix A.

Data

Data for this study are compiled from the USDA's 1987–88 Nationwide Food Consumption Survey (NFCS). The survey contains quantities and expenditures on more than 100 different cuts of beef. This study focuses on four disaggregate forms of beef: steak, roast, ground beef, and other beef. An equation for other meat is also included in the system. Price (unit value) for each product is derived from the reported expenditure and quantity, and regional averages are used as proxy prices for non-consuming households residing in corresponding regions.

In addition to prices and total meat expenditure, the explanatory variables include household age composition (numbers of household members in the three age groups of < 20, 20–64, and ≥ 65), education of the household head, and dummy variables indicating urbanization (urban), regions of residence (Northeast, Midwest, South), home ownership (homeowner), race (White), ethnicity (Hispanic), gender of meal planner (female planner), and food stamp recipient status (food stamp). Finally, per capita income is used to explain error heteroskedasticity [see equation (10)].

The NFCS contains 4,273 households, but upon recommendation by the USDA, approximately 200 non-housekeeping households are excluded from the sample. Additional households that did not consume any meat products during the week are also excluded, as expenditure shares are not defined. Consequently, a total of 4,050 households were selected for the empirical analysis.

The sample statistics are presented in table 1. On average, a household consumes 1.07 pounds of steak, 0.72 pound of roast, 1.71 pounds of ground beef, 0.19 pound of other beef, and 3.34 pounds of other meat per week. Among the consuming households for each product, the corresponding averages are 2.53 pounds, 3.20 pounds, 2.42 pounds, 1.48 pounds, and 3.63 pounds, respectively.

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[3] Kotz, Balakrishnan, and Johnson survey procedures to evaluate multivariate normal cdf's. Numerical procedures for evaluation of multivariate normal cdf's are available in the GAUSS software package. However, direct numerical evaluation of high-dimension cdf's (i.e., beyond three or four levels) is known to be time consuming.

Table 1. Sample Statistics (sample size = 4,050 households)

Variables		Mean	Std. Dev.
Quantities (pounds/week):			
▸ Steak:	Full sample	1.07	1.92
	Consuming households (1,711 observations)	2.53	2.25
▸ Roast:	Full sample	0.72	1.57
	Consuming households (909 observations)	3.20	1.74
▸ Ground Beef:	Full sample	1.71	1.92
	Consuming households (2,870 observations)	2.42	1.87
▸ Other Beef:	Full sample	0.19	0.70
	Consuming households (521 observations)	1.48	1.40
▸ Other Meat:	Full sample	3.34	4.05
	Consuming households (3,733 observations)	3.63	4.09
Prices ($/pound):			
▸ Steak		2.67	0.92
▸ Roast		1.85	0.36
▸ Ground Beef		1.52	0.40
▸ Other Beef		2.57	0.85
▸ Other Meat		2.17	0.80
Expenditure Shares:			
▸ Steak		0.16	0.24
▸ Roast		0.08	0.18
▸ Ground Beef		0.22	0.24
▸ Other Beef		0.03	0.12
▸ Other Meat		0.50	0.30
Demographic Variables:			
▸ Age (number of household members):	< 20 years	0.93	1.21
	20–64 years	1.57	0.93
	≥ 65 years	0.34	0.64
▸ Education (of household head): = 1 if ≤ 8 years of education = 2 if 9–12 years of education = 3 if 13–16 years of education = 4 if 17 or more years of education		2.36	0.82
▸ Income ($000s/week)		0.53	0.45
Demographic Variables (binary):			
▸ Urban (household resides in)		0.70	
▸ Northeast		0.20	
▸ Midwest		0.27	
▸ South		0.35	
▸ Homeowner		0.68	
▸ White		0.85	
▸ Hispanic		0.04	
▸ Female (meal) Planner		0.79	
▸ Food Stamp (recipient)		0.07	

Source: Data compiled from the Nationwide Food Consumption Survey, 1987–88 (USDA).

With respect to sociodemographic characteristics, table 1 shows a majority of respondents (85%, 68%, and 70%, respectively) were white, homeowners, and residing in urban areas. Survey respondents of Hispanic origin accounted for only 4% of the sample, and 7% of the respondents were participants in the food stamp program. In addition, 35% of the households resided in the South and 79% of the meal planners were female.

Average household size was slightly less than three persons, and the average household head had some college education.

The numbers (percentages) of zero observations are 2,339 (58%) for steak, 3,141 (78%) for roast, 1,180 (29%) for ground beef, 3,529 (87%) for other beef, and 317 (8%) for other meat. Therefore, failure to accommodate such censoring would produce unreliable results. The frequencies of zero observations suggest only 34 households (0.8%) consume all four beef products during the week. The other frequencies are 436 (10.8%) for one zero, 1,455 (35.9%) for two zeros, 1,657 (40.9%) for three zeros, and 468 (11.6%) for four zeros. Thus, over 50% of the sample requires evaluations of trivariate normal cumulative distribution functions (cdf's), and over 10% requires four-level integrations, for which the GHK probability simulator is also used.

Results

FIML and SML estimations are conducted with the equation for other meat deleted, based on alternative (numerical vs. simulation) evaluations of the likelihood function (9).[4] Initial estimates, critical for the model considered, are derived from iterated SUR and maximum-likelihood (ML) estimates ignoring censoring.[5] In the latter case, the likelihood contribution is simply the $(n - 1)$-variate normal probability density function (pdf) of the error vector $\mathbf{e}$. Both sets of initial estimates (ML and iterated SUR) converge to the same solutions for both FIML and SML. The FIML estimates also converged to SML results, and vice versa.

To accommodate heteroskedasticity of random errors, we considered including continuous variables such as income, household size, and education in the heteroskedasticity equation (10). Only income was found to be statistically significant in the ground beef equation for both FIML and SML estimates, which provides some evidence of heteroskedasticity. The elasticities calculated from the homoskedastic and heteroskedastic models are very similar, however.[6]

The FIML and SML parameter estimates, presented in table 2, are fairly close in magnitude and significance.[7] All estimated correlation coefficients (ρ_{ij}'s) are significant at the 1% level according to both the FIML and SML estimates, except for correlation between steak and other beef, which is significant at the 5% level according to the SML estimate. Apart from the need to impose cross-equation restrictions, the high and significant correlation among the error terms of beef products justifies estimation of the demand functions as a system. The large sample size allows the inclusion of a relatively large number of demographic variables. According to the FIML estimates, about half (31 out of 65) of the demographic coefficients (α_{ij}'s) and two-thirds of the price coefficients (β_{ij}'s) are significant at the 5% level or lower. The SML estimator performs equally well, as reflected by statistical significance of parameter estimates.

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[4] We are not aware of other large-scale cross-sectional applications with direct evaluations of four-level integrals. The estimation is computationally intensive, but feasible with today's hardware. For instance, starting from the iterated SUR estimates, FIML estimation converged in 373 minutes after 29 BHHH iterations (Berndt et al.) on a 2.2 GHZ Pentium 4 with 512K RAM, whereas SML converged in 174 minutes after 32 BHHH iterations with 200 GHK replications.

[5] Initial estimates for error standard deviations and correlations are obtained by decomposing SUR estimates of the error covariance matrix.

[6] Results for the homoskedastic specification are available from the authors upon request.

[7] Similarity of FIML and SML may be attributable to the small number of households (11.6% of the sample) for which four-level probability integrals are simulated. Whether the differences can be more pronounced between the FIML and SML estimates in other samples is worthy of further investigation.

Table 2. Maximum-Likelihood Estimation of Translog Demand System with Censored Dependent Variables

	Full-Information Maximum Likelihood (FIML)				Simulated Maximum Likelihood (SML)			
Variable/ Description	Steak	Roast	Ground Beef	Other Beef	Steak	Roast	Ground Beef	Other Beef
Prices (β_{ij}):								
Steak	0.131***				0.136***			
	(0.026)				(0.026)			
Roast	0.016	0.074*			0.024	0.073*		
	(0.029)	(0.039)			(0.030)	(0.041)		
Ground Beef	0.019	0.087***	-0.081***		0.020	0.087***	-0.071***	
	(0.019)	(0.025)	(0.022)		(0.019)	(0.026)	(0.022)	
Other Beef	-0.050**	-0.213***	-0.021	0.293***	-0.055**	-0.222***	-0.034*	0.308***
	(0.025)	(0.036)	(0.019)	(0.035)	(0.026)	(0.038)	(0.020)	(0.037)
Other Meat	0.104***	0.265***	-0.000	-0.011	0.089***	0.275***	0.008	-0.004
	(0.023)	(0.044)	(0.016)	(0.043)	(0.024)	(0.047)	(0.016)	(0.046)
Demographic Variables:								
Constant	0.288***	0.992***	-0.047	0.498***	0.266***	1.038***	-0.019	0.497***
	(0.062)	(0.108)	(0.034)	(0.097)	(0.063)	(0.110)	(0.035)	(0.100)
Age < 20	0.073***	0.046***	-0.038***	0.004	0.074***	0.051***	-0.038***	0.006
	(0.010)	(0.014)	(0.006)	(0.014)	(0.010)	(0.014)	(0.006)	(0.014)
Age 20–64	0.047***	0.002	-0.032***	0.005	0.046***	0.002	-0.032***	0.006
	(0.015)	(0.023)	(0.008)	(0.023)	(0.016)	(0.023)	(0.009)	(0.024)
Age ≥65	0.045**	-0.079**	0.002	-0.037	0.045**	-0.078**	0.003	-0.036
	(0.021)	(0.032)	(0.012)	(0.032)	(0.021)	(0.032)	(0.012)	(0.033)
Education	-0.018	-0.012	0.009	-0.008	-0.018	-0.014	0.008	-0.009
	(0.012)	(0.018)	(0.007)	(0.018)	(0.012)	(0.018)	(0.007)	(0.019)
Urban	-0.065***	0.033	0.012	0.007	-0.066***	0.027	0.010	0.007
	(0.021)	(0.030)	(0.012)	(0.031)	(0.022)	(0.031)	(0.012)	(0.032)
Northeast	0.071**	0.091**	0.030**	-0.016	0.076***	0.101**	0.033**	-0.021
	(0.028)	(0.045)	(0.015)	(0.042)	(0.029)	(0.046)	(0.015)	(0.043)
Midwest	0.136***	0.001	-0.017	0.089**	0.145***	0.006	-0.018	0.088**
	(0.028)	(0.043)	(0.016)	(0.041)	(0.029)	(0.043)	(0.016)	(0.042)
South	0.071***	-0.055	0.000	0.156***	0.073***	-0.051	-0.001	0.159***
	(0.026)	(0.040)	(0.015)	(0.041)	(0.027)	(0.041)	(0.015)	(0.043)
Homeowner	-0.024	-0.058*	0.023*	-0.007	-0.023	-0.064*	0.023*	-0.011
	(0.022)	(0.034)	(0.012)	(0.033)	(0.022)	(0.034)	(0.013)	(0.034)
White	-0.007	-0.013	-0.125***	0.055	-0.005	-0.017	-0.130***	0.061
	(0.028)	(0.041)	(0.017)	(0.047)	(0.029)	(0.042)	(0.018)	(0.049)
Hispanic	-0.153***	0.230***	-0.042	0.231**	-0.158***	0.228***	-0.045	0.244**
	(0.053)	(0.081)	(0.031)	(0.108)	(0.055)	(0.083)	(0.032)	(0.112)
Female Planner	-0.026	-0.063*	-0.004	-0.060*	-0.026	-0.070**	-0.007	-0.061*
	(0.022)	(0.035)	(0.012)	(0.034)	(0.023)	(0.035)	(0.012)	(0.035)
Food Stamp	0.145***	0.018	-0.073	-0.037	0.149***	0.023	-0.073***	-0.033
	(0.045)	(0.061)	(0.023)	(0.063)	(0.047)	(0.063)	(0.023)	(0.066)
Heteroskedasticity Equation:								
Constant	-0.801***	-0.622***	-1.129***	-0.752***	-0.822***	-0.623***	-1.118***	-0.728***
	(0.033)	(0.044)	(0.018)	(0.542)	(0.034)	(0.044)	(0.018)	(0.055)
Income	-0.019	0.019	-0.143***	0.044	-0.018	0.016	-0.143***	0.033
	(0.038)	(0.043)	(0.022)	(0.054)	(0.039)	(0.041)	(0.022)	(0.054)

(continued . . .)

Table 2. Continued

Variable/ Description	Full-Information Maximum Likelihood (FIML)				Simulated Maximum Likelihood (SML)			
	Steak	Roast	Ground Beef	Other Beef	Steak	Roast	Ground Beef	Other Beef
Correlation:								
Steak		-0.327***	-0.332***	-0.106***		0.301***	-0.076***	-0.070**
		(0.029)	(0.021)	(0.034)		(0.029)	(0.023)	(0.036)
Roast			-0.234***	-0.173***			-0.223***	-0.219***
			(0.029)	(0.041)			(0.029)	(0.039)
Ground Beef				-0.182***				-0.270***
				(0.033)				(0.032)
Log Likelihood		-6,830.643				-6,998.153		

Notes: Single, double, and triple asterisks (*) denote statistical significance at the 10%, 5%, and 1% levels, respectively. Numbers in parentheses are asymptotic standard errors. FIML and SML parameter estimates (and standard errors) for the own-price coefficients for other meat (β_{55}) are -0.679 (0.090) and -0.683 (0.100), respectively.

Censoring in the dependent variables must be accommodated in calculation of the elasticities. Parallel to the method used by McDonald and Moffitt for the univariate and linear tobit model, the effects of prices, total meat expenditure, and demographic variables can be explored further by decomposing the dependent variables. For product i, the probability, conditional mean, and unconditional mean of expenditure share (w_i) are, respectively:

$$\Pr(w_i > 0) = \Phi\left[f_i(\theta)/\sigma_i\right], \tag{11}$$

$$E(w_i|w_i > 0) = f_i(\theta) + \sigma_i\phi\left[f_i(\theta)/\sigma_i\right]/\Phi\left[f_i(\theta)/\sigma_i\right], \tag{12}$$

$$E(w_i) = \Pr(w_i > 0)E(w_i|w_i > 0), \tag{13}$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ are the univariate standard normal pdf and cdf, respectively. These probability and mean expressions follow from the normality of the marginal distribution of each error term ε_i. Elasticities are derived by differentiating these expressions, and the formulas are presented in appendix B.

The elasticities calculated from the FIML estimates, along with standard errors for these elasticities derived by the delta method, are presented in table 3.[8] The total (unconditional) price and expenditure elasticities are decomposed into two components: probability and conditional elasticities. The probability elasticity represents the percentage change in probability that a household will consume the beef product given a percentage change in the price of beef or household expenditure. The conditional elasticity represents the percentage change in the beef consumption level of the consuming households given a percentage change in beef price or household expenditure. The unconditional elasticity, as the sum of probability and conditional elasticities, is an overall measure of responsiveness of quantity demanded to changes in an explanatory variable.

[8] The elasticities calculated from the SML estimates are not reported here because they are very close and similar to those obtained from the FIML estimates. These unreported elasticities are available from the authors upon request.

Table 3. Elasticities: Full-Information Maximum-Likelihood (FIML) Estimates, by Probability, Conditional Level, and Unconditional Level

	Price of:						Household Composition		
	Steak	Roast	Ground Beef	Other Beef	Other Meat	Meat Expend.	Age < 20	Age 20–64	Age ≥ 65
	Probability								
Steak	-0.195***	-0.025	-0.028	0.075**	-0.152***	0.326***	-0.427***	-0.101***	-0.108***
	(0.037)	(0.043)	(0.028)	(0.037)	(0.034)	(0.018)	(0.091)	(0.013)	(0.035)
Roast	-0.174***	-0.288***	-0.167***	0.404***	-0.287***	0.512***	-1.868***	-0.081***	-0.005
	(0.055)	(0.070)	(0.047)	(0.066)	(0.069)	(0.031)	(0.187)	(0.024)	(0.068)
Ground Beef	0.021	-0.069**	0.111***	0.028	-0.068***	-0.022***	0.064	0.048***	0.068***
	(0.025)	(0.033)	(0.029)	(0.025)	(0.019)	(0.006)	(0.046)	(0.007)	(0.018)
Other Beef	-0.180**	0.252***	0.054	-0.792***	0.495***	0.172***	-1.356***	-0.010	-0.020
	(0.070)	(0.098)	(0.053)	(0.082)	(0.102)	(0.045)	(0.253)	(0.035)	(0.100)
Other Meat	0.001***	0.001**	0.000	0.000	0.001*	-0.002***	0.012***	0.000***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.004)	(0.000)	(0.000)
	Conditional Level								
Steak	-1.110***	-0.014	-0.016	0.042**	-0.086***	1.185***	-0.242***	-0.057***	-0.061***
	(0.021)	(0.024)	(0.016)	(0.021)	(0.019)	(0.010)	(0.051)	(0.007)	(0.020)
Roast	-0.057***	-1.094***	-0.055***	0.132***	-0.094***	1.168***	-0.611***	-0.027***	-0.002
	(0.018)	(0.023)	(0.015)	(0.022)	(0.022)	(0.010)	(0.059)	(0.008)	(0.022)
Ground Beef	0.021	-0.068**	-0.892***	0.027	-0.067***	0.978***	0.062	0.047***	0.066***
	(0.025)	(0.032)	(0.028)	(0.025)	(0.019)	(0.006)	(0.045)	(0.007)	(0.017)
Other Beef	-0.042***	0.058***	0.012	-0.183***	0.115***	1.040***	-0.314***	-0.002	-0.005
	(0.016)	(0.023)	(0.012)	(0.019)	(0.024)	(0.011)	(0.058)	(0.008)	(0.023)
Other Meat	0.129***	0.061***	0.003	0.002	-0.941***	0.747***	1.285***	0.038***	0.016
	(0.013)	(0.017)	(0.007)	(0.020)	(0.027)	(0.011)	(0.065)	(0.008)	(0.022)
	Unconditional Level								
Steak	-1.305***	-0.039	-0.044	0.117**	-0.239***	1.511***	-0.669***	-0.158***	-0.170***
	(0.058)	(0.067)	(0.043)	(0.058)	(0.052)	(0.027)	(0.141)	(0.020)	(0.056)
Roast	-0.231***	-1.382***	-0.221***	0.536***	-0.381***	1.680***	-2.479***	-0.108***	-0.007
	(0.073)	(0.093)	(0.063)	(0.088)	(0.091)	(0.040)	(0.245)	(0.031)	(0.090)
Ground Beef	0.042	-0.137**	-0.781***	0.056	-0.135***	0.956***	0.126	0.094***	0.134***
	(0.050)	(0.066)	(0.058)	(0.050)	(0.038)	(0.012)	(0.092)	(0.014)	(0.036)
Other Beef	-0.222**	0.310***	0.066	-1.975***	0.610***	1.211***	-1.670***	-0.013	-0.025
	(0.087)	(0.120)	(0.065)	(0.102)	(0.126)	(0.056)	(0.310)	(0.043)	(0.123)
Other Meat	0.131***	0.113***	-0.050***	-0.083***	-0.844***	0.733***	1.297***	0.038***	0.016
	(0.019)	(0.027)	(0.019)	(0.022)	(0.025)	(0.010)	(0.065)	(0.008)	(0.022)

Notes: Single, double, and triple asterisks (*) denote statistical significance at the 10%, 5%, and 1% levels, respectively. Numbers in parentheses are asymptotic standard errors.

As shown in table 3, the own-price elasticities of probability are negative and significant at the 1% level for steak, roast, and other beef. However, the own-price elasticity of probability is positive and significant (though very small numerically) for ground beef, and is zero for other meat. Among the 20 cross-price elasticities of probability, 14 are statistically significant at the 5% level or lower. All conditional own-price elasticities are significant and negative, which are greater than unity (in absolute values) for steak and roast, and less than unity for ground beef, other beef, and other meat.

The unconditional elasticities suggest the demands for roast and other beef are all price elastic, whereas the demands for steak, ground beef, and other meat are price inelastic.[9] Our own-price elasticities are much lower than those reported by Capps and Havlicek, which ranged from −1.52 for ground beef to −1.83 for roast. Other studies, however, have reported much lower own-price elasticities. For instance, Heien and Pompelli found own-price elasticities ranging from −0.73 for steak to −1.11 for roast, while estimates reported by Gao and Spreen vary from −0.43 for ground beef to −0.65 for roast. In contrast, the expenditure elasticities estimated here agree more with those of previous studies. Similar to findings by Capps and Havlicek, Gao and Spreen, and Heien and Pompelli, this study shows steak, roast, and other beef are meat-expenditure elastic, while the expenditure elasticities are less than unity for ground beef and other meat. Note that these are elasticities with respect to total meat budget and not income or total budget. Two previous studies (Gao and Spreen; Heien and Pompelli) also found that the demand for ground beef was inelastic with respect to household expenditure, while Capps and Havlicek suggested otherwise. On the other hand, Nayga reported very income-inelastic demand for beef cuts, with elasticities ranging from 0.08 for roast to 0.14 for steak.

While it is difficult to compare elasticity estimates across studies, and it is unclear to what extent these different elasticities are caused by the various estimation procedures and different data, the demand elasticities obtained in this study appear to fall between the bounds of those reported in the meat demand literature. Caution should be exercised, however, when making comparisons among different studies because the methodologies differ greatly due to the use of various estimation procedures to address the censoring issues in the sample.

Also presented in table 3 are household composition elasticities. The results reveal that 10 of the 15 unconditional elasticity estimates are significantly different from zero at the 5% level or less, suggesting the demand for beef products does respond to changes in household members in a certain age group. Although not strictly comparable, Nayga found the demand for beef is unresponsive to changes in household size. It is interesting to note that changes in household composition generally have greater impacts on the demand for beef products in terms of changes in probabilities than changes in consumption level. This result appears counterintuitive because if the household likes beef, changes in household size would simply affect the appropriate quantity to consume. A plausible explanation may be attributed to the type of data used in the study. Specifically, given the nature of the cross-sectional data, there is not a temporal change in the number of members of the same household. Instead, it is a comparison of households with varying sizes across different households in the sample.

Summary and Conclusions

The objective of this study was to demonstrate the FIML and SML estimation of a system of censored demand equations for disaggregated beef products based on the USDA's 1987–88 Nationwide Food Consumption Survey. The system of demand equations for steak, roast, ground beef, other beef, and other meat was specified based on the translog functional form, and demand elasticities with respect to price, expenditure, and household composition were calculated.

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[9] The unconditional (total) elasticities are the relevant elasticities for comparison with the findings of previous studies not addressing or decomposing the censored dependent variables.

The study differs from most previous investigations in at least two important respects: (*a*) the FIML and SML estimators are more efficient than popular two-step estimation procedures, and (*b*) the total (unconditional) demand elasticities are decomposed into probability and conditional elasticities to accommodate censoring in the dependent variables. Furthermore, this study also explicitly accounts for adding-up in the presence of censored dependent variables.

In general, the estimated coefficients are very significant for most of the price as well as the demographic variables. The demands for roast and other beef are price elastic, while the demands for steak, roast, and other beef are also elastic with respect to total meat expenditure. Although price appears to be the dominating factor influencing the demand for beef products, the results also document the important and significant effects of demographic characteristics—such as household composition, urbanization, regional location, home ownership, ethnicity, gender of meal planner, and food stamp participation—on demand for beef products.

The decomposition of the total elasticity into probability and conditional elasticities also provides additional insights into the effects of changing prices and demographic characteristics on the probability and level of consumption. As might be expected, the level of consumption in different beef cuts is mostly affected by a change in beef price or meat expenditure. In contrast, the effects of changes in the demographic profile, such as household composition, on the demand for beef are reflected mostly in the changes of the consumption probability.

Although the NFCS data set used here is relatively old, it is nevertheless one of the most recent among existing data sets containing both product price information and household demographic characteristics. More current data sources, such as scanner data, on the other hand, tend to contain much less information on consumer sociodemographic characteristics. Interestingly, the lack of demographic information in the scanner data might also limit the use of existing two-step estimation procedures because sociodemographic variables are crucial to the first-step estimation, and therefore to correction of sample selectivity biases in the system.

We recognize that the NFCS data may not reflect current beef market and demand structure. Despite this caveat, our findings suggest the importance of demographic influences on the demand for beef, and confirm that additional insights may be gained about the nature of beef demand by focusing on disaggregate beef cuts rather than beef in general. Such aspects of meat demand are worthy of further investigation when new national survey data become available. Alternatively, consumer panel data would be an ideal data source to use for furthering our understanding about consumer demand for food products and purchasing behavior.

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Appendix A: The GHK Probability Simulator

Consider evaluation of K-variate cdf $\int_{\{\eta|\eta\le\mathbf{u}\}} d\eta$, where $\eta \sim N(0,\Omega)$. First, decompose Ω by Cholesky factorization such that $\Omega = \mathbf{LL}'$, where $\mathbf{L}$ is a lower-triangular matrix with elements ℓ_{km}, where $\ell_{km} = 0$ for all $m > k$, and $\ell_{km} > 0$ for $m = k$. Denote the kth element of $\mathbf{u}$ as u_k. The Geweke-Hajivassiliou-Keane (GHK) simulation procedure proceeds as follows for replication r:

- Calculate $z_{r1} = u_1/\ell_{11}$, and draw a random observation ζ_{r1} from $N(0,1)$ conditional on $[-\infty, z_{r1}]$.
- For each $k(k = 2, 3, ..., K-1)$, calculate $z_{rk} = \left(u_k - \sum_{m=1}^{k-1} \ell_{km}\zeta_{rm}\right)/\ell_{kk}$, and draw a random observation ζ_{rk} from $N(0,1)$ conditional on $[-\infty, z_{rk}]$.
- Calculate $z_{rK} = \left(u_K - \sum_{m=1}^{K-1} \ell_{Km}\zeta_{rm}\right)/\ell_{KK}$.

Repeat the above steps for R replications to obtain standard normal values $z_{rk}(r = 1, 2, ..., R;\ k = 1, 2, ..., K)$. Then,

$$\int_{\{\eta|\eta\le\mathbf{u}\}} d\eta \approx \frac{1}{R}\sum_{r=1}^{R}\sum_{k=1}^{K}\Phi(z_{rk}).$$

The above procedure is appropriate for a K-variate normal random variable with a zero mean vector. A random variable with nonzero mean can be accommodated by a straightforward transformation of variables.

Appendix B: Elasticity Formulas

Denote the denominator of the share equations in text equation (2) as

$$D = -1 + \sum_{j=1}^{n}\sum_{i=1}^{n}\beta_{ij}\log(p_j/m),$$

and the inverse Mills' ratio as

$$\lambda_i = \phi\left[f_i(\theta)/\sigma_i\right]/\Phi\left[f_i(\theta)/\sigma_i\right].$$

By differentiating text equation (11), the elasticities of probability of consuming good i with respect to price j (e_{ij}^P) and with respect to total meat expenditure (e_{im}^P) are obtained as follows:

$$e_{ij}^P = \sigma_i^{-1}\lambda_i\left(\beta_{ij} - w_i\sum_{k=1}^{n}\beta_{kj}\right)/D,$$

$$e_{im}^P = \sigma_i^{-1}\lambda_i\left(-\sum_{j=1}^{n}\beta_{ij} + w_i\sum_{k=1}^{n}\sum_{j=1}^{n}\beta_{kj}\right)\Big/D,$$

$$e_{i\ell}^P = \sigma_i^{-1}\lambda_i\,\alpha_{i\ell}z_\ell\big/D.$$

Differentiating text equation (12) yields the following conditional elasticities of good i with respect to price j (e_{ij}^C), meat expenditure (e_{im}^C), and the ℓth demographic variable ($e_{i\ell}^C$):

$$e_{ij}^C = -\delta_{ij} + \left\{\frac{1}{E(w_i|w_i>0)} - \frac{1}{\sigma_i}\lambda_i\right\}\left\{\frac{1}{D}\left(\beta_{ij} - w_i\sum_{k=1}^{n}\beta_{kj}\right)\right\},$$

$$e_{im}^C = 1 + \left\{\frac{1}{E(w_i|w_i>0)} - \frac{1}{\sigma_i}\lambda_i\right\}\left\{\frac{1}{D}\left(-\sum_{j=1}^{n}\beta_{ij} + w_i\sum_{k=1}^{n}\sum_{j=1}^{n}\beta_{kj}\right)\right\},$$

$$e_{i\ell}^C = \left[\frac{1}{E(w_i|w_i>0)} - \frac{1}{\sigma_i}\lambda_i\right]\left(\frac{1}{D}\alpha_{i\ell}\right)z_\ell,$$

where δ_{ij} is the Kronecker delta (i.e., $\delta_{ij} = 1$ if $i = j$; $\delta_{ij} = 0$ otherwise), and $E(w_i|w_i > 0)$ is the conditional mean in text equation (12). Using the multiplicative property [text equation (13)] of probability and means, the corresponding unconditional (total) elasticities can be calculated by summing the probability and conditional elasticities. Thus,

$$e_{ij}^U = e_{ij}^P + e_{ij}^C,$$

$$e_{im}^U = e_{im}^P + e_{im}^C,$$

$$e_{i\ell}^U = e_{i\ell}^P + e_{i\ell}^C.$$