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Household Demand for Finfish: A Generalized Double-Hurdle Model

Steven T. Yen and Chung L. Huang

This study estimates household demand for finfish in the United States using a limited dependent variable model that accounts for both participation and consumption decisions and also accommodates nonnormal and heteroskedastic errors. Results suggest that own-price elasticity is near unitary and income elasticity is small. Price of finfish, shopping frequency, Northeast, Black and other non-Whites, and the life-cycle variable "young, single, no children" are the key factors that affect significantly both the probability of participation and the level of finfish consumption. Furthermore, a variable may exert opposite effects on the probability and level of consumption.

Key words: double-hurdle model, finfish, heteroskedasticity, inverse hyperbolic sine transformation

Introduction

Per capita seafood consumption in the United States rose from 11.7 pounds in 1970 to 14.9 pounds in 1993 [U.S. Department of Agriculture (USDA) 1994]. Before 1982, consumption of fishery products was relatively stable and fluctuated around 12 pounds per capita (fig. 1). Total seafood consumption increased dramatically after 1982 and peaked at 16.1 pounds per capita in 1987. Per capita consumption has been relatively stable in recent years. As shown in figure 1, nearly two-thirds of the seafood was consumed as fresh and frozen products. Among the fresh and frozen seafood products, finfish consumption increased from 4.5 pounds per capita in 1970 to 6.3 pounds in 1993, accounting for more than 56% of the total increase in seafood consumption.

With the growing importance of finfish, empirical findings on the price and income responses of finfish demand become increasingly important for producers and marketers alike. However, relatively little empirical evidence on seafood consumption is available in the United States. Early studies tend to be descriptive (Miller and Nash; Nash). The more recent and comprehensive studies have used survey data to analyze the U.S. demand for seafood at the household level (Capps; Cheng and Capps; Dellenbarger et al.; Keithly; Nayga and Capps).

A great barrier to using survey data is the significant proportion of households that report zero consumption. Such zero observations must be accommodated to obtain consistent parameter estimates. Previous studies of seafood demand have used the tobit model to address the problem of zero consumption (Dellenbarger et al.; Keithly). How-

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Steven T. Yen is lecturer in the Department of Economics, University of Illinois at Urbana-Champaign and formerly visiting assistant professor at Iowa State University, where research for this study was initiated. Chung L. Huang is professor in the Department of Agricultural and Applied Economics, University of Georgia.

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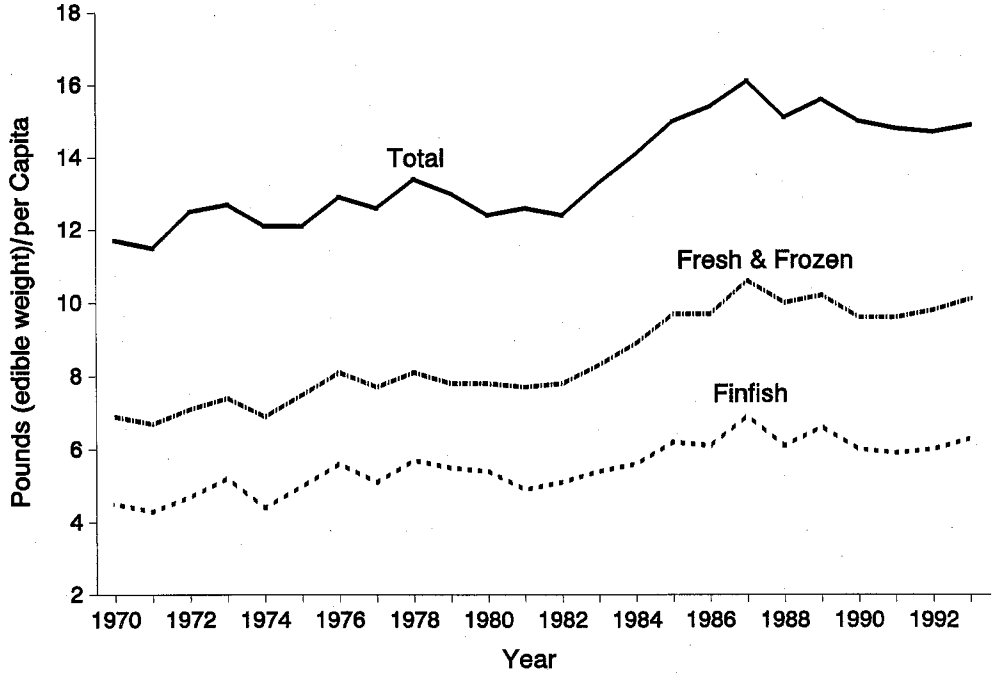

Figure 1. U.S. per capita consumption of fishery products, 1970–93

ever, the tobit model is very restrictive in its parameterization because the factors that affect the level of consumption are assumed the same as those that determine the probability of consumption. Furthermore, empirical results obtained with the tobit model often are not robust across distributional assumptions (Arabmazar and Schmidt 1981, 1982). Such limitations make the tobit model unpalatable for empirical analysis.

Cheng and Capps applied Heckman's two-step procedure in a study of U.S. seafood consumption. In the Heckman procedure, an inverse Mills ratio is included in the demand equation to correct for sample selectivity bias.[1] Although the Heckman procedure allows the flexibility of parameterizing the probability and level of consumption separately, it produces a less efficient estimator than the maximum likelihood (ML) tobit estimator and performs poorly when the normality assumption is violated. Some Monte Carlo experiments also show that the tobit estimator outperforms Heckman procedure under the assumption of normality, but neither performs well when the errors are Cauchy (Paarsch).[2]

We explore an alternative approach to addressing the zero observation issues in demand analysis with micro data. Specifically, we extend the double-hurdle model proposed by Cragg. The double-hurdle model is a parametric generalization of the tobit model, in which the decision to consume and the level of consumption are determined by two separate stochastic processes. In some respects, parameterization of the double-hurdle model is similar to that of the Heckman procedure in that two separate sets of parameters are obtained in both cases. More significantly, the objective of this study is to develop

[1] With this procedure, correction for heteroskedasticity can be considered but may not always be accommodated (Capps and Cheng).

[2] Since the tobit likelihood is generally well behaved, there is little advantage in using the Heckman two-step technique.

and estimate a generalized double-hurdle model that accommodates both nonnormality and heteroskedasticity of the error terms. The generalized model was used to estimate U.S. household demand for finfish, using data obtained from the 1987–88 Nationwide Food Consumption Survey (NFCS) (USDA 1992).

The Generalized Double-Hurdle Model

As pointed out, the tobit model has gained increasing popularity among demand analysts who use household or individual survey data to study consumption pattern and behavior. The tobit model is very restrictive in the sense that the variables and parameters determining the probability of consumption also determine the level of consumption. Cragg proposed the double-hurdle model, which allows separate stochastic processes for the participation and consumption decisions. The double-hurdle model has a participation equation:

$$d_t^* = z_t'\alpha + \eta_t, \tag{1}$$

and a consumption equation:

$$y_t^* = x_t'\beta + \epsilon_t, \tag{2}$$

where d_t^* is a latent participation indicator, y_t^* is latent consumption, z_t and x_t are vectors of explanatory variables, and α and β are conformable vectors of parameters. The error terms η_t and ϵ_t are independently and normally distributed such that $\eta_t \sim N(0, 1)$, $\epsilon_t \sim N(0, \sigma_t)$, and ϵ_t is truncated at $-x_t'\beta$. The observed consumption (y_t) relates to the latent consumption (y_t^*) such that

$$\begin{aligned} y_t &= y_t^* && \text{if } d_t^* > 0, \\ &= 0 && \text{otherwise.} \end{aligned} \tag{3}$$

The likelihood function for the double-hurdle model can be constructed using (1), (2), and (3) (Cragg). The double-hurdle model reduces to the tobit model when $z_t = x_t$ and $\alpha = \beta/\sigma_t$. Empirical applications of the double-hurdle model include Haines, Guilkey, and Popkin and Reynolds.

The double-hurdle model is built upon the normality assumption of the error terms η_t and ϵ_t. However, the usual ML estimates which assume normality are inconsistent when the normality assumption is violated (Arabmazar and Schmidt 1982). One way to accommodate nonnormal error terms is by transforming the dependent and latent variables, in which case the latent consumption equation can be written as:

$$T(y_t^*) = x_t'\beta + \epsilon_t, \tag{4}$$

where $T(\cdot)$ is some form of transformation. The observed consumption (y_t) relates to the latent consumption (y_t^*) such that

$$T(y_t) = \begin{cases} T(y_t^*) & \text{if } d_t^* > 0, \\ T(0) & \text{otherwise.} \end{cases} \tag{5}$$

Yen used the Box-Cox transformation with the double-hurdle model and his findings suggest nonnormal errors.

One major problem with the Box-Cox transformation is that the error terms ϵ_t in (2) cannot strictly be normally distributed because the Box-Cox transformation is not defined when $y_t^* < 0$ (Maddala). To overcome this problem, alternative transformations must be used. Reynolds and Shonkwiler incorporated the inverse hyperbolic sine (IHS) transformation in the tobit model. In this study, we incorporate the IHS transformation in the more flexible double-hurdle model, which circumvents the restrictive parameterization imposed by the tobit model. The IHS transformation of random variable v is defined as (Burbidge, Magee, and Robb):

$$(6) \qquad \begin{aligned} T(v) &= \log[\theta v + (\theta^2 v^2 + 1)^{1/2}]/\theta \\ &= \sinh^{-1}(\theta v)/\theta, \end{aligned}$$

for all values of θ. Since the transformed variable is symmetric about 0 in θ, one can consider only $\theta \geq 0$. The transformation is linear when θ approaches zero and behaves logarithmically for large values of v for a wide range of θ; it also has the desirable property of being scale-invariant (MacKinnon and Magee). In addition, this transformation can be performed on any random variables with positive and negative values.

The likelihood function of the IHS transformed double-hurdle model (5) can be written as

$$(7) \qquad L = \prod_{y_t=0} [1 - \Phi(z_t'\alpha)] \prod_{y_t>0} \Phi(z_t'\alpha)\left[\Phi\left(\frac{x_t'\beta}{\sigma_t}\right)\right]^{-1} \frac{1}{\sigma_t}\phi\left[\frac{T(y_t - x'_t\beta}{\sigma_t}\right]\frac{1}{(1 + \theta^2 y_t^2)^{1/2}},$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ are standard normal density and cumulative distribution functions, respectively.

In assessing the generalized double-hurdle model's appropriateness for demand analysis, we note that zero-valued observations in household survey data may be generated from different sources such as abstention, misreporting, and infrequency of purchases. Unfortunately, survey data generally do not contain detailed enough information to identify the different sources of zero observations. Yen has argued that, when carefully interpreted, the probability of consumption in the double-hurdle model also reflects the probability of purchase, and therefore, the double-hurdle model is also appropriate in modeling demand relationship with zeros resulting from infrequency of purchases. Jones and Posnett, appealing to the reduced-form argument of Hausman, suggest that the double-hurdle model can be viewed as the reduced form of a structural model that augments the demand equation with separate hurdles for different nonbehavioral sources of zeros.

The likelihood function (7) nests the IHS tobit model considered by Reynolds and Shonkwiler when $z_t = x_t$ and $\alpha = \beta/\sigma_t$. In addition, imposing restriction $\theta = 0$ on the generalized double-hurdle and IHS tobit models leads to the standard double-hurdle and tobit models, respectively. Thus, selection among these models can be done conveniently by the likelihood-ratio (LR) tests or, for restrictions involving a single parameter, t tests.

In limited dependent variable models, heteroskedastic errors cause inconsistency of the parameter estimates (Arabmazar and Schmidt 1981). To correct for potential heteroskedastic errors, the standard deviation σ_t can be specified as:

$$(8) \qquad \sigma_t = \exp(w_t'\gamma),$$

where w_t is a vector of exogenous variables, and γ is a conformable parameter vector. The exponential form in (8) is common among heteroskedastic specifications in traditional regression models and limited dependent variable models (e.g., Maddala). The unknown parameters are α, β, σ, θ, and γ; these can be estimated by the ML method.

Examining the Effects of Variables

McDonald and Moffitt suggest that in the tobit model the total or unconditional effect of an explanatory variable on the dependent variable can be examined in terms of the effects on the probability of participation and the conditional level of consumption. Such a decomposition of effects is especially complicated for the generalized double-hurdle model considered here. The transformation of variable, the double-hurdle parameterization, and the heteroskedastic error specification have drastically increased the complexity in decomposing the effects. For the generalized double-hurdle model, the probability of observing positive consumption is

$$(9) \qquad \mathrm{Prob}(y_t > 0) = \Phi(z_t'\alpha),$$

and the conditional mean of y_t, which measures the average consumption given that the probability of participation is greater than zero, is

$$(10) \qquad E(y_t|y_t > 0) = \left[\Phi\left(\frac{x_t'\beta}{\sigma_t}\right)\right]^{-1} \int_0^\infty y_t \frac{1}{\sigma_t}\phi\left[\frac{T(y_t) - x_t'\beta}{\sigma_t}\right]\frac{1}{(1 + \theta^2 y_t^2)} \, dy_t.$$

Then, the unconditional mean of y_t, which measures the overall average consumption, is

$$(11) \qquad E(y_t) = E(y_t|y_t > 0)\ \mathrm{Prob}(y_t > 0).$$

In order to calculate the elasticities of the probability of participation, conditional level, and unconditional level of consumption with respect to an explanatory variable, we need to derive the marginal effects. These marginal effects are obtained by differentiating (9), (10), and (11) with respect to the particular explanatory variable. Note that with the standard double-hurdle model ($\theta = 0$), the Jacobian of transformation $1/(1+\theta^2 y_t^2)^{1/2}$ on the right-hand side of (10) vanishes and the conditional mean reduces to that of a truncated normal regression model, which involves only evaluations of the univariate normal distribution function (Amemiya, p. 367; Maddala, p. 158). For the unrestricted case, such convenient form does not exist and the conditional mean, unconditional mean, and the corresponding elasticities must be evaluated with numerical procedures.

For statistical inferences, we also calculated the standard errors of the estimated elasticities. Denote the vector of all parameters as $\tau = [\alpha', \beta', \theta, \gamma']'$, with ML estimator $\hat{\tau}$ and variance-covariance matrix Σ, and denote a specific elasticity (a scalar) as $e = h(\hat{\tau})$. Then, the variance of e can be approximated by the "delta method" (Serfling):

$$(12) \qquad \mathrm{var}(e) = \left[\frac{\partial h(\hat{\tau})}{\partial \hat{\tau}'}\right] \Sigma \left[\frac{\partial h(\hat{\tau})}{\partial \hat{\tau}}\right].$$

The major difficulty with this calculation is the differentiation of the already complicated function for the elasticity $h(\hat{\tau})$ with respect to $\hat{\tau}$. This can be done with numerical differentiation.

Data

The data for this study came from the 1987–88 U.S. Nationwide Food Consumption Survey (NFCS), which was conducted by the Human Nutrition Information Service (HNIS) of the U.S. Department of Agriculture from April 1987 to August 1988 (USDA 1992). The survey collected detailed information on household food use during a seven-day period as well as socioeconomic and demographic characteristics of the household. For over fifty years, the food consumption surveys conducted by the USDA have provided the most comprehensive data available for analyzing food consumption behavior and dietary status of Americans. However, it should be noted that the reliability and validity of the 1987–88 NFCS data might have been compromised due to potential non-response biases and quality control problems. For instance, the final response rate for the household component of the survey was only 37% (Guenther and Tippett).

For each product, the quantity (pounds) and cost (dollars) of weekly household consumption were recorded. Such information allows derivation of the unit value. The use of unit values as prices has presented some difficulties and has received much attention in cross-sectional demand analysis. On the one hand, unit values are not defined for nonconsuming households; this is the missing data (regressors) problem. On the other hand, as discussed by Deaton, the unit values derived in this manner reflect more than spatial price variations. Consumers choose the quality of their purchases, and unit values reflect this choice (Deaton). Therefore, these unit values should be adjusted for quality variations before they can be used in a demand equation. Using only the subsamples of consuming households, Cox and Wohlgenant estimated unit value equations for three broad aggregated vegetable products. The estimated price equations were then used to predict "quality-adjusted" prices for nonconsuming households. The major difficulty of this approach is, in most cases, it is impossible to obtain consistent estimates for the unit value equation independent of the quantity equation (Wales and Woodland).[3] The use of multiple predicted prices also inevitably introduces heteroskedasticity in the error terms, further complicating the estimation procedure.

In view of these difficulties, we took a more practical approach to this complex problem.[4] Based on information from the consuming households, we calculated the averages of unit values for nine geographic regions (New England, Middle Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, and Pacific) and four seasons, giving a total of 36 prices. The calculation filters out quality variations in the unit values. To capture cross-price effects, prices for canned tuna fish and meat were derived following the same procedure.

The original sample contains 4,495 households. However, the HNIS suggested that only data for 4,273 housekeeping households are suitable for analysis because these households contain more comprehensive information on home food practice (USDA 1992).[5] In addition, households with missing information on important variables were excluded. This resulted in a final sample of 4,066 households.

[3] We thank an anonymous reviewer for referring us to this literature.

[4] Aside from the estimation difficulties, previous empirical findings seem to support the use of a more practical approach. For instance, Cox and Wohlgenant concluded that while failing to adjust prices for quality effects could induce parameter biases, the differences caused by these adjustments, if any, were small. Their study shows that this result holds even at the broad aggregated commodity level such as vegetables, which apparently was not sufficiently heterogenous to induce significant quality effects.

[5] The housekeeping household is defined as a household with at least one person having 10 or more adjusted meals (or 21 meal-at-home equivalent) from the household food supply during seven days prior to the interview (USDA 1992).

In the empirical model, the dependent variable is the quantity of all fresh and frozen finfish purchased (lbs. per household). Included as explanatory variables are prices for finfish, canned tuna fish, and meat; weekly household income; and a set of demographic variables. Use of demographic variables is common in previous studies of seafood demand (Capps; Cheng and Capps; Dellenbarger et al.; Keithly; Nayga and Capps). The demographic variables commonly considered include: household size, urbanization, race, education, region, and employment. For instance, Cheng and Capps concluded that demographic variables such as household size, race, geographic region, and urbanization are important factors in explaining the variation of household expenditures on fresh and frozen seafood commodities for at-home consumption. Nayga and Capps also found urbanization, region, race, ethnicity, age, and seasonality to be significant determinants of at-home fish and shellfish consumption based on the individual intake data of the 1987–88 NFCS.

The demographic variables specified in the empirical model include household size, dual income status, race, education, and occupation of the household head, urbanization and location of residence, type of store shopped, shopping frequency, and a set of family life-cycle variables. Except for education and household size, variables representing household socioeconomic characteristics are specified as binary variables. Specifically, the occupation of the household head is classified as professional, clerical, or other. For households reporting major grocery shopping at a nonsupermarket, the nonsupermarket variables is coded 1; 0 otherwise. For households reporting frequent shopping (at least once a week), the shopping frequency variable is coded 1; 0 otherwise. A total of 10 family life-cycle variables are also defined based on age and marital status of the household head and presence of children (Murphy and Staples).

Table 1 presents the sample statistics of all variables used. The results suggest that 70.7% of the households live in urban areas (central city and suburban), 20.6% live in the Northeast, 26.2% live in the Midwest, and 18.6% live in the West. Comparisons of these sample characteristics with the U.S. Census statistics (U.S. Department of Commerce) suggest that these sample characteristics are representative of the U.S. population, except that households from the West may be marginally underrepresented (t-value = 1.61). The mean household size is 2.83, which is significantly different from the population mean in 1987; this is likely due to the fact that households with exactly two adults and those with a male and a female head were overrepresented (Guenther and Tippett, p. 6).

The proportion of households with zero observations is high, with only 1,059 households (26%) reporting positive consumption of finfish during the sampling period. This proportion of nonzero observations for finfish is slightly lower than that reported by Cheng and Capps (27.6%). The weekly consumption of finfish averages about 2.27 lbs. for the consuming households and 0.59 lb. for the full sample.

Parameter Estimates

The generalized double-hurdle model was estimated by maximizing the logarithm of the likelihood function (7).[6] As theory provides no guidance in the choice of regressors to

[6] Numerical optimization was carried out with the quadratic hill-climbing algorithm. The Hessian matrix was derived by numerically differentiating the analytic gradient and was inverted to derive the variance-covariance matrix of the ML estimates. The log-likelihood, analytic gradient, and outer product of the gradient were programmed in double-precision FORTRAN, using numerical optimization routines from the GQOPT program released by Professor Richard Quandt of Princeton University.

Table 1. Sample Statistics: Household Demand for Finfish

Variable	Mean	Standard Deviation
Finfish (lbs./week)	0.591 (2.268)[a]	1.809 (2.960)[a]
Price of finfish ($/lb.)	2.984	0.472
Price of canned tuna ($/lb.)	2.183	0.237
Price of meat ($/lb.)	1.628	0.130
Income ($00/week)	5.327	4.511
Household size	2.826	1.441
Education of head (years)	12.925	3.042
Binary variables (yes = 1; 0 otherwise):		
Urban	0.707	
Shopping frequency (>1)	0.617	
Nonsupermarket	0.053	
Dual income	0.307	
Northeast	0.206	
Midwest	0.262	
West	0.186	
Professional	0.335	
Clerical	0.077	
Blacks and other non-Whites	0.152	
Family life-cycle (binary) variables:		
Young (≤34), single	0.046	
Young, single, with children	0.038	
Young, married, no children	0.045	
Young, married, with children	0.137	
Middle age (35–64), single, no children	0.081	
Middle age, single, with children	0.049	
Middle age, married, no children	0.172	
Middle age, married, with children	0.211	
Older (≥65), single	0.104	
Older, married (reference)	0.119	

Source: Compiled from the 1987–88 Nationwide Food Consumption Survey (USDA 1992).
Note: The sample size was 4,066.
[a] Computed from the subsample of 1,059 consuming households.

explain the first and second hurdles, the same set of variables was used in both the participation and consumption equations.[7] With respect to specification of the variance equation (8), we experimented with various variables and different functional forms, including the linear form and the implied square-root form used by Reynolds and Shonkwiler.[8] The exponential form (8) led to a slightly larger likelihood value than the others, but the parameter estimates and statistical significance were very similar across all functional forms considered.

[7] The different sets of parameters (α and β) nevertheless provide flexibility in explaining the two decisions.
[8] This approach is tedious but offers a practical solution to correcting for heteroskedasticity of unknown forms. We did not use the information matrix test because the Hessian matrix is extremely complicated for the model used here. We chose the more convenient LR tests.

Only household size and the intercept were statistically significant and included in the final variance equation.

In our preliminary analysis we also estimated the double-hurdle, the standard tobit, and the IHS tobit models. Likelihood-ratio tests reject all these restricted models. In terms of distributional assumptions of the error terms, the null hypotheses that the errors are homoskedastic and distributed as truncated normal are both rejected. In addition, the Box-Cox double-hurdle model (Yen) was also considered but was rejected based on a nonnested LR test (Vuong).

The parameter estimates of the generalized double-hurdle model are presented in table 2. Consistent with the LR test, the estimate of the IHS parameter (θ) is significantly different from zero at the 0.10 significance level. The results show that price of finfish, shopping frequency, Northeast, Black and other non-Whites, and the life-cycle variable "young, single, no children" are the key factors that significantly affect both the probability of participation and the level of finfish consumption.

The significant but opposite effects of shopping frequency on participation and consumption are particularly noteworthy. The result suggests that households doing grocery shopping frequently (more than once a week) are more likely to purchase finfish than others. However, the levels of consumption among the frequent shoppers are lower than those of less frequent shoppers. This result interestingly suggests that the consumption pattern of frequent shoppers is significantly different from that of less frequent shoppers. Specifically, the frequent shoppers tend to purchase finfish more often, but the amount of their purchases are relatively small as compared with less frequent shoppers. Income, price of canned tuna fish, and binary variables representing urban and Midwest significantly affect the probability of purchasing finfish but not the conditional level of consumption. The opposite is true for household size, price of meat, and sociodemographic variables representing dual income, nonsupermarket shoppers, professional, West, and life-cycle variables "young, married, no children" and "young, married, with children" and "middle age, single with children;" these variables are significant in the consumption equation but not in the participation equation. These different/conflicting effects of variables on participation and consumption particularly highlight the flexibility and advantage of the double-hurdle parameterization, which is not possible in the tobit model.

Elasticities and Effects of Binary Variables

The elasticities of probability of participation, conditional and unconditional level of consumption, and their corresponding standard errors are evaluated at the sample means of all variables. The results are presented in table 3. The effects of own price are significant and negative on the probability and levels of consumption. In particular, a 1% increase in the price of finfish decreases the probability of consumption by 0.47%, the conditional level of consumption by 0.62%, and the unconditional level of consumption by 1.09%. These own-price elasticities are large relative to the income elasticities. Cheng and Capps reported a much lower own-price elasticity of -0.67 for at-home consumption of fresh and frozen finfish. The own-price elasticity reported in Cheng and Capps is based on the second-step estimation of the Heckman procedure, which, in fact, can be interpreted as an equivalent measure of the conditional elasticity obtained in this study.

Canned tuna is a gross substitute to finfish. The price of canned tuna fish has a significant

Table 2. Maximum Likelihood Estimates of the Generalized Double-Hurdle Model: Household Demand for Finfish

Variable	Participation	Consumption	Heteroske-dasticity
Constant	−1.652*	2.921	2.014*
	(0.474)	(12.313)	(0.090)
Finfish price	−0.125*	−5.103*	
	(0.076)	(1.984)	
Canned tuna price	0.218*	1.494	
	(0.110)	(3.149)	
Meat price	0.271	−12.662*	
	(0.254)	(6.425)	
Income	0.016*	−0.013	
	(0.006)	(0.151)	
Household size	0.004	2.685*	−0.044*
	(0.024)	(0.565)	(0.020)
Education	0.006	0.194	
	(0.009)	(0.239)	
Urban	0.147*	−1.283	
	(0.051)	(1.415)	
Shopping frequency (>1)	0.094*	−2.847*	
	(0.046)	(1.239)	
Nonsupermarket	−0.075	5.744*	
	(0.100)	(2.604)	
Dual income	−0.053	−3.357*	
	(0.057)	(1.474)	
Northeast	0.265*	6.515*	
	(0.105)	(2.687)	
Midwest	0.102*	0.741	
	(0.061)	(1.612)	
West	0.116	7.942*	
	(0.093)	(2.587)	
Professional	0.090	5.280*	
	(0.055)	(1.515)	
Clerical	0.118	2.421	
	(0.085)	(2.316)	
Blacks and other non-Whites	0.242*	16.252*	
	(0.064)	(2.114)	
Young, single, no children	−0.382*	−8.666*	
	(0.132)	(3.892)	
Young, single, with children	−0.052	−4.119	
	(0.132)	(3.771)	
Young, married, no children	−0.110	−7.444*	
	(0.126)	(3.241)	
Young, married, with children	−0.005	−7.739*	
	(0.097)	(2.624)	
Middle age, single, no children	−0.154	−4.835	
	(0.104)	(3.173)	
Middle age, single, with children	−0.064	−5.806*	
	(0.121)	(3.013)	
Middle age, married, no children	−0.016	−0.388	
	(0.084)	(2.422)	
Middle age, married, with children	0.008	−4.148	
	(0.096)	(2.536)	
Older, single	−0.008	−6.708*	
	(0.098)	(2.803)	
θ		0.123*	
		(0.019)	
Log-likelihood	−4,107.372		

Note: Asymptotic standard errors in parentheses. Asterisk indicates significance at the 0.10 level.

Table 3. Elasticities with Respect to Continuous Variables: Household Demand for Finfish

Variable	Probability	Conditional Level	Unconditional Level
Finfish price	−0.470*	−0.618*	−1.088*
	(0.286)	(0.243)	(0.375)
Canned tuna price	0.599*	0.132	0.731*
	(0.303)	(0.277)	(0.410)
Meat price	0.557	−0.838*	−0.281
	(0.521)	(0.429)	(0.675)
Income	0.107*	−0.003	0.104*
	(0.039)	(0.042)	(0.058)
Household size	0.015	0.072	0.088
	(0.085)	(0.107)	(0.137)
Education	0.094	0.102	0.196
	(0.149)	(0.132)	(0.199)

Note: Asymptotic standard errors in parentheses. Asterisk indicates significance at the 0.10 level.

and positive effect on the probability of consumption but not on the conditional level of consumption. The resulting elasticity of unconditional level is positive (0.73) and significant. The elasticity of probability of consumption with respect to canned tuna price is about 0.6, which accounts for approximately 82% of the total elasticity of unconditional level of finfish consumption. The magnitude and significance of the elasticity of probability relative to the elasticity of conditional level of consumption suggest that the probability of consumption is the dominant factor that affects finfish consumption. More specifically, the result shows that as the tuna price increases, its major impact is to increase the probability of nonconsuming households to purchase finfish instead of increasing the level of consumption for those consuming households. Thus, the effect of tuna price on household seafood consumption is concentrated primarily on attracting consumers to enter into or exit from the finfish market.

Surprisingly, the price of meat has a significant and negative effect on the conditional level of consumption and a positive, though insignificant, effect on the probability of consumption. The resulting effect of price of meat is insignificant on the unconditional level of consumption because of the offsetting effects on the probability of participation and conditional level of consumption. This finding is in agreement with that of Cheng and Capps, which shows cross-price effects of red meat and poultry on household consumption of seafood products were virtually nonexistence and statistically insignificant. Overall, the cross-price elasticities are small relative to the own-price elasticities, suggesting that substitutions between finfish and other meat/fish products do occur but are not the dominating factors in finfish consumption.

Household income increases consumption by increasing the probability of participation but not the conditional level of consumption. However, the income elasticities are very small. In particular, a 1% increase in household income increases the probability and unconditional level of consumption by only about 0.1%. The low-income elasticities suggest finfish consumption is not likely to increase dramatically as household income increases or during economic booms. Given that the own-price effect is elastic, it seems that aggressive pricing strategies would be a more effective means for seafood marketers to promote and boost sales. Household size and education have no significant effects on the probability of partic-

Table 4. Effects of Binary Variables: Household Demand for Finfish

Variable	Probability	Conditional Level	Unconditional Level
Urban	0.046*	−0.104	0.066
Shopping frequency (>1)	0.030*	−0.233*	0.001
Nonsupermarket	−0.024	0.564*	0.086
Dual income	−0.017	−0.256*	−0.097
Northeast	0.087*	0.535*	0.317
Midwest	0.032*	0.049	0.068
West	0.036	0.694*	0.243
Professional	0.029	0.446*	0.174
Clerical	0.038	0.183	0.121
Blacks and other non-Whites	0.082*	2.298*	0.894
Young, single	−0.110*	−0.704*	−0.371
Young, single, with children	−0.017	−0.390	−0.138
Young, married, no children	−0.035	−0.628*	−0.230
Young, married, with children	−0.002	−0.647*	−0.177
Middle age, single, no children	−0.048	−0.446	−0.213
Middle age, single, with children	−0.021	−0.518*	−0.178
Middle age, married, no children	−0.005	−0.043	−0.023
Middle age, married, with children	0.003	−0.393	−0.100
Older, single	−0.003	−0.580*	−0.161

Note: The effects of each binary variable were calculated as the changes in probability, conditional level, and unconditional level of consumption resulting from a finite change in the variable. See text for details.
Asterisk indicates significance of corresponding parameter estimates at the 0.10 level (see table 2).

ipation or conditional and unconditional levels of consumption. Contrary to the common belief that the educated may be better informed about healthy diets and tend to consume more fish than red meats, we find no evidence that higher educational attainment significantly increases the level of participation or consumption of finfish in the United States.

For binary variables, elasticities are not strictly defined. The effects of each binary variable were obtained by calculating the changes in probability, conditional, and unconditional level of consumption as a result of a finite change (e.g., from 0 to 1) in the variable, ceteris paribus. The results are presented in table 4. Relative to other households, Blacks and other non-Whites are about 8% more likely to consume finfish and, conditional on consumption, consume about 2.3 lbs. more per week than Whites. Overall, the total unconditional effect indicates that weekly consumption of finfish among the non-White households is about 0.9 lb. more than other households. This finding is in accordance with Cheng and Capps, who reported that Blacks and other non-Whites are more likely than their counterparts to consume finfish in terms of participation and level of consumption. A recent study by Nayga and Capps also confirms that Blacks are more likely to consume fish. The interpretation of other binary variables is similar.

Table 5 summarizes and compares the results of this study with a number of other studies. The comparison is focused primarily on the effects of common key variables: prices, income, household size, education, and race. Our own-price elasticity (of the unconditional level of consumption) is much higher, in absolute value, than that reported by Capps (on total seafood), and Cheng and Capps. While the income elasticity obtained

Table 5. Results from Other Studies of Fish and Finfish

Product	Study and Data Source	Elasticities: Own Price	Meat Price	Income	Household Size	Education	Blacks/Other Non-Whites
Finfish	Current study/1987–88 NFCS Household	−1.09	N.S.[a]	0.10	N.S.	N.S.	More likely and more
Finfish	Keithly/1977–78 NFCS Household			0.15	0.56		
Finfish	Cheng and Capps/1981 Seafood Consumption Survey	−0.67	N.S.	0.14	0.33	N.S.	Positive
Total seafood	Capps/1972–74 BLS CES-Diary	−0.47		0.17	0.23		
Fish and shellfish at home[b]	Nayga and Capps/1987–88 NFCS Individual Intake			Positive	N.S.		Positive[c]

[a] N.S. denotes the estimated coefficient for the variable was not statistically significantly different from zero.
[b] Binary choice analysis.
[c] Blacks only.

in this study is slightly smaller than those reported in the literature, it is consistent with previous findings that the income elasticity is under 0.2 and relatively inelastic. As in Cheng and Capps, we find the price of meat does not affect finfish consumption. Interestingly, similar to Cheng and Capps, and Nayga and Capps, we find Blacks and other non-Whites are more likely than Whites to consume finfish both in terms of probability of participation and the level of consumption. Perhaps a marketing campaign directed towards this group will have a great potential of promoting sales.

Concluding Remarks

This study addresses the issues of zero-valued observations in household consumption of finfish by using a generalized double-hurdle model that incorporates the inverse hyperbolic sine transformation of the dependent variable. The major advantages of this model are that it provides flexibility in parameterization and also accommodates non-normal and heteroskedastic errors. The results attest to previous findings that, in some cases, a tobit model may be inappropriate for modeling the underlying consumption behavior due to its restrictive parameterization. Based on likelihood-ratio tests, the tobit parameterization, normality, and homoskedasticity are all rejected.

The generalized double-hurdle model is particularly relevant for studying seafood consumption behavior because the decisions on participation and consumption are likely to differ. Results of this kind of analysis are useful for seafood marketers in planning and developing marketing strategies, because they allow differentiating between variables explaining if finfish is consumed and the variables determining how much is consumed. For instance, the significant and positive effect of income on the probability of consumption and its insignificant effect on the conditional level of consumption suggests that, during economic booms, those consuming finfish are not likely to consume a lot more, while those "marginal consumers" may start consuming seafood. Likewise, when the price of canned tuna fish increases, more people will consume finfish because the effect of that price on the probability of consumption is significant and positive. However, those consuming finfish are not likely to consume more because of its insignificant effect on the conditional level of consumption.

The generalized double-hurdle model considered in this study features two stochastic processes that determine the probability and conditional level of consumption. These two stochastic processes are assumed to be independent. In some cases, dependence between the participation and consumption decisions may be important. Therefore, further studies might consider incorporating such dependence. In addition, while we focus on a single-commodity framework and consider only finfish, the information on household consumption of other fish and seafood products will be very useful for the seafood industry. Further research might consider the use of the generalized double-hurdle model or other two-step decision model in a multicommodity framework. Although a multicommodity system framework will provide more specific and definitive results, the theoretical development for such a framework is likely to be very complicated. The difficulty arises primarily because two decisions (participation and consumption) have to be explained for each commodity and the interdependency of those decisions has to be considered and modeled within a simultaneous framework.

Finally, in view of the potential problems associated with the quality of the 1987–88 NFCS data, the findings reported in this study should be interpreted with caution. It may be advisable for future studies to consider adjustment for nonresponse biases, through some weighted estimation procedure, when using the 1987–88 NFCS data. Further studies might also consider the use of other, more recent data sources, such as USDA's Continuing Surveys of Food Intakes by Individuals or Bureau of Labor Statistics' Consumer Expenditure Surveys, in which case, results of the current study can be compared.

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References

Amemiya, T. *Advanced Econometrics.* Cambridge MA: Harvard University Press, 1985.

Arabmazar, A., and P. Schmidt. "Further Evidence on the Robustness of the Tobit Estimator to Heteroskedasticity." *J. Econometrics* 17(1981):253–58.

———. "An Investigation of the Robustness of the Tobit Estimator to Non-Normality." *Econometrica* 50(1982):1055–63.

Burbidge, J. B., L. Magee, and A. L. Robb. "Alternative Transformations to Handle Extreme Values of the Dependent Variable." *J. Amer. Statis. Assoc.* 83(1988):123–27.

Capps, O., Jr. *Analysis of Aggregate Fish and Shellfish Expenditure.* Bull. No. 82–1, Virginia Agr. Exp. Sta. and Dept. of Agr. Econ., Virginia Polytechnic Institute and State University, May 1982.

Capps, O., Jr., and H. Cheng. "The Missing Income Problem in Analyses of Engel Functions." *West. J. Agr. Econ.* 11(1986):31–39.

Cheng, H., and O. Capps Jr. "Demand Analysis of Fresh and Frozen Finfish and Shellfish in the United States." *Amer. J. Agr. Econ.* 70(1988):533–42.

Cox, T. L., and M. K. Wohlgenant. "Prices and Quality Effects in Cross-Sectional Demand Analysis." *Amer. J. Agr. Econ.* 68(1986):908–19.

Cragg, J. G. "Some Statistical Models for Limited Dependent Variables with Applications to the Demand for Durable Goods." *Econometrica* 39(1971):829–44.

Deaton, A. "Quality, Quantity, and Spatial Variation of Price." *Amer. Econ. Rev.* 78(1988):418–30.

Dellenbarger, L. E., J. Dillard, A. R. Schupp, H. O. Zapata, and B. T. Young. "Socioeconomic Factors Associated with At-Home and Away-from-Home Catfish Consumption in the United States." *Agribus.: An Internat. J.* 8(1992):35–46.

Guenther, P. M., and K. S. Tippett. "Evaluation of Nonresponse in the Nationwide Food Consumption Survey, 1987–88." Nationwide Food Consumption Survey 1987–88, NFCS Rep. No. 87-M-2. U.S. Department of Agriculture, Human Nutrition Information Service, Washington DC, September 1993.

Haines, P. S., D. K. Guilkey, and B. M. Popkin. "Modeling Food Consumption as a Two-Step Decision." *Amer. J. Agr. Econ.* 70(1988):543–52.

Hausman, J. A. "The Econometrics of Non-Linear Budget Sets." *Econometrica* 53(1985):1255–282.

Heckman, J. J. "The Common Structure of Statistical Models of Truncation, Sample Selection and Limited Dependent Variables and a Simple Estimator for Such Models." *Annals Econ. and Social Meas.* 5(1976):475–92.

Jones, A. M., and J. Posnett. "Charitable Donations by UK Households: Evidence from the Family Expenditure Survey." *Appl. Econ.* 23(1991):343–51.

Keithly, W. R., Jr. "Socioeconomic Determinants of At-Home Seafood Consumption: A Limited Dependent Variable Analysis of Existing and Latent Consumers." Unpub. Ph.D. diss., University of Florida, 1985.

MacKinnon, J. G., and L. Magee. "Transforming the Dependent Variable in Regression Models." *Internat. Econ. Rev.* 31(1990):315–39.

Maddala, G. S. *Limited-Dependent and Qualitative Variables in Econometrics.* Cambridge UK: Cambridge University Press, 1983.

McDonald, J. F., and R. A. Moffitt. "The Uses of Tobit Analysis." *Rev. Econ. and Statis.* 62(1980):318–21.

Miller, M. M., and D. A. Nash. *Regional and Other Related Aspects of Shellfish Consumption—Some Preliminary Findings from the 1969 Consumer Panel Survey.* National Marine Fisheries Service Circulation No. 361, Washington DC, June 1971.

Murphy, P. E., and W. A. Staples. "A Modernized Family Life Cycle." *J. Consum. Res.* 6(1979):12–22.

Nash, D. A. *A Survey of Fish Purchases of Socio-Economic Characteristics.* U.S. Department of Commerce, National Marine Fisheries Service Data Rep. No. 62, Washington DC, April 1971.

Nayga, R. M., Jr., and O. Capps, Jr. "Factors Affecting the Probability of Consuming Fish and Shellfish in the away from Home and at Home Markets." *J. Agr. and Appl. Econ.* 27(1995):161–71.

Paarsch, H. J. "A Monte Carlo Comparison of Estimators for Censored Regression Models." *J. Econometrics* 24(1984):197–213.

Reynolds, A. "Analyzing Fresh Vegetable Consumption from Household Survey Data." *S. J. Agr. Econ.* 22(1990):31–38.

Reynolds, A., and J. S. Shonkwiler. "Testing and Correcting for Distributional Misspecifications in the Tobit Model: An Application of the Information Matrix Test." *Empirical Econ.* 16(1991):313–23.

Serfling, R. J. *Approximation Theorems of Mathematical Statistics.* New York: John Wiley, 1980.

U.S. Department of Agriculture, Human Nutrition Information Service, Nationwide Food Consumption Survey 1987–88: Household Food Use. Documentation of Public-Use Tape, Washington DC, 1992.

———. Economic Research Service. *Food Consumption, Prices, and Expenditures, 1970–93.* Statis. Bull. No. 915, Washington DC, December 1994.

U.S. Department of Commerce, Bureau of the Census. Current Population Survey, March 1987. Conducted by the Bureau of the Census for the Bureau of Labor Statistics. Computer data file, 1987.

Vuong, Q. H. "Likelihood Ratio Tests for Model Selection and Nonnested Hypotheses." *Econometrica* 57(1989):307–33.

Wales, T. J., and A. D. Woodland. "Sample Selectivity and the Estimation of Labor Supply Functions." *Internat. Econ. Rev.* 21(1980):437–68.

Yen, S. T. "Working Wives and Food Away from Home: The Box-Cox Double Hurdle Model." *Amer. J. Agr. Econ.* 75(1993):884–95.