Wife's Employment and Food Expenditures Away From Home

A double-hurdle model is used to study FAFH consumption in the United States. The empirical specification accounts for heteroscedasticity and nonnormal distribution of the errors. Findings suggest that wife's employment has a positive effect on the level of lunch consumption away from home, but not the other types of meals. Income effects are significant. The roles of demographics, region, and seasonality are also important.

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Introduction

Expenditures for food consumed away from home represent a relatively large share of the food budgets of consumers in the United States. Since the late 1970s, expenditures for food away from home (FAFH) have represented about 4.5% of disposable personal income, and maintained that share until 1990, in the face of a continuing fall in the share of the overall budget going to food (Putnam and Allshouse 1993). Since 1990 the FAFH share of disposable personal income has fallen to 4.2%, at a level of $184 billion in 1992. This amount represented 36.5% of total food expenditures in 1992.

The reasons behind the growing importance of food prepared away from home have been summarized in several recent studies (Chern and Lee 1994; Kolodinsky 1987; Yang 1988). Among factors often identified are rising incomes, increased female labor-force participation, changes in household demographics, changes in "lifestyle", and the expanded availability and variety in fast food establishments (Manchester 1992). A better understanding of the factors associated with FAFH has become increasingly important in order to explain changes in the food market, anticipate implications of changes in eating patterns on dietary quality, design effective nutrition intervention programs, and to understand factors which motivate consumer behavior related to food choices.

The demands for increased information about FAFH expenditures are faced with problems in data availability. No existing national data set appears to meet all needs for analysis of demand. The Bureau of Labor Statistics Consumer Expenditures Survey data do provide information on meal expenditures. The aspect of the market addressed in this paper is that FAFH purchases are not the same: they differ by type of meal, among other attributes (such as place of eating).

This paper uses a relatively straightforward economic behavior model, based on a household production framework which accounts for constraints on the availability of time, as well as income, as determinants of consumer choice. Although the same set of variables is used in the estimation of expenditures on different meals, there are reasons to expect different effects on the probability of purchases and the level of expenditures. In part, the differences stem from varying constraints on time use by time of day and location of activities (e.g., work and school location). For example, lunch purchases are more likely for households with more earners employed, increased labor force participation of wives and higher numbers of school age children. In addition, differences in opportunities for joint household production may differ by type of meal: the entertainment value attached to dinner time may increase the willingness to pay for the dinner-time commodity, in contrast to breakfast.

Empirical Model

The demand for FAFH and its components can be derived from the household production theory. In household production theory, consumer goods and time enter the household utility function, and are maximized subject to the household production function, full-income constraint, and time constraint. Solving the constrained utility maximization problem, the demand for FAFH is a function of prices, wage rates, non-wage income, and other socio-demographic variables. Since cross-section prices are expected to be constant the expenditure equation for FAFH, say commodity i, is specified as

$$E_i = E_i (h, v, d) \qquad (1)$$

where E_i is expenditures on meal i, h is wife's labor

hours, v is non-wage earnings, and $\mathbf{d}$ is a vector of demographic and dummy variables. Since women are traditionally the primary food preparers (and represent the largest share of self-identified main meal preparers in the USDA food surveys), husband's wage earnings are included in wife's non-wage income (henceforth, income).

Statistical Model

Zero observations are common features of observed expenditure data in cross-section surveys. For cross-sectional demand analysis with zero observations in the sample, the double-hurdle model has become increasingly popular (Haines, Guilkey, and Popkin 1988; Wang and Jensen 1994). The double-hurdle model, specified by Cragg (1971), is characterized by a probit mechanism which determines participation in the market, and a Tobit mechanism to accommodate corner solutions in consumer choice. For positive consumption to occur, two hurdles have to be overcome: to participate in the market, and to actually consume. Thus, the double-hurdle model can be expressed by a participation equation $\mathbf{z}_t\boldsymbol{\alpha} + v_t$ and a consumption equation $\mathbf{x}_t\boldsymbol{\beta} + u_t$ such that

$$y_t = \boldsymbol{x}_t\boldsymbol{\beta} + u_t \text{ if } \boldsymbol{z}_t\boldsymbol{\alpha} + v_t > 0$$
$$\text{and } \boldsymbol{x}_t\boldsymbol{\beta} + u_t > 0. \quad (2)$$
$$= 0 \text{ otherwise}$$

where y_t is the observed dependent variable, $\mathbf{z}_t$ and $\mathbf{x}_t$ are vectors of explanatory variables accounting for participation and consumption respectively, $\boldsymbol{\beta}$ and $\boldsymbol{\alpha}$ are parameter vectors and the error terms u_t and v_t are independent and are distributed as $u_t \sim N(0, \sigma_t)$ and $v_t \sim N(0,1)$. By allowing separate stochastic processes to determine participation and consumption, the double-hurdle model relaxes one of the most restrictive features of the Tobit model.[3]

The specification (2) relies crucially on the homoscedasticity and normality assumptions of the error terms u_t and v_t; these assumptions are often made in empirical studies. However, maximum-likelihood (ML) estimation produces inconsistent parameter estimates when either assumption is violated (Arabmazar and Schmidt 1981, 1982). To allow for nonnormal errors, the dependent variable can be transformed. We consider the inverse hyperbolic sine (IHS) transformation (Burbidge, Magee, and Robb 1988)

$$y_t(\theta) = \log[\theta y_t + (\theta^2 y_t^2 + 1)^{1/2}]/\theta$$
$$= \sinh^{-1}(\theta y_t)/\theta, \quad (3)$$

where θ is an unknown parameter. The transformation is linear when θ approaches zero and behaves logarithmically for large values of θ and y_t; it is also known to be well suited for handling extreme values. Applying the IHS transformation to the dependent variable y_t in (2), the IHS double-hurdle model can be expressed as

$$y_t(\theta) = \boldsymbol{x}_t\boldsymbol{\beta} + u_t \text{ if } \boldsymbol{z}_t\boldsymbol{\alpha} + v_t > 0$$
$$\text{and } \boldsymbol{x}_t + u_t > 0 \quad (4)$$
$$= 0 \text{ otherwise.}$$

To overcome the restrictions of homoscedasticity, the standard deviation σ_t is allowed to vary across observations and is specified as a function of exogenous variables $\mathbf{w}_t$

$$\sigma_t = \exp(\boldsymbol{w}_t\boldsymbol{\gamma}), \quad (5)$$

where $\boldsymbol{\gamma}$ is a parameter vector. The IHS double-hurdle model (4) can be estimated by the method of maximum-likelihood.

The nonlinear (IHS) transformation of the dependent variable, the heteroscedastic error specification, and the double-hurdle parameterization all complicate the interpretation of parameter estimates and, hence, the ability to easily evaluate the effects of explanatory variables on the dependent variable. This can be overcome by decomposing the unconditional mean of the dependent variable y_t into the probability and the conditional mean of consumption. Then, marginal responses or elasticities can be evaluated for these components of the dependent variable.[4]

Data and Variables

The sample for the present study was drawn from the Bureau of Labor Statistics' 1989 and 1990 Consumer Expenditure Diary Surveys. The diary surveys were conducted on sampled consumer units during two consecutive one-week periods. For this study, the two-week period for each household was the period of observation. Per capita household expenditures on total FAFH, breakfast, lunch, and dinner during the two-week period were the dependent variables.

Table 1. Sample statistics: FAFH by meal type and explanatory variables

	Full sample		Consuming households		
	Mean	St. dev.	Mean	St. dev.	N
Per-capita FAFH expend. ($/2 wks.)					
Total	19.38	22.57	21.43	22.79	3140
Breakfast	1.48	4.41	3.69	6.34	1395
Lunch	8.13	9.80	9.55	9.96	2954
Dinner	9.77	14.32	12.30	15.07	2756
Wife's employment (hrs/wk.)					
Observed	25.17	18.58			
Predicted[a]	23.94	7.39			
Number of earners	2.01	0.79			
Household composition					
Aged ≥ 6	0.72	1.12			
Aged 7-18	0.69	0.97			
Aged 19-44	1.50	0.87			
Aged 45-64	0.58	0.85			
Aged ≤ 65	0.11	0.41			
Income per capita ($00/2 wks.)	10.87	8.56			
Dummy variables (yes=1; no=0)					
Homeowner	0.73				
White	0.91				
Wife high-school educated	0.51				
Wife college educated	0.44				
Rural (reference group)	0.14				
Urban Northeast	0.17				
Urban Midwest	0.23				
Urban South	0.26				
Urban West	0.21				
Spring (reference)	0.16				
Summer	0.24				
Fall	0.28				
Winter	0.33				

SOURCE: Compiled from BLS' 1989 and 1990 Consumer Expenditure (Diary) Surveys.
[a] Predicted from ML Tobit estimates of the wife's labor supply equation.

Estimation of the double-hurdle models requires the selection of two separate sets of regressors. One primary explanatory variable of interest is wife's labor hours. This variable has been found to be endogenous in FAFH consumption. Therefore, use of the observed labor hours in the expenditure equation, which ignores such endogeneity, will cause simultaneous equation bias (Bryant 1988). To avoid such bias, the variable for wife's labor hours was predicted using ML Tobit estimates of the wife's labor supply equation. The explanatory variables in the labor supply equation included number of pre-school children, age of wife, husband's wage earning, and dummy variables indicating education, home ownership, race, and regions.

The other variables used as predictors of expenditures include the number of earners, household age composition, education, per-capita income, and dummy variables indicating home ownership, race, education, region, and season during which the interview took place, all of which were found to be important determinants in previous studies of FAFH.

This study focuses on husband-and-wife households in which the husband was employed. Households with missing information for any of the above variables were excluded, as were households that completed only one week of the survey. This resulted in

a final sample of 3471 observations, of which 1993 came from the 1989 Diary Survey and 1478 from the 1990 Diary Survey. Of the final sample, 3140 households (or 90.46 per cent) reported expenditure on FAFH during the two-week period. The proportions of consuming households for each specific meal-type are lower. Table 1 includes definitions of the variables used and sample statistics.

Empirical Results

The IHS double-hurdle model was estimated for total FAFH, and breakfast, lunch, and dinner away from home. One major specification issue in estimation of the model is selection of variables to account for the first- and second hurdles; the number of variables is typically limited and theory provides little guidance. Regressors believed *a priori* to be significant determinants of participation and others with statistically significant effects in preliminary analysis were included in the final probit specification of the participation equation. The whole set of variables was used in the consumption equation.

Another specification issue is the choice of variables for the heteroscedastic equation. The household age composition variables were selected for the heteroscedastic equation. The variance-covariance matrix of parameter estimates was derived by inverting the numerical Hessian of the log-likelihood function. Because predicted labor hours was used as a regressor, the variance-covariance matrix was also adjusted (Yen 1993).

For all commodities considered, the IHS parameter (θ) is significantly different from zero, which indicates the condition of nonnormality in the expenditure data and the need for the transformation. Household age composition variables are significant in the hetero-scedasticity equation. Thus, the homoscedasticity assumption is also rejected.

In summarizing the parameter estimates, a number of variables appear to affect participation and consumption differently. For instance, for lunch, the age composition variables have conflicting signs in the participation and consumption equations. Similar patterns are observed for age composition and a number of other variables in the breakfast equation. These conflicting signs of variables highlight one of the advantages of the double-hurdle parameterization and the importance of examining the effects of variables by elasticities.

Table 2 presents the elasticities of probability, conditional and unconditional level, along with the results of tests of statistical significance. The standard errors for elasticities were calculated using mathematical approximation. The estimated effects on probability explain the binary decision on consumption, i.e., to consume or not to consume. The effects on the conditional level explain what make those consuming to consume either more or less. The effects on the unconditional level provide an overall assessment of the variable's contribution to the consumption level by increasing (or decreasing) either the probability or conditional level. The elasticities are evaluated at the sample means of variables.[5] Overall, these elasticities suggest that household demographics are important factors in FAFH consumption, as are seasonality and region. The effects of these variables are consistent across all meal types. Among the more notable results are significant effects of home ownership, which are in line with findings by Soberon-Ferrer and Dardis (1991). College education has a significant and positive effect on both probability and levels of consumption of lunch and total FAFH; it does not have a significant effect on lunch and affects dinner consumption only by increasing the probability to consume. Similar, although weaker, effects are observed for high school education.

All age composition variables have significant and negative effects on per-capita consumption of all types of meals away from home, and the elasticities differ across age categories and meal types. Income effects are significant and positive. Except for lunch, all regional dummies have significant and positive effects on the probability and levels of consumption. This result suggests that urban households consume more FAFH, in total and by meal types, than their rural counterparts. Seasonal effects also indicate less consumption of FAFH in summer and winter, although the seasonal effects of breakfast and lunch are not as strong. The negative effects of seasonal and regional dummies may also reflect the effects of prices.

Wife's employment, conditional on holding number of earners constant, has only a marginally positive and significant effect on the conditional level of lunch consumption; the effects on all other meals are not significant. The negative, although insignificant, effects of wife's employment are in line with previous findings that as housewives devote more time to work, consumption of FAFH decreases because consumption is time consuming.

It is sometimes argued that evaluating the effects of discrete variables by elasticities is not strictly correct. For each of the binary variables, the effects on probability, conditional level, and unconditional level of consumption are calculated as the finite changes in these components of consumption as the value of the variable changes from zero to one, evaluated at the sample means

Table 2. Elasticities With Respect to Exogenous Variables[a]

Variable	Total			Breakfast		
	Prob	Cond level	Uncond level	Prob	Cond level	Uncond level
Homeowner	0.03**	0.06**	0.09**	0.09**	0.08**	0.17**
No. earners	0.07**	0.19**	0.26**	0.20**	0.17**	0.37**
Aged ≤ 6	-0.01**	-0.20**	-0.21**	-0.03	-0.27**	-0.30**
Aged 7-18	-0.01**	-0.14**	-0.15**	-0.03*	-0.24**	-0.27**
Aged 19-44	-0.06**	-0.25**	-0.31**	-0.14*	-0.39**	-0.53**
Aged 45-64	-0.04**	-0.09**	-0.13**	-0.10**	-0.06	-0.16**
Aged ≥ 65	-0.01**	-0.02**	-0.03**	-0.01	-0.03	-0.03*
Income	0.04**	0.24**	0.28**	0.12**	0.10**	0.22**
Wife's emp.	-0.02	-0.04	-0.05	-0.23	-0.19	-0.41
White	0.03**	0.06	0.09*	-0.02	-0.02	-0.04
High School	0.03**	0.06	0.09	0.06	0.05	0.11
College	0.05**	0.11**	0.15**	0.07	0.05	0.12
Northeast	0.003**	0.05**	0.05**	0.05**	0.04**	0.09**
Midwest	0.002**	0.03**	0.03**	0.05**	0.04**	0.10**
South	0.003**	0.05**	0.06**	0.06**	0.05**	0.11**
West	0.002**	0.03**	0.03**	0.04**	0.03**	0.08**
Summer	-0.001*	-0.02*	-0.02*	-0.01	-0.01	-0.02
Fall	0.000	0.01	0.01	0.00	0.00	0.00
Winter	-0.002**	-0.04**	-0.04**	-0.03**	-0.03**	-0.06**

Variable	Lunch			Dinner		
	Prob	Cond level	Uncond level	Prob	Cond level	Uncond level
Homeowner	0.02**	0.06**	0.08**	0.04**	0.04	0.08**
No. earners	0.08**	0.22**	0.30**	0.10**	0.05	0.15*
Aged ≤ 6	-0.01*	-0.17**	-0.18**	-0.02**	-0.10**	-0.21**
Aged 7-18	-0.01	-0.09**	-0.10**	-0.02**	-0.17**	-0.18**
Aged 19-44	-0.13**	-0.23**	-0.36**	-0.04	-0.27**	-0.30**
Aged 45-64	-0.05**	-0.07**	-0.12**	-0.05**	-0.07**	-0.12**
Aged ≥ 65	-0.01**	-0.02*	-0.02**	-0.01**	-0.02*	-0.03**
Income	0.08**	0.22**	0.29**	0.07**	0.24**	0.31**
Wife's emp.	0.01	0.03*	0.04	-0.05	-0.02	-0.07
White	0.00	0.00	0.00	0.10**	0.08	0.18**
High School	0.04**	0.10**	0.14**	0.04**	0.03	0.07
College	0.05**	0.13**	0.18**	0.06**	0.09	0.15**
Northeast	0.01**	0.03**	0.04**	0.01**	0.04**	0.05**
Midwest	0.01	0.02	0.02	0.01*	0.03**	0.04**
South	0.01**	0.04**	0.05**	0.01**	0.04**	0.05**
West	0.004	0.01	0.02	0.01*	0.03**	0.03**
Summer	-0.01**	-0.04**	-0.05**	0.000	0.002	0.003
Fall	-0.001	-0.002	-0.00	0.001	0.006	0.008
Winter	-0.01**	-0.04**	-0.05**	-0.01*	-0.03**	-0.04**

Asterisks indicate levels of significance: ** Significant at 5%
* Significant at 10%

Table 3. Effects of Binary Variables[a]

Variable	Total			Breakfast		
	Prob	Cond level	Uncond level	Prob	Cond level	Uncond level
Homeowner	0.046	1.430	2.184	0.053	0.318	0.292
White	0.037	1.245	1.832	-0.010	-0.063	-0.059
High School	0.056	2.095	3.028	0.047	0.294	0.273
College	0.092	4.721	6.167	0.061	0.382	0.355
Northeast	0.012	5.444	5.345	0.111	0.759	0.725
Midwest	0.006	2.245	2.215	0.099	0.661	0.627
South	0.010	4.029	3.969	0.093	0.609	0.576
West	0.007	2.516	2.481	0.082	0.541	0.512
Summer	-0.005	-1.393	-1.382	-0.015	-0.091	-0.084
Fall	0.001	0.412	0.408	0.000	0.002	0.002
Winter	-0.007	-2.091	-2.073	-0.042	-0.256	-0.236
	Lunch			Dinner		
Variable	Prob	Cond level	Uncond level	Prob	Cond level	Uncond level
Homeowner	0.026	0.598	0.698	0.042	0.582	0.925
White	0.001	0.023	0.028	0.106	0.915	1.825
High School	0.061	1.509	1.749	0.065	0.661	1.244
College	0.088	2.313	2.668	0.115	2.087	2.994
Northeast	0.043	1.214	1.394	0.031	2.690	2.624
Midwest	0.019	0.495	0.572	0.019	1.450	1.422
South	0.041	1.115	1.284	0.022	1.710	1.676
West	0.018	0.466	0.538	0.019	1.432	1.404
Summer	-0.047	-1.054	-1.227	0.002	0.111	0.109
Fall	-0.002	-0.045	-0.052	0.004	0.250	0.246
Winter	-0.034	-0.809	-0.940	-0.015	-0.993	-0.981

[a] Computed at the sample means as the changes in probability, conditional level, and unconditional level as the value of each binary variable changes from zero to one.

of all other variables. Table 3 presents selected results. Relative to other groups, homeowners are about 4.6 percent more likely to consume total FAFH and, conditional on consumption, consume about $1.43 more per person during the two-week period. Overall, the effect on the unconditional level suggests homeowner consume about $2.18 more per person. The interpretation of other dummy variables is similar. Overall, the effects of variables differ across meal types.

Concluding Remarks

This study investigates FAFH consumption using an econometric model that accommodates zero observations in the sample. Parameterization of the model allows for separate decision processes on participation and level of consumption, and the stochastic specification accommodates nonnormality and heteroscedasticity of the error terms. We find wife's employment has a positive effect on the level of lunch consumption away from home, but not the other types of meals. Income effects are significant and positive. Decreases in real income will lead to reductions in FAFH expenditures. This suggests the contributing role of the income effects in the declining growth of per-capita FAFH consumption in the 1990s. The roles of demographics, region, and seasonality are also important. Overall, the effects of most variables differ on the consumption of different types of meals away from home.

The fact that there are significant differences in

the contribution of income and other demographic factors in predicting meal expenditure patterns is consistent with models of consumer behavior that recognize constraints on household members' time and differences in production of the household meal commodities. Although estimation of total FAFH captures the overall effects of income, wive's labor force participation and other demographics, the differences associated with the probability and the level of expenditure of specific meals suggest consideration of meals separately for the development of selected consumer education programs and specific regulations which affect available consumer information. For example, relatively greater responsiveness of the 19-44 and 45-64 year old age groups on the probability of consuming breakfast away from home suggests opportunities for expanded FAFH markets for this age group at breakfast. On the other hand, few differences among consumers with different educational backgrounds for the breakfast estimates indicate that one should not expect that consumers of different educational background would respond differently to targeted information for this meal, in contrast to the results indicated by the total FAFH estimates.

Whether these results continue to hold as lifestyles change and meal and snacking patterns evolve in response to changes in work and household demands is a question that cannot be resolved by the type of analysis presented here. "Take-out food" options have been increasing recently, meeting new needs for convenience without costs associated with time in consuming FAFH. As options for collecting the structure of data which describe food consumption and expenditures, both at home and away, are considered, increasing attention will need to be paid to the availability and form of products which meet consumers' interest in convenient food, and food which meets needs for nutrition and other desired attributes.

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Endnotes

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3. See Lin and Schmidt (1984) for problems with Tobit parameterization.
4. The decomposition of the unconditional mean is similar to that of McDonald and Moffitt (1980) for the standard Tobit model.
5. Another option is to evaluate the elasticities at each sample point and then average the estimates, as one reviewer pointed out. However, calculation of the elaticities and standard errors for the estimated model requires numerical integration and differentation many times. It is not feasible.