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EFFECTS OF INCOME SOURCES ON HOUSEHOLD FOOD EXPENDITURES*

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Abstract

A purchase infrequency model and a Tobit model are used to examine impacts of different income sources on food expenditures using BLS's Consumer Expenditure Diary Survey data. Results show that four income components have significantly different effects on the expenditures of food, food at home, and food away from home.

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The affordability of food to American households continues to be a public issue. There are concerns about adequate nutrition from food consumed by the households and the coverage and high costs of food distribution and assistance programs (West and Price). Transfer payments and food subsidy programs are two major public assistance vehicles to help low income households improve their level of living especially in food consumption. In order to improve the effectiveness and efficiency of these programs, policy makers need to understand the effects of transfer payments, food stamp program, and selected household characteristics on food consumption.

A previous study of the impacts of various income sources on food consumption was conducted by Hymans and Shapiro. They used panel data from a five-year period and found that various income sources had distinguished impacts on food consumption for different household groups. The marginal propensities to consume food out of subsidies and transfer payments are higher than those from wages and other income sources. The evidence clearly implies that various income-supplement programs aimed at raising the level of food consumption for the poor were effective. The Hymans and Shapiro study examined only total food expenditure. Since the consumption of food away from home has been increasing rapidly during the 1980's, it is important to investigate and compare the effects of various income sources on food consumption at home and away from home.

The main objective of this study is to utilize a recent consumer expenditure survey data set for analyzing the impacts of various income sources on the consumption of total food, food at home, and food away from home. The empirical results will provide valuable information for evaluating the effectiveness of food subsidy and transfer payment programs. For the remainder of this paper, the theoretical framework will be discussed first. The data source and statistical model are next described. We will then present the regression results, marginal propensities to consume (MPC's) and expenditure elasticities with respect to various income sources. The paper ends with some concluding comments.

Theoretical Framework

A neoclassical demand function, derived from the maximization of a utility function subject to a budget constraint, can be specified as:

$$(1) \qquad Q = Q(P, X; \gamma(D)),$$

where Q is quantity demanded of a commodity, P is a vector of prices of all goods, X is household income, and $\gamma(D)$ is a vector of unobserved preference parameters which are non-stochastic functions of a vector of observed household characteristics D. Various income components are considered to be homogeneous in the neoclassical demand model, and household income in (1) is an aggregate of these components.

In this study, we assume income of different sources may affect food consumption behavior differently. In order to test this hypothesis, (1) is modified as:

$$(2) \qquad Q = Q(P, X_1, X_2, \ldots, X_n; \gamma(D)),$$

where $\Sigma X_i = X$, and X_i represents the i*th* income source. It is obvious that (2) is a more general model than (1), and the two models would be identical if different income sources have the same impact on consumption. For instance, if earned income and food stamp income have identical marginal propensity to consume food, then theoretically these two income components can be combined as an aggregate income in a demand function. One advantage of (2) is that it allows us to examine whether various income sources have any differentiable effects on consumption.

For empirical inquiry in this study, two forms of (2) are considered, namely the linear and log-linear forms. Typically, prices are assumed to be constant when using household data in one period. For the data we use in this study, although households can be identified on a monthly basis within the survey year of 1986, prices exhibit very little variation over the period (with a coefficient of variation of less than 1.5%) and are therefore considered to be constant. Therefore, the demand functions estimated in this study are basically Engel functions, with prices P dropped out of (2).

Data

The data needed for this study include food expenditures, income of different sources, and demographic characteristics of households. All data are available from the Bureau of Labor Statistics' (BLS) 1986 Consumer Expenditure Diary Survey.

Data in the diary survey were collected from a national probability sample of households designed to be representative of the national, noninstitutional population. The diary survey was completed by each sample consumer unit for two consecutive one-week periods. In this study, data on expenditures and income of various sources are converted to a weekly basis within the month. Expenditure variables include total food expenditure, food at home, and food away from home. Household income can be identified in four main components: (1) wages and salaries; (2) transfer income including social security benefits and public assistance or welfare; (3) value of food stamps; (4) other income including interests, pensions, dividends, unemployment compensation, etc. In addition, demographic variables such as age, race, region, family size, and family compositions are also considered as explanatory variables.

Note that food expenditures in the diary survey include transaction costs, such as excise and sales taxes, for goods and services acquired during the survey reference period. The full cost of each purchase is recorded, even though full payment may not have been made at the time of purchase. It is also noted that expenditures incurred by members of the consumer unit while away from home over night or longer are excluded from the diary survey.

The observations to be analyzed in this study are randomly selected from the public-use tape of the diary survey of consumer expenditure for 1986. Prior to the random sampling, households with negative before-tax income were excluded. The sample size is 2,198 or about 20% of the households from the original survey. The sample mean of total weekly food expenditure is $62.38 per household, consisting of $38.57 for food at home and $23.81 for food away from home. The sample mean of total weekly income is $489.43 per household consisting of wages and salaries ($370.64), transfer income ($35.28), food stamp income ($1.69) and other income ($81.81). The transfer income and value of food stamps accounted for only 22.53% of average household income in 1986.

The Statistical Model

The neoclassical demand model (2) captures the relationship between consumption of a commodity and explanatory variables. One major problem in demand analysis using survey data is that these data are often collected in a very short observation period, thus frequently reflecting zero purchases. A common approach to demand estimation using data with zero realized values for the dependent variable is through the specification and estimation of the normal censored regression model, known as the Tobit model (Tobin). In the Tobit model, zero realization of the dependent variable represents a corner solution or a negative value for the underlying latent variable. Thus, households with observed zero values for the dependent variable are interpreted as having zero consumption, with a reservation price lower than the corresponding market price. For commodities necessarily consumed by the households, the use of Tobit model is inappropriate. Most seriously, fitting a household demand model to what fundamentally are household purchase data presents obvious problems.

Recently, Deaton and Irish provided a simple generalization to the Tobit model by adding a simple binary censor, which came to be known as the P-Tobit model. The P-Tobit model combines a true demand model, defined in terms of unobservable consumption, and a purchasing model which provides a link between consumption and purchases and allows for temporarily zero purchases of commodities which are consumed in the long run. Let y^*_i be the latent variable representing true consumption for the good by household i (which depends on a vector of exogenous variables x_i), y_i be the corresponding observed consumption, and $P_i = P(y^*_i, x_i)$ be the probability of observing a purchase of the good during the survey period. Assume consumption and purchase are equal on average. Then,

(3) $$E(y_i \mid y^*_i, x_i) = y^*_i.$$

Since $$E(y_i \mid y^*_i, x_i) = E(y_i \mid y_i > 0, y^*_i, x_i)\ P(y^*_i, x_i),$$

(4) $$E(y_i \mid y_i > 0, y^*_i, x_i) = y^*_i \ / \ P(y^*_i, x_i).$$

Therefore, the P-Tobit model implies the following censoring rule:

(5) $y_i = 0$ with probability $1 - P(y^*_i, x_i)$;

(6) y_i is distributed as $g[y_i \mid y^*_i / P(y^*_i, x_i), x_i]$, with probability $P(y^*_i, x_i)$,

where $g[\cdot]$ is a p.d.f. of y_i with mean $y^*_i / P(y^*_i, x_i)$ conditional on x_i.

Specification of the P-Tobit model, and its various generalizations, is complete by choosing a certain probability density function $g[\cdot]$ and a probability distribution function for the purchase probability $P(\cdot)$.

It is interesting to note that the standard Tobit model is a special case of the P-Tobit structure. It assumes that $y^*_i = y_i$ and that

$$(7) \qquad P(y^*_i, x_i) = 0 \qquad \text{for } y^*_i = 0;$$

$$(8) \qquad P(y^*_i, x_i) = 1 \qquad \text{for } y^*_i > 0.$$

Then, specifying y^*_i as $N(x_i\beta, \sigma^2)$, for a sample of size N with observations on y_i and x_i, the sample log-likelihood for the standard Tobit model can be written as (also see Amemiya, p. 363):

$$(9) \qquad \log L = \sum_0 \log(1 - \Phi(x_i\beta/\sigma)) + \sum_+ (-\log\sigma + \log\phi((y_i - x_i\beta)/\sigma)),$$

where Σ_0 and Σ_+ refer to summation over observations with zero and positive observed y_i, and $\Phi(\cdot)$ and $\phi(\cdot)$ refer to the standard normal cumulative and density functions, respectively.

Deaton and Irish generalized the Tobit model by using a constant purchase probability P in (8), and estimated the probability as a parameter. The generalization of the P-Tobit model we consider in this study follows from Blundell and Meghir, which came to be known as the infrequency of purchase (henceforth, Infre) model. In particular, the purchase probability is specified as the standard normal distribution function

$$(10) \qquad P(y^*_i, x_i) = \Phi(z_i\alpha),$$

where z_i is a vector of explanatory variables determining the purchase probability. In addition, the latent variable y^*_i is assumed to be log-normally distributed:

$$(11) \qquad \log y^*_i \sim N(x_i \beta, \sigma^2).$$

Note that in principle z_i in (10) can be any variables observed in household i. Conceptually, z_i may be included in (but may not be distinctly different from) x_i. For convenience in further discussion, z_i and x_i are referred to as "probit variables" and "Tobit variables", respectively. Based on the censoring rule (5) and (6), for a sample of size N with observations on y_i, z_i and x_i, the sample log-likelihood for the Infre model can be written as:

$$(12) \qquad \log L = \sum_0 \log(1 - \Phi(z_i \alpha))$$

$$+ \sum_+ [(-\log\sigma + \log\phi((\log y_i + \log\Phi(z_i \alpha) - x_i \beta)/\sigma)) + \log\Phi(z_i \alpha) - \log y_i].$$

For prediction with the Tobit and Infre models, we need to know the mean of the dependent variable. For the Tobit model, the mean is (Amemiya, p. 368)

$$(13) \qquad E(y_i) = \Phi(x_i \beta/\sigma)\, x_i \beta + \sigma\, \phi(x_i \beta/\sigma),$$

from which the MPC out of the *jth* income source (say x_{ij}) and the associated elasticity can be derived as, respectively,

$$(14) \qquad \frac{\partial E(y_i)}{\partial x_{ij}} = \Phi(x_i \beta/\sigma)\, \beta_j,$$

$$(15) \qquad \frac{\partial E(y_i)}{\partial x_{ij}} \cdot \frac{x_{ij}}{E(y_i)} = \Phi(x_i \beta/\sigma)\, \beta_j\, x_{ij} \,/\, [\Phi(x_i \beta/\sigma) + \sigma\, \phi(x_i \beta/\sigma)],$$

where β_j is the coefficient associated with x_{ij}. For the Infre model, as y_i is assumed to be log-normally distributed, the mean is (Aitchison and Brown)

$$(16) \qquad E(y_i) = \exp(x_i \beta + \sigma^2 / 2).$$

Therefore, the MPC and elasticity can be derived as

(17) $$\frac{\partial E(y_i)}{\partial x_{ij}} = \beta_j E(y_i)$$

(18) $$\frac{\partial E(y_i)}{\partial x_{ij}} \cdot \frac{x_{ij}}{E(y_i)} = \beta_j x_{ij}.$$

Model Selection Tests for Non-Nested Models

In this study, we test and compare results from the Tobit and Infre models. As the two models are obviously non-nested, we follow the likelihood-ratio test procedure of Vuong. For convenience, denote the Infre model as F_θ, with log-likelihood

(12a) $$L(\theta) = \sum_{t=1}^{n} \log f(y_t \mid x_t; \theta),$$

where $f(\cdot)$ is the contribution of observation t to the likelihood. Likewise, denote the Tobit model as G_γ, with log-likelihood

(9a) $$L(\gamma) = \sum_{t=1}^{n} \log g(y_t \mid x_t; \gamma).$$

We test the following hypothesis H_o against H_f or H_o against H_g, with

$$H_o:\ E^o\left[\log \frac{f(y_t \mid x_t; \theta_*)}{g(y_t \mid x_t; \gamma_*)}\right] = 0 \qquad (F_\theta \text{ and } G_\gamma \text{ are equivalent});$$

$$H_f:\ E^o\left[\log \frac{f(y_t \mid x_t; \theta_*)}{g(y_t \mid x_t; \gamma_*)}\right] > 0 \qquad (F_\theta \text{ is better than } G_\gamma);$$

$$H_g:\ E^o\left[\log \frac{f(y_t \mid x_t; \theta_*)}{g(y_t \mid x_t; \gamma_*)}\right] < 0 \qquad (F_\theta \text{ is worse than } G_\gamma),$$

where $E^o[\cdot]$ denotes the expectation with respect to the true joint distribution of (y,x), and θ_* and γ_* are the pseudo-true values of θ and γ

(White). Vuong has shown that, under the null hypothesis,

$$(19) \qquad \hat{z} = n^{-1/2}\, LR(\hat{\theta}, \hat{\gamma}) / \hat{\omega} \xrightarrow{D} N(0,1), \text{ where}$$

$$\hat{\omega}^2 = \frac{1}{n}\sum_{t=1}^{n}\left[\log \frac{f(y_t \mid x_t;\hat{\theta})}{g(y_t \mid x_t;\hat{\gamma})}\right]^2 - \left[\frac{1}{n}\sum_{t=1}^{n}\log \frac{f(y_t \mid x_t;\hat{\theta})}{g(y_t \mid x_t;\hat{\gamma})}\right]^2,$$

$$LR(\hat{\theta}, \hat{\gamma}) = L(\hat{\theta}) - L(\hat{\gamma}) = \sum_{t=1}^{n} \log \frac{f(y_t \mid x_t;\hat{\theta})}{g(y_t \mid x_t;\hat{\gamma})},$$

where $\hat{\theta}$ and $\hat{\gamma}$ are the maximum likelihood (ML) estimators for θ and γ respectively. To test the hypothesis, select a significance level α and the critical value z_α. If $\hat{z} > z_\alpha$, then F_θ is better than G_γ in that F_θ is closer to the true law generating the observations; if $\hat{z} < -z_\alpha$, then F_θ is worse than G_γ; if $|\hat{z}| \leqslant z_\alpha$, then F_θ is not statistically different from G_γ.

Parameter Estimates, Elasticities and Marginal Propensity to Consume

ML estimation of the Infre and Tobit models for food, food at home, and food away from home were accomplished by using GQOPT5[1], with the log-likelihood functions [see (9), (12)] and gradients programmed in FORTRAN by the authors.[2] The results are reported in Table 1. For the Infre model, various probit variables were considered as determinants of the purchase probability. For each equation the variables considered included total income, household size, and dummy variables for households with adult(s) over 64, households with children under 18, age, race, and regions; only significant variables are retained as determinants of the purchase probability. For the Engel function, various demographic variables were also considered but none were found significant. In addition, prices were found insignificant in all equations and therefore were not included.[3] Thus, the Tobit variables include only the four sources of income. Based on the ML estimates, likelihood-ratio test statistics [see (19)] were computed for pairwise comparisons of the Infre and Tobit models. The results (Table 1) suggest rejection of the Tobit models at a significance level of less than 0.01 for all three equations considered.[4]

In evaluating the parameter estimates, among the probit variables, total income increases the purchase probabilities for food, food at home, and food away from home, as do household size and presence of aged adults (over 64) for food at home. As for the Tobit variables, wage income, transfer income and other income consistently increase the consumption of food, food at home, and food away from home. Most interestingly, both the Tobit and Infre models suggest that food stamp income has a positive impact on food at home (although not significant for the Infre model), but a negative impact on food away from home. This is consistent with our expectation, since as households participate in the food stamp program, they are likely to eat more at home and less away from home. Food stamp income is not significant in the total food equation according to both models. This is likely due to the opposite impacts of food stamp income on food at home and food away from home.

Based on the parameter estimates, the MPC's [see (14), (15)] out of various income sources and the corresponding income elasticities [see (17), (18)] are computed for the food stamp participant, nonparticipant and pooled samples (Table 2). According to results from all three samples, the estimated MPC's out of wage income, transfer income and other income are lower for food stamp participants than non-participants, and exhibit the same pattern across samples. Out of food stamp income, the Infre model suggests a much lower MPC for food at home (although the coefficient is not significant in the Infre model) than the Tobit model, according to computations from both the participant and pooled samples. For food away from home, both models suggest significant and negative MPC's out of food stamp income. The expenditure elasticities also exhibit significant difference across income sources and between models. These elasticities, however, have to be interpreted with caution as they rely heavily on values of the explanatory variables in question.

Focusing on the infre models (as the likelihood-ratio tests favor these models), the mean probabilities of purchase are estimated to be 0.96, 0.92, and 0.78, and the mean expenditures are estimated to be $69.42, $44.21, and $27.24 for food, food at home, and food away from home respectively. In addition, there are considerable differences among the MPC's out of (and elasticities with respect to) different income sources for all three foods considered.

Summary and Conclusions

The statistical tests suggest that the purchase infrequency model is a better alternative to the Tobit model in modeling food demand when zero values for the dependent variables are present. The two models suggest quantitatively different, although qualitatively similar, results for the effects of wage income, transfer income and other income on the consumption of food, food at home, and food away from home. Results for the impacts of food stamp income are less conclusive and differ more drastically between the two models. To sum up, the empirical findings do support our earlier assertion that various income sources have different effects on household food consumption.

Footnotes

[1] GQOPT5 is prepared and released by Professors Stephen Goldfeld and Richard Quandt of the Princeton University.

[2] The FORTRAN codes for all these estimations are available from the authors.

[3] We also included aggregate food price in the food equation and own- and cross-prices in the equations for food at home and food away from home. All prices were insignificant and the results, not reported here, suggest very similar parameter estimates, MPC's, and income elasticities. Thus, the empirical results also support specification of the equations without prices.

[4] We also estimated the Infre models for all the goods using the linear specification of the Engel functions. The likelihood-ratio test results, not reported here, suggest that the linear specification is inferior to both the (log-linear) Infre models and the (linear) Tobit models.

Table 1. ML Estimates of Purchase Infrequency and Tobit Models: Engel Functions[a]

	Purchase Infrequency Models			Tobit Models		
Variable	Total Food	Food at Home	Food Away from Home	Total Food	Food at Home	Food Away from Home
Probit Variables						
Constant	1.606164***	.947327***	.361421***			
	(.066946)	(.079900)	(.044210)			
Total Income	.000299***	.000164*	.000981***			
	(.000119)	(.000091)	(.000089)			
Household Size		.130451***				
		(.034214)				
Adult over 64		.214341**				
		(.091397)				
Tobit Variables						
Constant	3.356992***	2.880598***	2.155230***	35.039424***	22.334086***	4.599632***
	(.032291)	(.039119)	(.045563)	(1.743635)	(1.455178)	(1.220550)
Wage Income	.000974***	.000752***	.001136***	.056588***	.027353***	.035678***
	(.000050)	(.000060)	(.000065)	(.002675)	(.002200)	(.001856)
Transfer Income	.001069***	.002069***	.000019	.059015***	.069935***	-.020672*
	(.000292)	(.000349)	(.000400)	(.015852)	(.012256)	(.011458)
Food Stamp Income	-.002471	.000724	-.006219*	.138536	.230365**	-.198255**
	(.002328)	(.002700)	(.003488)	(.125130)	(.098730)	(.094893)
Other Income	.000585***	.000362***	.000893***	.037374***	.015970***	.025431***
	(.000079)	(.000095)	(.000101)	(.004317)	(.003540)	(.003094)
σ	.826921***	.975758***	.991500***	46.976238***	37.933651***	31.623778***
	(.012881)	(.015355)	(.016461)	(.729229)	(.590598)	(.558470)

(Table 1 Continued)

Log-likelihood	-11067.98	-10118.75	-8527.53	-11203.70	-10291.23	-8719.14
$\bar{z}$ (Infre vs. Tobit)[b]	2.59	3.12	3.60			

[a] Asymptotic standard errors in parentheses. Asterisks *** indicate significance at 0.01 level, ** at 0.05 level, and * at 0.10 level. Coefficients for the Tobit and Purchase Infrequency models are not directly comparable as the latter are specified as log-linear.

[b] The statistic $\bar{z}$ is asymptotically normal N(0,1).

Table 2. Estimated Marginal Propensities to Consume and Income Elasticities by Income Sources: Various Models[a]

Income Sources	Purchase Infrequency Models: Total Food	Purchase Infrequency Models: Food at Home	Purchase Infrequency Models: Food Away from Home	Tobit Models: Total Food	Tobit Models: Food at Home	Tobit Models: Food Away from Home
			Pooled Sample			
Wage Income	.0676	.0332	.0309	.0500	.0225	.0249
	(.3611)	(.2787)	(.4210)	(.2484)	(.1894)	(.3183)
Transfer Income	.0742	.0915	.0005	.0521	.0576	-.0145
	(.0377)	(.0730)	(.0007)	(.0325)	(.0506)	(-.0266)
Food Stamp Income	-.1715	.0320	-.1694	.1223	.1898	-.1386
	(-.0042)	(.0012)	(-.0105)	(.0039)	(.0081)	(-.0139)
Other Income	.0406	.0160	.0243	.0330	.0132	.0178
	(.0479)	(.0296)	(.0731)	(.0382)	(.0248)	(.0545)
			Foodstamp Participants			
Wage Income	.0410	.0257	.0145	.0469	.0222	.0177
	(.0386)	(.0298)	(.0450)	(.0351)	(.0228)	(.0510)
Transfer Income	.0450	.0707	.0002	.0489	.0568	-.0103
	(.0577)	(.1117)	(.0010)	(.0530)	(.0783)	(-.0460)
Food Stamp Income	-.1040	.0247	-.0792	.1149	.1870	-.0985
	(-.0697)	(.0204)	(-.1755)	(.0647)	(.1350)	(-.2308)
Other Income	.0246	.0124	.0114	.0310	.0130	.0126
	(.0103)	(.0063)	(.0156)	(.0108)	(.0060)	(.0175)

(Table 2 Continued)

Nonparticipants

Wage Income	.0693	.0377	.0320	.0502	.0226	.0254
	(.3817)	(.2947)	(.4450)	(.2620)	(.2000)	(.3354)
Transfer Income	.0761	.0928	.0005	.0523	.0577	-.0147
	(.0364)	(.0705)	(.0006)	(.0312)	(.0488)	(-.0253)
Food Stamp Income	-	-	-	-		
Other Income	.0417	.0163	.0252	.0331	.0132	.0181
	(.0503)	(.0311)	(.0768)	(.0400)	(.0260)	(.0568)

[a] In parentheses are expenditure elasticities with respect to different income sources.

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