Household Composition and Brazilian Food Purchases: An Expenditure System Approach

Jorge M. Agüero[1] and Brian W. Gould[2]

[1] *Department of Agricultural and Applied Economics, University of Wisconsin, Madison, Wisconsin.*
[2] *Wisconsin Center for Dairy Research and Department of Agricultural and Applied Economics, University of Wisconsin, Madison, Wisconsin.*

The use of household level data for food demand analysis requires the researcher to address issues such as purchase censoring and the impacts of household age/gender composition on such demand. This analysis adopts an estimation approach to modeling censored food expenditures. The major methodological contribution of this analysis is our incorporation of an endogenous equivalence scale measure within the expenditure system. Our empirical application is concerned with Brazilian household food expenditures. We use the estimated adult equivalence scales to evaluate a measure of household welfare represented by per-adult equivalent food expenditures. We find a significant shift of the distribution of per capita food distributions when comparing member count versus adult equivalent-based per capita distributions.

L'utilisation de données sur les ménages pour analyser la demande d'aliments exige ddu chercheur qu'il aborde diverses questions comme la censure des achats et l'incidence de la composition du ménage (âges/sexes) sur la demande. Pour leur analyse, les chercheurs ont recouru à une technique d'estimation qui modélise les achats d'aliments censurés. Le principal apport méthodologique de leur approche est l'intégration d'une échelle d'équivalence endogène au système de dépenses. La méthode a été appliquée de manière empirique au budget d'alimentation de la famille brésilienne. Les auteurs ont utilisé les échelles d'équivalence adulte pour évaluer le bien-être des ménages d'après leurs achats d'aliments par équivalent adulte. On constate un déplacement important de la distribution des aliments par habitant quand on compare celle-ci par personne plutôt que par équivalent adulte.

INTRODUCTION

The use of household level data for food demand analysis requires the applied researcher to address two problems. First, the level of commodity disagregation often results in a significant number of households (individuals) not purchasing a particular commodity. These zero purchases may arise for a number of reasons including infrequency-of-purchase (IOP) relative to the survey time-period or may represent a true corner solution to the consumer's utility maximization problem.

Table 1 presents an overview of weekly household food purchases from a random sample of urban Brazilian households using fairly aggregate commodity definitions. The proportion of households purchasing specific commodities ranges from 90% for bread products to 18% for fish. The presence of a large proportion of data being composed of zero valued purchases represent a potential problem for the researcher, as the use of traditional ordinary least squares (OLS) techniques may result in biased coefficient estimates (Maddala 1983, 53).

The per capita food purchase values shown in Table 1 are obtained by using the number of household members as a deflator of total household food expenditures. The implicit assumption associated with the use of member count as a deflator is that each member has an equal impact on food purchases/expenditures. In reality, the impacts of household size will vary depending on age and gender composition of household members. For example, the food consumption needs of children can typically be met at lower cost than that of adults (Deaton and Muellbauer 1986; Dreze and Srinivasan 1997).

One approach that can be used to avoid the assumption of equal marginal expenditure impacts of members is to use an equivalence scale. This measure is used to assign different weights to household members depending on their age and gender[1] (Deaton and Muellbauer 1986). Given the determination of an appropriate equivalence scale, a comparison of food expenditures for households of differing composition can then be undertaken. The recognition of the need to obtain estimates of food adult equivalents has resulted in the development of a number of alternative econometric estimation approaches. These have ranged from the use of demographically translated, utility-consistent demand systems to more *ad hoc* single-equation approaches (Barton 1964; Gorman 1976; 1980; Muellbauer 1986; Gould, Cox and Perali 1991).

As noted above, there are a number of reasons for nonpurchase of specific foods. For example, in an analysis of the presence of IOP with respect to a single commodity, Gould (1992) and Blundell and Meghir (1987) show that such an analysis does not require explicit information about purchase timing or whether survey respondents had ever purchased the commodity in question. Instead, a likelihood function is formulated, and evidence of IOP is inferred from specific parameter hypothesis tests. The main obstacle to adopting the IOP structure in the current analysis is our desire to evaluate a system of food expenditures. As will become evident below, to incorporate IOP into our two-step model, the methodology for estimating the discrete choice decision would need to be modified as well as the formulation of the seemingly unrelated regression (SUR) system. Though interesting, such an extension is beyond the scope of the present analysis and will be the focus of future research.

For the present analysis, we therefore assume that observed zero purchase values represent true corner solutions.[2] There are a number of econometric approaches that can be used to account for the censoring of such purchases. These approaches range from the censored demand systems of Wales and Woodland (1983), Lee and Pitt (1986) and Kao, Lee and Pitt (2001) to the two-step approaches of Perali and Chavas (2001) and Shonkwiler and Yen (1999). Given that the data used in this analysis do not contain information that would enable us to estimate unit-values, we adopt the estimation procedure of Shonkwiler and Yen (1999) and estimate a set of correlated censored Engel curves.

Similar to other two-step estimation methods, we analyze the discrete purchase decisions for specific foods via the use of a series of univariate probit models. A system of Engel curves is estimated using a likelihood function where food purchase censoring is explicitly accounted. We adopt a systems approach for the second-stage estimation, given our desire to obtain a single endogenously determined measure of household size, where this measure relates to total food expenditures.

Table 1. Overview of weekly per capita food purchases by urban Brazilian households, 1996

Food group	Expenditure	% total expenditure	% FAH expenditure	% households purchasing	Conditional expenditure
Total food	13.07	100.0	—	100.0	13.07
Total food-at-home	9.40	71.9	100.0	97.6	9.62
Cereals	0.60	4.6	6.4	46.4	1.29
Breads	1.26	9.6	13.4	90.0	1.40
Pastas	0.47	3.6	5.0	48.1	0.98
Vegetable/root crops	0.58	4.4	6.2	58.1	1.00
Fruits	0.73	5.6	7.7	51.4	1.41
Red meat	1.33	10.2	14.2	57.4	2.32
Pork	0.35	2.7	3.7	29.5	1.19
Poultry	0.82	6.3	8.7	59.6	1.38
Fish/seafood	0.27	2.1	2.9	18.3	1.47
Fluid milk	0.84	6.4	8.9	65.3	1.29
Other dairy	0.62	4.7	6.6	47.7	1.30
Nonalcoholic beverages	0.74	5.7	7.9	57.9	1.28
Other FAH	0.79	6.0	8.4	58.4	1.35
Food away-from-home	3.67	28.1	—	66.6	5.51

All values are shown in Brazilian Real using monetary values as of 15 September 1996. 1 Brazilian Real = US$ 1.02 in 1996.
Source: 1995–96 POF for households who reported positive total food expenditures.

Given our use of household level data and the desire to analyze expenditures for a detailed set of commodities, we use the general Shonkwiler and Yen (1999) methodology to account for expenditure censoring within the SUR system. The major contribution of our analysis over previous applications of Shonkwiler and Yen (1999) is the incorporation of an endogenously determined total food equivalence scale and the analysis of equivalent-based food expenditure distributions based on this analysis.[3]

Incorporation of the endogenous adult equivalence scale within a SUR system of Engel curves causes this system to be nonlinear with respect to model parameters. In spite of this complication, the methodology used here continues to require only the evaluation of univariate normal probability density function (PDF) and cumulative distribution function (CDF) distributions. Thus, not being numerically intensive, this methodology can then be applied to a large system of expenditure (demand) equations. In the present application, we examine the structure of expenditures on 14 food types while using a expenditure data for a random sample of 15,000 urban Brazilian households.

For this analysis, we incorporate the Tedford, Capps and Havlicek (1986) measure of a total food adult equivalence scale (TAES). A review of this methodology is presented in the next section. Unlike Gould, Cox and Perali (1991), who estimated commodity-specific equivalence scales within a demand system, we derive the systemwide TAES. We provide an overview of the Engel SUR system estimation in the following section. This is followed by an overview of the Brazilian expenditure survey used as a basis of our analysis. The structure of food purchases by Brazilian households is discussed in the conclusion.

ESTIMATION OF ENDOGENOUS EQUIVALENCE SCALES

For this analysis, we assume that household food demand is separable from that of other goods. We assume that utility obtained from food purchases can be represented by an indirect utility function, V. This utility function represents the maximum equally distributed equivalent indirect utility for each household member:

$$V = V(P, I|C) = \max\left[U(X;C)|P'X \le I\right] \tag{1}$$

where
U = the household's utility function
X = a vector of purchased food amounts with corresponding price vector P
C = a vector of demographic characteristics
I = the household's food budget.

That is, V represents the level of per capita utility, if shared by each household member, that would yield the same aggregate well-being as the actual distribution of utility within the household (Phipps 1998).

As shown by Blundell and Lewbel (1991), an equivalence scale, d, can be derived from the household expenditure functions, E, via the following:

$$d = \frac{E(V, P|C)}{E\left(V,\ P\middle|C^R\right)} \tag{2}$$

where C^R = the vector of characteristics of an arbitrary reference household. Members of a household with characteristic vector C, facing prices, P, with household food expenditure, I, experience the same utility level as the reference household facing the same prices but with food budget, I/d. Phipps (1998) notes that such equivalence scales are of interest in that they allow for interhousehold comparisons of utilities and a determination of expenditure levels at which members of households with different characteristics, such as the age or gender composition of household members, are equally well off.

Phipps (1998) provides an overview of the estimation of equivalent scales within a demand system framework. Unfortunately, given the nature of the data available for this analysis, we limit our analysis to a set of censored Engel curves. We adopt the expenditure-based approach to estimating equivalent scales suggested by Tedford, Capps and Havlicek (1986) where an adult equivalence scale (AES) value for the mth individual in the nth household can be represented as:

$$AES_{m,n} = AES\left(S_{m,n}, A_{m,n}\middle|S_{r,n}, A_{r,n}\right) \tag{3}$$

where
A_m = the mth member's age
S_m = the member's gender
M_n = the number of household members in the nth household
$AES_{m,n}$ = conditional on age, A_r, and gender, S_r, of a reference household member, r.

Following Tedford, Capps and Havlicek (1986), each household member can be categorized as being in one of the series of **development** and **transitional** stages (Levinson et al

1978). Cubic spline functions are used to join these development and transitional periods. As noted by the authors, "events and activities which under during the developmental periods shape the character of living . . . [while] the transitional periods serve as boundaries to link the development periods, thereby providing continuity to the changes in the outgoing and income development phases" (Tedford, Capps and Havlicek 1986, 323–25).

For our analysis, developmental periods, as in Tedford, Capps and Havlicek, are defined as infancy, $A_m \le 1$, childhood and adolescence, $1 \le A_m \le 18$, early adulthood, $23 \le A_m \le 40$, middle adulthood, $46 \le A_m \le 60$, and late adulthood, $66 \le A_m \le 80$. Transitional periods are represented by birth, $A_m = 0$, early adulthood, $18 \le A_m \le 22$, middle adulthood, $41 \le A_m \le 45$, late adulthood, $60 \le A_m \le 65$ and late-late transition periods, $A_m \le 80$.[4]

The number of adult equivalents are derived from cubic spline functions based on the above gender- and age-based categories following Tedford, Capps and Havlicek (1986, 322–26). The number of adult equivalents (TAES) in a particular household is obtained by summing Eq. 3 over all households members. It can be shown that the TAES can be calculated via the following:

$$\begin{aligned} TAES_n = {} & \psi_1 AES_{1n} + \psi_2 AES_{2n} + \psi_3 AES_{3n} + \psi_4 AES_{4n} + \psi_5 AES_{5n} \\ & + \theta_2 AES_{6n} + \theta_3 AES_{7n} + \theta_4 AES_{8n} + \theta_5 AES_{9n} \\ & + \lambda_{11} AES_{10n} + \lambda_{21} AES_{11n} + \lambda_{31} AES_{12n} + \lambda_{41} AES_{13n} \\ & + \lambda_{12} AES_{14n} + \lambda_{22} AES_{15n} + \lambda_{32} AES_{16n} + \lambda_{42} AES_{17n} \end{aligned} \tag{4}$$

where AES_1 through AES_{17} represent age/gender-dependent, weighted-sum variables.[5] Using the above age categories, the parameters Ψ_1 to Ψ_5 and θ_2 to θ_5 measure the impact of food consumption expenditures of adding:

- a newborn baby
- male aged 18–22 years
- male aged 61–65 years
- male aged over 80 years of age
- female aged 18–22 years
- female aged 41–45 years
- female aged 61–65 years
- female over 80 years of age.

These parameters are defined relative to a base household member, which in our analysis is assumed to be a male between 41 and 45 years of age (i.e., $\Psi_3 = 1$). The parameters λ_{11} to λ_{41} and λ_{12} to λ_{42} correspond to the cubic functions for male and female developments periods, respectively (Tedford, Capps and Havlicek 1986, 327). We obtain estimates of the parameters contained in Eq. 4 by using the TAES as an explanatory variable in a SUR system of censored food expenditures. This structure restricts the TAES variable to be the same across commodities.[6]

We are interested in characterizing the structure of Brazilian food expenditures where we differentiate food to be consumed at home (FAH) into 13 categories (red meat, pork, poultry, fish, cereals, breads, pastas, vegetable/root crops, fruits, fluid milk, other dairy products, nonalcoholic beverages, and other FAH) and an aggregate expenditure for purchases in restaurants and other food-away-from home (FAFH) sources.

We can represent the relationship between observed expenditures on the ith commodity by the nth household, y_{in}, and a vector of household characteristics, C_n, as:

$$y_{in} = C_n\beta_i + \varepsilon_{in}(i = 1,\ldots,M; n = 1,\ldots,N) \tag{5}$$

where
β_i= a conformable vector of regression coefficients
M = the number of commodities
N = total number of households
ε_i = an $N \times 1$ error vector.

Given the censored nature of food expenditures illustrated in Table 1, OLS-based Engel curve parameter estimates are likely to be biased (Maddala 1983). In order to overcome the censored characteristic of the distribution of food expenditures, we follow the approach proposed by Shonkwiler and Yen (1999). For the estimation of a system of expenditure functions as in Eq. 5, we differentiate latent, y^*, and observed, y, expenditures. The two-stage purchase process can be represented as:

$$\begin{aligned}
&Stage\,1: \begin{cases} d_{in}^* = Z_{in}'\alpha_i + \upsilon_{in} \\ d_{in} = \begin{cases} 1 \text{ if } d_{in}^* > 0 \\ 0 \text{ if } d_{in}^* \leq 0 \end{cases} \end{cases} \\
&Stage\,2: \begin{cases} y_{in}^* = X_{in}\beta_i + e_{in} \\ y_{in} = d_{in}y_{in}^* \end{cases} \qquad (i = 1,2,\ldots,M; n = 1,2,\ldots,N)
\end{aligned} \tag{6}$$

where
$d_{in}{}^*$ = the unobserved difference in utility with and without the purchase of the ith commodity
d_{in} = the observed dichotomous variable representing whether a household has purchased particular commodity
Z_n = an $L \times 1$ vector of exogenous variables hypothesized to impact the discrete purchase decision
α_i = a conformable parameter vector
e_{in}, v_{in} = random errors.

Heien and Wessells (1990) propose a method to estimate parameters of a system of censored expenditure share equations. As Shonkwiler and Yen (1999) note, their two-step procedure involves:

- estimation of a series of univariate probit equations to account for the discrete purchase decision
- using the associated probit estimates of to evaluate commodity specific inverse Mills ratios
- incorporating these ratios as explanatory variables within a SUR system of Engel curves.

The Heien and Wessells (1990) two-step approach has been extensively used over the past decade (Byrne, Capps, and Saha 1996; Hein and Durham 1991; Saha, Capp and Byrne 1997). Unfortunately, as shown by Shonkwiler and Yen (1999), if the problem is one of a demand system, there is no invariance of the estimated parameters to the omitted equation, given that each equation will not have identical regressors. In addition, there is a theoretical inconsistency given the structure implied by Eq. 6, given that under Heien and Wessells (1990):

$$E(y_{it}) = f(X_{in}, \beta_i) + 2\delta\phi(Z'_{in}\alpha_i) \tag{7}$$

This implies that as $Z'_{in}\alpha_i \to -\infty, E(y_{it}) = f(X_{in}, \beta_i)$. The inconsistency can be seen by examining Eq. 6, which has the characteristic that as $Z'_{in}\alpha_i \to -\infty, y_{it} \to 0$.[7]

Following the results of Wales and Woodland (1980), Shonkwiler and Yen (1999) propose an alternative to the above two-step approach that does not exhibit the above inconsistency. If one assumes that error terms e_{it} and v_{it} are distributed bivariate normal with covariance, δ , then the conditional and unconditional expected expenditures can be represented as:

$$\begin{gathered} E(y_{it} | d_{it} = 1) = f(X_{in,}\beta_i) + \delta\frac{\phi(Z'_{in}\alpha_i)}{\Phi(Z'_{in}\alpha_i)} \\ E(y_{it}) = \Phi(Z'_{in}\alpha_i) f(X_{in}, \beta_i) + \delta\phi(Z'_{in}\alpha_i) \end{gathered} \tag{8}$$

This implies that the system of equations represented in Eq. 5 can be reformulated to be:

$$\begin{gathered} y_{in} = \Phi(Z'_{in}\alpha_i) f(X_{in}, \beta_i) + \delta_i\phi(Z'_{in}\alpha_i) + \xi_{in} \\ (i = 1, 2, \ldots, M;\ n = 1, 2, \ldots, N) \end{gathered} \tag{5$'$}$$

with the error term, $\xi_{in} = y_{in} - E(y_{in}|X_{in}, Z_{in})$. Shonkwiler and Yen (1999) argue that the system of expenditure equations in Eq. 5 can be estimated using a two-step procedure encompassing all observations regardless of purchase decision. Within the first step (e.g., the **purchase decision**), maximum likelihood (ML) probit estimates $\hat{\alpha}_i$ of α_i are obtained by regressing the binary variable d_{in} against Z_{in}, for each commodity. Given the estimation of the univariate probit equations, in the second step (e.g., the **quantity decision**) the standard normal CDF, Φ (·), and PDF, ϕ (·), functions are evaluated at the estimated values of $\hat{\alpha}_i$ and used in Eq. 5′, whose parameters are then estimated using a ML (or SUR) procedure:

$$\begin{gathered} y_{in} = \Phi(Z'_{in}\hat{\alpha}_i) f(X_{in}\ \beta_i) + \delta_i\phi(Z'_{in}\hat{\alpha}_i) + \xi_{in} \\ (i = 1, 2, \ldots, M;\ n = 1, 2, \ldots, N) \end{gathered} \tag{5$''$}$$

The above represents a general framework for estimating a system of censored Engel curves. To the above, we need to augment the vector of explanatory variables with the endogenously determined TAES variable. Observed expenditures can then be represented as:

$$\begin{gathered} y_{in} = \Phi(Z'_{in}\hat{\alpha}_i)\ (X'_{in}\beta_i + \Gamma_i \mathrm{TAES}) + \delta_i\phi(Z'_{in}\hat{\alpha}_i) + \xi_{in} \\ (i = 1, 2, \ldots, M;\ n = 1, 2, \ldots, N) \end{gathered} \tag{9}$$

where TAES is defined by Eq. 4 and Γ_i = coefficients to be estimated. From Eq. 9, the TAES variable is the same regardless of Engel curve and also is composed of a set of unknown coefficients that are estimated simultaneously with β_i and Γ_i.

Given that we incorporate a common endogenously estimated TAES in the 14 Engel curves, we estimate equation parameters via a nonlinear SUR procedure where the likelihood function for the nth household is:

$$LLF_{SUR,n}\left(\beta, \Sigma \middle| y_n, X_n Z_n, \hat{\alpha}\right) = -\frac{M}{2}\ln(2\pi) \\ -\frac{1}{2}\ln|\Sigma| - \frac{1}{2}\xi_n' \Sigma^{-1}\xi_n \\ (n = 1, \ldots, N) \tag{10}$$

where

Σ = the $M \times M$ error term covariance matrix for the M commodities, which is assumed to be the same across observation

ξ_n = an $M \times 1$ vector of equation error terms (Greene 2000).

Both the Heien and Wessells (1990) and Shonkwiler and Yen (1999) methods for estimating the above system of censored Engel curves can be classified as being one of a general class of two-step estimation procedures. That is, we first estimate a set of probit equations used to explain the discrete purchase decision and in the second stage, we obtain SUR parameter estimates by maximizing the conditional likelihood function in Eq. 10 using these probit estimates.

Given our use of univariate probit equations, the joint likelihood of the discrete decisions to purchase our 14 foods, LLF_{Stage_1}, can be represented by the summation of the individual probit log-likelihood functions, $LLF_{PROBIT,j}$:

$$\begin{aligned} LLF_{Stage\_1,n} &= \sum_{j=1}^{M} LLF_{PROBIT,jn}\left(\alpha_j \middle| d_{jn}, Z_n\right) \\ &= \sum_{d_{jn}=0} \ln\left[1 - \Phi\left(Z_{jn}'\alpha_j\right)\right] + \sum_{d_{jn}=1} \ln\ \Phi\left(Z_{jn}'\alpha_j\right) \\ &(n = 1, \ldots, N) \end{aligned} \tag{11}$$

From this likelihood function we assume the following structure of the $[M * L] \times ([M * L]$ coefficient covariance matrix for Step 1 parameters, V_1:

$$V_1 = \begin{bmatrix} V_{1,1} & & & & \\ & V_{1,2} & & & \\ & & \ddots & & \\ & & & V_{1,M-1} & \\ & & & & V_{1,M} \end{bmatrix}$$

where V_{1j} is the $L \times L$ coefficient covarianc e matrix associated with the jth commodity.

Greene (2000) and Murphy and Topel (1985) show that the use of the predicted probit coefficients in the second-stage SUR system implies the coefficient error covariance matrix from this system may be biased. If we represent Λ_2 as the collection of parameters estimated in the second step and V_2 as the associated covariance matrix of these coefficients, then the second-stage maximum likelihood estimation of Λ_2 is consistent and asymptotically normally distributed with covariance matrix V_2*:

$$V_2^* = V_2 + V_2\left[CV_1C' - RV_1C' - CV_1R'\right]V_2$$

where

$$C = E\left[\frac{\partial LLF_{SUR}}{\partial \Lambda_2}\frac{\partial LLF_{SUR}}{\partial \alpha'}\right] \tag{12}$$

$$R = \left[\frac{\partial LLF_{SUR}}{\partial \Lambda_2}\frac{\partial LLF_{Stage\_1}}{\partial \alpha'}\right]$$

(Greene 2000, 135). One can then use Eq. 12 to adjust the nonlinear SUR parameter standard errors given the above two-step estimation procedure.

DESCRIPTION OF THE BRAZILIAN HOUSEHOLD SURVEY DATA

The data used for this analysis are obtained from the Brazilian household survey, 1995–96 *Pesquisa de Orçamentos Familiares* (POF). This survey is used in the construction of the national system of Consumer Price Indexes. A representative random survey of households in the 11 major urban areas across the country was undertaken in the construction of this data set. One component of this survey contains a one-week, detailed diary of food expenditures by urban Brazilian households. The survey includes information on household characteristics as well sources of member income. Surveyed households were required to record food purchase values. Though not mandatory, they also were asked to record quantity purchased. Upon evaluation of the data, we found a large number of households did not record purchase amounts. As such, we were forced to limit our analysis to food expenditures. There were originally 16,013 households in the raw data set. We exclude households from our sample if they did not record any food expenditures during the survey period, had missing household-related information or recorded excessively high food expenditure values. The final sample size used in this analysis was 15,065, a 6% reduction in sample size.[8]

Table 2 provides an overview of the size and composition of our sample households. The average household contained 3.9 members. The extended nature of households can be seen, given that more than 16% of the households had six or more members present. There were on average 1.5 children under the age of 18 in these households. The diversity of household composition can be seen with one-third of the households having at least one child under the age of 6, 42% of the households with a child between 6 and 13 years of age and more than 21% of the households had someone in the household greater than 60 years of age.

We use the TAES variable in the Engel curve SUR model to endogenously quantify the equivalence of household members of alternative age and gender with respect to total food expenditures. In addition, we use a number of other additional household characteristics to characterize the structure of the intensive and extensive purchase process. Table 3 provides an overview of these characteristics. Besides the natural logarithm of household income, *TOTINC*, other household characteristics included in the analysis include the percentage of adult household members that work outside the home, *EMP_PER*, a dichotomous variable identifying whether the household owns a refrigerator and/or freezer, *REFRIGD*, and the percentage of household members in a number of age groups. We also include variables identifying meal planner educational attainment, region of residence and dichotomous variables to capture possible differences in expenditures during public holidays or the Carnival season.[9]

THE STRUCTURE OF FOOD EXPENDITURES IN BRAZIL AND THE IMPACT OF HOUSEHOLD COMPOSITION

Parameter values that maximize the likelihood functions represented in Eqs. 10 and 11 are obtained by using the GAUSS software system and BHHH optimization algorithm. Analytical gradients and the inverse of the information matrix is used in the calculation of the first-stage probit coefficients (Judge et al 1988, 792). For SUR estimation, numerical gradients are used in the BHHH algorithm. Given the number of parameters (> 575) and sample size (> 15,000), we use the inverse of the sums of squares and cross-products of parameter gradients across observations evaluated at optimal parameter values as an estimator of the asymptotic covariance matrix of these parameters (Judge et al 1988, 526).

Factors Impacting Food Choice

Appendix A shows the estimated parameters for the probit and SUR regression models for the 14 food categories included in this analysis.[10] In regards to the structure of whether to purchase a particular food group, a vast majority of estimated coefficients were statistically significant. Given the number of significant coefficients, it is not surprising that log-likelihood ratio tests of the joint null hypothesis that all slope coefficients are zero generate statistically significant χ^2 values for all commodities.

In terms of income effects, we find a positive and statistically significant income impact for nine of the 14 food categories. Only for cereal products do we find a negative impact of income on purchase probability. Income probability elasticities are calculated from the estimated coefficients and means of the exogenous variables. These elasticities are shown in the first column of data in Table 4. All income elasticities are relatively small, with the largest values obtained for pork, FAFH, other dairy, fish and fruits.

We find significant impacts of ownership of a refrigerator/freezer for nine of the 14 commodities. Household composition as represented by the percentage of members in the three age groups is found to impact food choice. Of particular importance is the positive impact of children and teenage members on fluid milk purchase probability and the negative impact of very small children on the probability of purchasing food for consumption away from home. We also find that relative to Rio de Janeiro there are significant regional differences in purchase probability across commodity. For example, for the red meat, poultry and fruit commodity groups, there is a greater probability of purchase for all regions.

Factors Impacting Quantity Purchased

From the estimated probit coefficients, we evaluate $\Phi\left(Z'_{in}\hat{\alpha}_i\right)$and $\Phi\left(Z'_{in}\hat{\alpha}_i\right)$and estimate the SUR Engel curve system represented in Eq. 9. The resulting SUR coefficients are presented in Appendix A. Except for fluid milk, SUR coefficients associated with income are statistically significant and positive.

Table 2. Frequency distribution of sample household size and age composition of household members

	Household size (μ= 3.94)		Number of members < 5 years (μ= 0.44)		Number of members 5–13 years (μ= 0.65)		Number of members 13–18 years (μ= 0.44)		Number of members 18–25 years (μ= 0.51)		Number of members 25–40 years (μ= 0.94)		Number of members 40–60 years (μ= 0.68)		Number of members older than 60 years (μ= 0.27)	
	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%
0	—	—	10262	67.3	8834	57.9	10470	68.7	9786	64.2	5842	38.3	7888	51.7	12098	79.3
1	1059	6.9	3592	23.6	3755	24.6	3245	21.3	3568	23.4	4972	32.6	4460	29.2	2205	14.5
2	2389	15.7	1123	7.4	1941	12.7	1227	8.0	150	39.9	4032	26.4	2823	18.5	889	5.8
3	3190	20.9	164	1.1	558	3.7	261	1.7	297	1.9	318	2.1	55	0.4	55	0.4
4	3675	24.1	108[a]	0.7	161[a]	1.1	46[a]	0.3	95[a]	0.6	85[a]	0.6	23[a]	0.2	2[a]	0.0
5	2419	15.9														
6	1205	7.9														
7	643	4.2														
7+	669	4.4														

[a]These values represent the number of households with at least this number of members of this age group. The total number of households in the sample is 15,065. The μ values represent the mean number of household members (column 1) and the mean number of members in a particular age group.

Table 3. Description of exogenous variables

Variable	Description	Units	Mean	Model[a]
Household characteristics				
TOTINC	monthly household pre-tax income[b]	000 Real	1.65	P, E
EMP_PER	% of adults working outside home	%	45.50	P
REFRIGD	household own refrig/freezer	0/1	0.87	P, E
PERLT6	% of household members < 6 years	%	9.67	P
PER6_13	% of household members, 6–13 years	%	13.70	P
PERTEEN	% of household members, 14–18 years	%	10.01	P
PERSENIOR	% of household members > 60 years	%	9.24	P
Meal planner education[c]				
NO_ED[d]	no formal education	0/1	0.098	E
GRADE	elementary school	0/1	0.427	E
JR_HIGH	junior high	0/1	0.193	E
HIGH	high school	0/1	0.191	E
TECH	technical college	0/1	0.084	E
OTH_COLL	nontechnical college	0/1	0.005	E
Region of residence				
RIO[d]	Rio de Janeiro	0/1	0.100	P, E
PORTO	Porto Alegre	0/1	0.078	P, E
BELO	Belo Horizonte	0/1	0.098	P, E
RECIFE	Recife	0/1	0.119	P, E
SAOPAULO	Sao Paulo	0/1	0.082	P, E
BRASILIA	Brasilia	0/1	0.055	P, E
BELEM	Belem	0/1	0.091	P, E
FORTAL	Fortaleza	0/1	0.125	P, E
SALVA	Salvador	0/1	0.093	P, E
CURITIBA	Curitiba	0/1	0.069	P, E
GOINAS	Goinas	0/1	0.089	P, E
Special times of year				
HOLIDAY	week contains a holiday	0/1	0.078	E
CARNIVAL	Carnival occurred during survey period	0/1	0.040	E

[a]P identifies variables used in probit models and E variables used in Engel curve estimation.
[b]Monetary values at 15 September 1996 prices. 1 Brazilian Real = US$1.02 in 1996.
[c]The meal planner is assumed to be female head, if present.
[d]This dichotomous variable is used as the base of comparison.
Source: 199–996 POF. All households with positive total food consumption.

For a majority of food categories defined for this analysis, household income positively impacts both the intensive and extensive purchase decisions. In terms of unconditional expenditure elasticities, it is not unexpected that the fish/seafood commodity exhibits the highest value, given that the percentage of sample households that purchased this commodity is the smallest of any of the commodities. Mean monthly income for households not pur-

Table 4. Income impacts on purchase probabilities and income and TAES impacts on expenditures

Commodity	Purchase probability income elasticities $\Phi(Z_i'\alpha)$	Expenditure income elasticities $E(Y)$	Expenditure income elasticities $E(Y\|Y>0)$	Expenditure TAES elasticities $E(Y)$	Expenditure TAES elasticities $E(Y\|Y>0)$
Red meat	0.003	0.271	0.073	0.801	0.459
Pork	0.176	0.49	0.191	1.418	0.415
Poultry	–0.001	0.214	0.163	0.950	0.565
Fish/seafood	0.129	1.952	0.421	2.772	0.502
Fluid milk	0.023	0.358	0.194	0.495	0.323
Other dairy	0.149	0.698	0.269	0.657	0.312
Cereals	–0.023	0.240	–0.005	0.970	0.449
Pastas	0.014	0.739	0.272	0.953	0.457
Vegetables/roots	0.053	0.354	0.204	0.659	0.382
Fruits	0.128	0.051	0.159	0.401	0.205
Bread	0.010	0.328	0.233	0.634	0.571
NAB	0.056	0.315	0.272	0.522	0.302
Other FAH	0.003	0.487	0.232	0.619	0.361
FAFH	0.164	0.895	0.616	0.093	0.062

chasing fish or seafood was 1,650 Real, compared with a mean income of 5,430 Real for purchasing households. For households consuming fish/seafood, the income elasticity is estimated to be 0.42.

The primary motivation for undertaking this research is to examine the role household member age and gender composition plays in determining household food expenditures and the impact of such differences on the evaluation of household welfare. In Appendix A we present the estimated Γ_i coefficients, which provide an indication of the sign of the marginal impacts of the TAES variable on household expenditures.[11] All of the TAES expenditure-related coefficients are found to be positive and statistically significant.

From the estimated coefficients shown in Appendix A, we evaluate three types of elasticities. The elasticity impacts of a change in income on the probability of purchasing the *i*th commodity is calculated from the CDF, $\phi\left(Z_i{'}\hat{\alpha}\right)$ where $\hat{\alpha}$ is the vector of estimated coefficients obtained from the *i*th commodity's probit equation. From the relationships shown in Eq. 8, conditional and unconditional expenditure income and *TAES* coefficients are also evaluated. The probability and expenditure elasticities are shown in Table 4.[12]

Calculation of Household-specific Endogenous Equivalence Scales

The estimated TAES component coefficients represented in Eq. 4 are presented in Appendix A. Similar to the results obtained by Demousssis and Mihalopoulos (2001), Sabates, Gould and

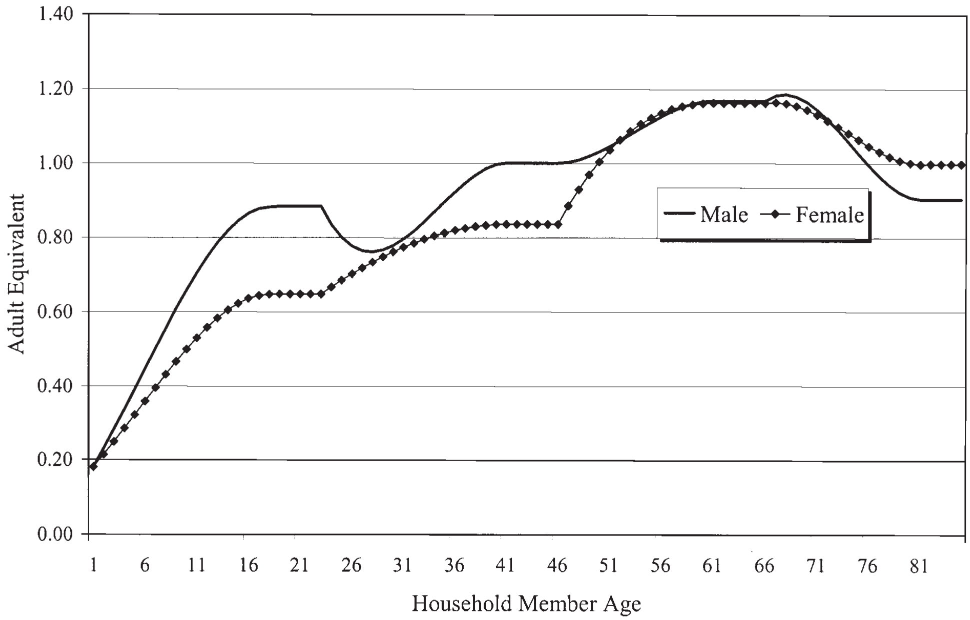

Figure 1. Comparison of adult equivalent scales by gender

Villareal (2001) and by Tedford, Capps and Havlicek (1986), the transitional period coefficients are all found to be statistically significant and positive. These TAES paramater estimates are used to simulate adult equivalent profiles for male and female household members over a range of ages (Figure 1). As an example of how to interpret these profile values, in terms of total food expenditures, a male child 10 years old represents 0.70 adult equivalents. A female child the same age represents 0.53 adult equivalents. Surprisingly, maximum adult equivalent values are obtained for male and female members 60 years of age with adult equivalent values of 1.16

There are several trends to obtain from these profiles:

- the similarity of the profiles across gender
- the general increase in adult equivalents until age 65
- the male profile lies above the female profile for most age categories
- the surprisingly high TAES values for older household members.

One possible reason for the relatively high TAES value for older members may be better reporting of household food expenditures for households that have adults with lower labor force participation rates. Given the standard error associated with coefficients Ψ_4 and θ_4, these maximum values are not statistically different from 1.0, the base TAES value for a male between 41 and 45 years of age. In fact of all the adults represented by the various transitional period age groupings, only females between the ages of 18 and 22 have estimated coefficients that are at least two standard deviations from the base value of 1.0.

From the estimated TAES related coefficients, Figure 2 portrays empirical CDFs of weekly **per capita** food expenditures, where household member count and the endogenously determined household TAES are used as deflators. As Deaton (1997) notes, in developing

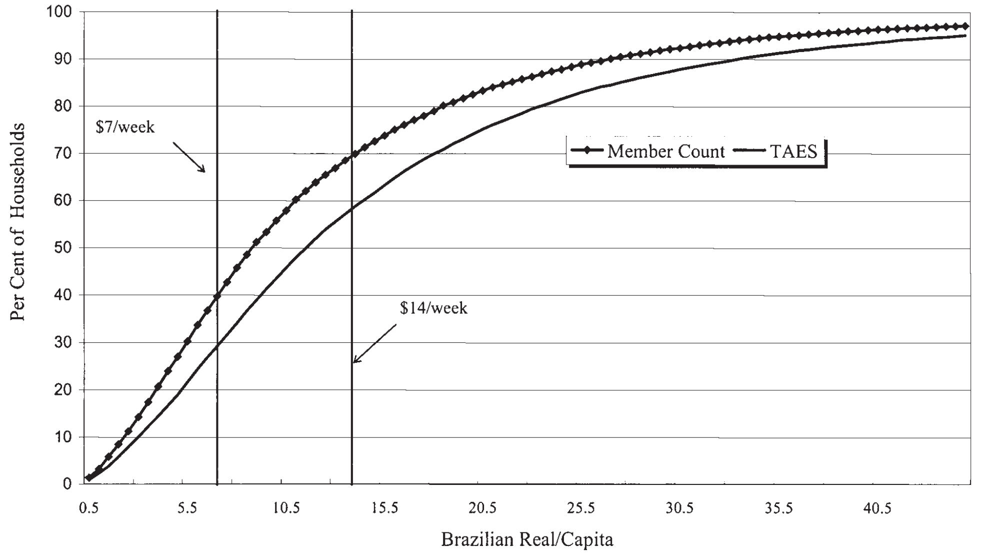

Figure 2. Cumulative distribution of per capita food expenditures under alternative deflators

country settings, one measure of overall welfare is the level of per capita food intake or expenditure. An important question that needs to be answered is: Does the evaluation of household welfare depend on how one takes account of the differential needs of household members of varying age/gender?

With per capita food expenditures an indicator of household welfare, in Figure 2, we see a shift to the right of the per capita expenditure CDF when using TAES versus the CDF based on member count. This shift provides some evidence that households may have higher welfare (as measured by per capita expenditures) relative to reliance on the membercount-derived value of per capita expenditures. The World Bank has established a standard that defines a person as being **poor** if food expenditures are less than US$2 per day and **extremely poor** if expenditures are less than US$1 per day (World Bank 2001, 17). Assuming a 1:1 exchange rate, 39.6% of our sample was estimated to spend less than $7 Real per capita per week based on household member count versus 28.8% of household when using the endogenously determined TAES, a difference of 10.5% (Figure 2).[13] At $14 Real per capita per week, 69.9% of the sample spend less than this on food, compared with 58.8%, a difference of 11.1%.

With the distributions shown in Figure 2, we undertake a χ^2 test to determine whether the above CDFs are indeed different. Using per capita food expenditure increments of 2 Brazilian Real, we obtain a χ^2 value of 80.4, implying a rejection of the null hypothesis of the equality of the two CDFs. An overview of the characteristics of the distribution of the two measures of per capita expenditures is shown in Table 5. There is an increase in the estimated per capita value from 12.5 Real per capita when using member count to 15.8 when using the TAES as the deflator. Following Snedecor and Cochran (1967), we test for the degree of skewness of these per capita measures. The coefficient of skewness statistic, Ω, is calculated as:

Table 5. Characteristics of the distribution of weekly per capita expenditures using member count and TAES deflators

Deflator	Mean	Standard deviation	Skewness	
			Ω	*Z*-value
Member count	12.5	12.1	2.42	121.1
Adult equivalents	15.8	14.8	2.45	122.9

$$\Omega = \frac{\Omega_3}{\Omega_2 \sqrt{\Omega_2}}$$

where

$$\begin{aligned} \Omega_3 &= \frac{\sum_{n=1}^{N} \left(PC_n - \overline{PC}\right)^3}{N} \\ \Omega_2 &= \frac{\sum_{n=1}^{N} \left(PC_n - \overline{PC}\right)^2}{N} \\ \Omega &\sim N\left(0, \frac{6}{N}\right) \end{aligned} \tag{13}$$

PC = per capita total food expenditures (Snedecor and Cochoran 1967, 86–87).

Surprisingly, we find little difference in the degree of skewness with both member count and TAES-based distributions being positively skewed.

Using our estimated TAES values, we evaluate the elasticity impacts of a change in the number of adult equivalents on food expenditures. In Table 4, we see that, for purchasing households, estimated TAES elasticities are less than one. This could be evidence of either increasing economies, decreasing per TAES quantities purchased, changes in the quality of food purchased or a combination of the above (Dong and Gould 2000). Only for fish/seafood and pork is there a elastic response to changes in TAES on unconditional expenditures.

Given the profiles shown in Figure 2, are there differences in the impacts on food expenditures across household member gender? Are there differences across the age of household member? To answer these questions, we undertake two hypothesis tests using nested versions of the base model that has been discussed above. First, we test the null hypothesis that the TAES profiles are the same across gender and age of household member. Second, we test the hypothesis that gender does not impact the level of food expenditures (e.g., the female profile shown in Figure 1 is the same as the male profile). Both of the specifications implied by the above two tests are nested within the original model specification. Given that the two specifications are indeed nested, an evaluation of the null hypotheses can be evaluated using likelihood ratio statistics based on restricted and unrestricted likelihood function values and that are asymptotically distributed χ_J^2 where J is the number of parameter restrictions associated with the nested model. The null hypothesis of profile equality resulted in a χ_8^2 value of 29.0. This value exceeds the critical χ_8^2 value at the 0.01 significance level. The null hypothesis of no age or gender impacts results in a value of 334.0,, which again implies a rejection of this null hypothesis. These rejections provide justification for the need to account for household size and composition when analyzing food expenditures.

CONCLUSION

In this analysis we incorporate an endogenous measure of household size within a system of censored food expenditures. We do this to provide a more accurate assessment of household welfare and to allow for interhousehold comparisons. The endogenously determined equivalence scales are obtained from the estimation of a SUR system of Engel curves for a sample of urban Brazilian households who recorded detailed weekly food expenditures.

Given our use of household level data and the desire to analyze expenditures for a detailed set of commodities, we use a recently developed econometric procedure that allows us to account for expenditure censoring within the SUR system. Our analysis represents an extension of previous use of this methodology via the inclusion of the above endogenous equivalence scales as explanatory variables. An obvious limitation of our analysis is the adoption of the corner-solution assumption. That is, we did not allow for possible IOP effects. Future research will be undertaken to examine the implications of such effects on the econometric model specification. That is, how would IOP impact the formulation of the first-stage modeling and estimation of the system of unconditional food expenditures?

Our results provide support for the need to account for household composition effects when undertaking interhousehold welfare comparisons. We provide evidence that, after controlling for the differential consumption needs of members of alternative age and gender, our evaluation of the welfare of the sample of households included in the present analysis is higher than would have been reached had such evaluations been undertaken using a count of household members as a measure of household "size."

NOTES

[1]When applied to an analysis of household income, adult equivalence scales are employed to adjust household budgets to permit welfare comparisons across different size and composition. For a review of the methodological issues involved with the estimation of adult equivalence scales for welfare evaluation, refer to Blaylock (1991).

[2]As noted by an anonymous Journal reviewer, if IOP is a serious problem in our data, then the parameter estimates associated with our econometric model may be considered biased but consistent. This is an empirical question and worthy of future investigation.

[3]For an example of an application of the Shonkwiler and Yen (1999) methodology, refer to Su and Yen (2000).

[4]As noted by an anonymous Journal referee, the Tedford, Capps and Havlicek (1986) age cut-offs used in this analysis were developed for the U.S. and may not be appropriate for a developing country situation. We recognize this and note that in Sabates, Gould and Villareal (2001) country-specific age cut-off structures were estimated where these structures were based on observed differences in life expectancy in Argentina, Brazil and Mexico. Given the robustness of the results obtained by the authors in their comparative analyses to the Tedford, Capps and Havlicek (1986) age cut-off categories, they used them. Life expectancy data by age and gender are available from the World Health Organization (2003) for large number of countries. Using 1995 data for three regions of Brazil and the

U.S., we find very similar life expectancy values for individuals older than one year of age. For example, for a one-year-old female, the WHO estimates a life expectancy in 1995 of 75 years in Brazil and 78 in the U.S. For a 45-year-old female, the Brazilian life expectancy is estimated to be 33 years, compared with 36 years in the U.S. A Brazilian 65-year-old female is projected to have a life expectancy of 17 years, compared with 19 years in the U.S. For males, these differences are even smaller. Given the above, we decided to continue to use the Tedford, Capps and Havlicek (1986) age cut-offs in the present analysis.

[5]For a detailed review of this derivation, refer to Tedford, Capps and Havlicek (1986, 333).

[6]This is assumption is justified given that:

- the estimation of commodity specific TAES variables for each commodity would require the estimtion of 224 parameters (i.e., 16 TAES parameters (14 commodities) in addition of the parameters for expenditure
- as noted by an anonymous Journal reviewer, a single TAES would be justified under theassumption of a single age- and gender-specific food or nutrition demand.

[7]For an alternative analysis of the bias that may result when using the Heien and Wessells (1990) procedure, refer to Vermeulen (2001).

[8]For the estimation of the probit and SUR models, unweighted data are used.

[9]As suggested by Shonkwiler and Yen (1999), an alternative to the method used here is to estimate both the probit and SUR maximum likelihood models within a single aggregate model. We attempt such a specification where we include the TAES as an explanatory variable in both the probit and SUR models. For reasons not completely understood, we cannot obtain a consistent parameter covariance matrix.

[10]Due to space limitations, the probit and SUR coefficients associated with the 10 regional dummy variables are not presented but can be obtained from the authors upon request. In the probit equations, 126 out of 140 region-related coefficients are statistically significant. In the SUR regressions, 62 are statistically significant.

[11]To capture possible nonlinear impacts, we use the logarithm of the TAES variable in the estimation of each Engel curve. Tedford, Capps and Havlicek (1986) use TAES and $TEAS^2$ variables to capture such nonlinear impacts. We attempt to estimate such a model but cannot obtain reasonable TAES coefficients.

[12]In evaluating the probability elasticities, overall sample means of the explanatory variables are used. In the calculation of income and TAES elasticity impacts on unconditional and conditional commodity expenditures (i.e., Eq. 8) overall sample means of the explanatory variables are also used. Unconditional and conditional expenditures are used in the associated expenditure elasticity.

[13]During June 1995, the average exchange rate was US$1.094 per Real. In January 1996, the average exchange rate was US$1.026 per Real. In June 1996, this exchange rate decreased to US$0.999 per Real.

ACKNOWLEDGMENT

The authors would like to thank the Babcock Institute for International Dairy Research and Development, University of Wisconsin-Madison, for providing research support and two anonymous Journal referees for their comments, which greatly improved the quality of the manuscript. Any errors or omissions remain the responsibility of the authors. No senior authorship is implied.

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APPENDIX

Table A-1. Estimated maximum likelihood probit and SUR coefficients[a]

Exogenous variable	Red meat		Pork		Poultry		Fish/seafood		Fluid milk		Other dairy		Cereals	
	Coeff.	Std. dev.	Coeff.	Std. dev.	Coeff.	Std. dev.	Coeff.	Std. dev.	Coeff.	Std. dev.	Coeff.	Std. dev.	Coeff.	Std. dev.
Probit coefficients:														
Intercept	**–0.269**	**0.051**	**–0.745**	**0.055**	**–0.218**	**0.052**	**–1.138**	**0.062**	**–0.212**	**0.051**	**–0.637**	**0.052**	**–0.399**	**0.052**
LN(TOTINC)	0.005	0.011	**0.156**	**0.012**	–0.002	0.011	**0.088**	**0.013**	**0.044**	**0.011**	**0.194**	**0.011**	**–0.027**	**0.011**
EMP_PER	**–0.082**	**0.023**	**–0.054**	**0.025**	**–0.123**	**0.024**	–0.038	0.028	**–0.073**	**0.024**	**–0.066**	**0.023**	–0.040	0.023
REFRIGD	**0.128**	**0.034**	–0.031	0.036	–0.059	0.035	–0.055	0.039	**0.330**	**0.034**	**0.134**	**0.034**	**–0.145**	**0.034**
PERLT6	0.101	0.075	**0.296**	**0.079**	**0.390**	**0.076**	**0.207**	**0.091**	**1.077**	**0.078**	**0.463**	**0.075**	**0.197**	**0.075**
PER6_13	**0.347**	**0.061**	**0.394**	**0.064**	**0.551**	**0.062**	**0.230**	**0.073**	**0.481**	**0.063**	**0.438**	**0.061**	**0.377**	**0.061**
PERTEEN	**0.335**	**0.071**	**0.279**	**0.076**	**0.533**	**0.072**	**0.395**	**0.085**	**0.449**	**0.073**	**0.254**	**0.071**	**0.443**	**0.071**
PERSENIOR	**–0.131**	**0.050**	**–0.312**	**0.057**	**–0.179**	**0.050**	0.044	0.063	**0.216**	**0.052**	–0.085	0.051	–0.050	0.051
Engel curve coefficients:														
Intercept	–5.135	2.718	–1.437	1.671	**–2.091**	**1.028**	**–15.909**	**4.400**	**7.985**	**0.846**	2.639	1.598	1.684	1.719
LN(TOTINC)	**1.91**	**0.178**	**0.734**	**0.147**	**0.684**	**0.093**	**1.950**	**0.247**	0.549	0.511	**1.012**	**0.365**	**0.422**	**0.187**
REFRIGD	**1.453**	**0.515**	0.482	0.385	**0.498**	**0.224**	–0.095	0.326	**–1.065**	**0.426**	0.379	0.519	–0.186	0.304
GRADE	0.805	0.425	0.481	0.317	0.135	0.199	–0.365	0.342	**0.694**	**0.229**	0.511	0.362	0.012	0.240
JR_HIGH	**1.03**	**0.459**	**0.919**	**0.342**	–0.195	0.229	–0.638	0.391	**1.272**	**0.252**	**0.994**	**0.391**	–0.407	0.286
HIGH	0.292	0.463	**0.794**	**0.348**	**–0.494**	**0.242**	**–1.062**	**0.398**	**1.373**	**0.264**	**2.235**	**0.382**	**–1.249**	**0.329**
TECH	–0.627	0.525	0.627	0.377	**–1.015**	**0.305**	**–0.916**	**0.456**	**1.436**	**0.338**	**3.046**	**0.416**	**–1.625**	**0.445**
OTH_COLL	–1.395	2.265	–0.197	1.062	0.881	0.990	1.775	1.047	1.080	1.038	**3.409**	**0.677**	–0.654	1.500
HOLIDAY	0.022	0.336	**1.272**	**0.210**	**0.514**	**0.184**	0.121	0.269	–0.086	0.195	–0.204	0.243	–0.031	0.266
CARNIVAL	0.271	0.498	–0.731	0.417	0.145	0.272	**0.495**	**0.466**	0.021	0.268	–0.303	0.322	0.343	0.322
Ω	**6.520**	**2.549**	1.682	1.200	**3.724**	**1.015**	**11.305**	**2.665**	**–8.669**	**0.996**	–1.706	1.305	1.728	1.542
LN(TAES)	**5.101**	**0.364**	**2.104**	**0.261**	**3.111**	**0.199**	**3.204**	**0.376**	**1.600**	**0.178**	**1.500**	**0.204**	**3.146**	**0.237**

Continued on Page 344

Table A-1. Continued

Exogenous variable	Pastas		Vegetable/roots		Fruits		Breads		Nonalcholic bev.		Other FAH		FAFH	
	Coeff.	Std. dev.	Coeff.	Std. dev.	Coeff.	Std. dev.	Coeff.	Std. dev.	Coeff.	Std. dev.	Coeff.	Std. dev.	Coeff.	Std. dev.
Probit coefficients:														
ONE	**–0.553**	**0.053**	**–0.254**	**0.050**	**–0.712**	**0.052**	**0.618**	**0.064**	**–0.161**	**0.051**	**–0.256**	**0.051**	**0.362**	**0.053**
LN(TOTINC)	0.017	0.011	**0.083**	**0.011**	**0.179**	**0.011**	**0.060**	**0.015**	**0.087**	**0.011**	0.005	0.011	**0.405**	**0.012**
EMP_PER	**–0.101**	**0.024**	**–0.115**	**0.023**	**–0.097**	**0.023**	**–0.121**	**0.032**	**–0.074**	**0.023**	**–0.088**	**0.023**	**0.091**	**0.025**
REFRIGD	**–0.110**	**0.035**	**0.200**	**0.033**	**0.255**	**0.034**	**0.327**	**0.043**	0.008	0.034	–0.051	0.034	–0.034	0.035
PERLT6	**0.691**	**0.076**	0.120	0.075	**0.358**	**0.075**	**0.681**	**0.101**	**0.362**	**0.075**	**0.489**	**0.076**	**–0.241**	**0.078**
PER6_13	**0.446**	**0.062**	**0.296**	**0.061**	**0.135**	**0.061**	**1.066**	**0.089**	**0.500**	**0.061**	**0.461**	**0.062**	**0.236**	**0.065**
PERTEEN	**0.392**	**0.073**	**0.250**	**0.071**	0.035	0.071	**0.756**	**0.099**	**0.376**	**0.071**	**0.414**	**0.072**	**0.416**	**0.077**
PERSENIOR	–0.010	0.052	–0.008	0.050	**0.123**	**0.051**	0.093	0.064	**–0.114**	**0.050**	–0.086	0.050	**–0.890**	**0.054**
Engel curve coefficients:														
Intercept	**3.200**	**1.342**	–0.464	1.141	4.084	2.763	**1.803**	**0.495**	–0.500	0.994	2.580	1.525	**13.274**	**2.631**
LN(TOTINC)	**0.523**	**0.194**	**0.768**	**0.121**	**0.978**	**0.253**	**0.733**	**0.146**	**1.094**	**0.146**	**0.933**	**0.239**	**10.282**	**0.569**
REFRIGD	0.181	0.232	**0.527**	**0.254**	0.027	0.554	–0.023	0.213	**0.493**	**0.272**	0.255	0.376	–2.333	1.254
GRADE	0.217	0.175	**0.470**	**0.213**	0.689	0.368	**0.557**	**0.153**	0.197	0.241	0.352	0.347	0.572	1.501
JR_HIGH	–0.043	0.197	**0.827**	**0.229**	**1.164**	**0.391**	**1.013**	**0.170**	0.332	0.261	0.635	0.380	2.762	1.539
HIGH	–0.150	0.199	**0.791**	**0.232**	**1.715**	**0.397**	**1.199**	**0.174**	0.417	0.267	0.681	0.395	**5.751**	**1.541**
TECH	**–0.465**	**0.264**	**1.004**	**0.256**	**2.469**	**0.433**	**1.353**	**0.199**	**0.611**	**0.298**	**1.685**	**0.498**	**13.274**	**1.606**
OTH_COLL	0.625	0.876	**3.430**	**0.501**	**4.332**	**0.679**	**1.713**	**0.526**	–0.032	0.805	**2.744**	**1.064**	**15.222**	**2.132**
HOLIDAY	0.021	0.155	**–0.394**	**0.165**	**0.609**	**0.205**	–0.384	0.145	0.891	0.176	–0.195	0.270	–1.309	0.778
CARNIVAL	0.017	0.211	–0.056	0.209	0.210	0.289	0.185	0.173	0.099	0.255	**0.510**	**0.339**	–0.247	1.066
Ω	**–2.218**	**1.165**	1.220	1.164	–2.268	2.270	**–4.587**	**1.125**	**2.195**	**1.021**	–0.771	1.493	6.083	3.190
LN(TAES)	**2.121**	**0.141**	**1.591**	**0.136**	**1.053**	**0.193**	**3.202**	**0.112**	**1.764**	**0.174**	**2.123**	**0.231**	**1.086**	**0.505**

[a]Boldface coefficients identify those with *t*-values greater than 1.96. Due to space limitations, the estimation regional coefficients used in the probit and SUR regressions are not presented. They can be obtained from the authors upon request.

Table A-2. Estimated maximum likelihood taes component coefficients

Age/gender category		Coefficient	Standard deviation
Newborn baby	Ψ_1	**0.182**	**0.065**
Transitional period coefficients:			
Male			
18–22	Ψ_3	**0.883**	**0.070**
60–64	Ψ_4	**1.168**	**0.122**
over 80	Ψ_5	**0.904**	**0.181**
Female			
18–22	θ_2	**0.647**	**0.057**
41–45	θ_3	**0.836**	**0.090**
60–64	θ_4	**1.162**	**0.115**
over 80	θ_5	**0.999**	**0.140**
Developmental period cubic coefficients:			
Male			
1–17	λ_{11}	0.048	0.032
23–40	λ_{21}	**–0.055**	**0.027**
46–60	λ_{31}	0.001	0.050
65–80	λ_{41}	0.020	0.078
Female			
1–17	λ_{21}	0.032	0.030
23–40	λ_{22}	0.019	0.025
46–60	λ_{32}	0.052	0.045
65–80	λ_{42}	0.005	0.067

Ψ_2 is assumed to equal 1.0. Boldface numbers indicate a *T*-ratio greater than 1.96.