Food Demand in Mexico: A Quasi-Maximum Likelihood Demand System Approach

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Introduction

The North American Free Trade Agreement (NAFTA) enacted in 1994 is no doubt impacting the level of trade between the U.S., Canada and Mexico. With the adoption of the NAFTA, an expanding economy and growing population, Mexico has become U.S.'s third largest trading partner after the European Union and Canada. Mexico's share of U.S. agricultural exports has steadily increased from less than 7% in 1990 to12.7% in 2000. In 2001, U.S. food and agricultural exports to Mexico was $7.4 billion, an increase of nearly 58% since implementation of NAFTA in 1994. This trend is expected to continue given that by the end of 2003, a majority of Mexican import tariffs will be lifted. In addition, during April 2002 the U.S. Secretary of Agriculture signed a joint agreement with her Mexican counterpart to create the Consultative Committee on Agriculture. This is a bi-lateral team with the mandate to strengthen the cooperation on agricultural trade issues between the two countries.

Besides the impacts of the tariff reductions experienced under NAFTA, the ultimate determinant of the level of trade between these countries is the underlying structure of food demand. For this paper we attempt to quantify the determinants of the demand for food by Mexican households using a household survey of food expenditures and quantities purchased. It is important that U.S. manufacturers and traders obtain a better understanding of such determinants so as to provide some guidance of future expenditure patterns that may be impacted by changing economic conditions. This analysis will answer such questions as: How do food consumers in Mexico allocate these expenditures across commodities? What is the role of household composition in determining the demand for specific foods? How sensitive are household food purchases to price changes?

This analysis makes a contribution to the literature in terms of its analysis of the determinants of the demand for food for an important market for U.S. agricultural products as well as from a methodological perspective with respect to the recognition of the censoring of commodity purchases within our system estimation framework.

Table 1 shows per capita food purchases for a 1998 urban sample of Mexican households.[1] Purchase amounts are obtained by dividing total household purchases by the number of household members. This count of household members is often used when defining per capita consumption or as a measure of household size. The implicit assumption associated with the use of head count is that each household member has an equal impact on food purchases/expenditures. In reality, the impacts of household size will vary depending on the age and gender composition of household members (Deaton and Muellbauer, 1986). For example it does not recognize the fact that the consumption needs of children can typically be met at lower cost than that of adults (Dreze and Srinivasan, 1997). The use in empirical demand analysis of a single household count variable as a deflator of food expenditures or its use as an explanatory variable is common practice. It is important to remember that such use incorporates the implicit assumption of the uniform impacts on expenditures of household members of differing age and gender.

One approach that can be used to avoid the assumption of equal expenditure impacts is the use of endogenously determined equivalence scales which assign different weights to household members according to their age and gender (Deaton and Muellbauer, 1986).[2] Given the determination of an appropriate equivalence scale, a comparison of food expenditures for

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[1] This sample is not representative of Mexican households as we limit our analysis to urban households with a male and female head present.

[2] 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. That is, these scales are used to account for the role of household size and composition in the transformation of income into welfare. For a review of the methodological issues involved with the estimation of adult equivalence scales for welfare evaluation refer to Blaylock (1991).

households of differing composition can be undertaken. As an example, suppose the weight given to a male adult between 25 and 45 years of age is 1.0, a female adult in the same age group a weight of 0.85 and a female child under 10 years of age a weight of 0.35, then a four-member household consisting of one male and two female adults and one female child in the above age groups would result in the household being composed of 3.05 *adult equivalents.* A single parent household with one female adult would possess the corresponding adult equivalent of 1.20. The per capita expenditures patterns of these two households can then be compared where the *adult equivalents* instead of a simple count of household members are used as the expenditure deflator.

Given the recognition of the need to obtain estimates of food adult equivalents to allow for cross-household expenditure comparison, a number of approaches have been suggested for the estimation of endogenously determined adult equivalent scales. These approaches have ranged from the use of demographically translated utility consistent demand systems to more ad hoc single equation approaches (Muelbauer, 1980). The present paper uses a demand system approach in an analysis of at-home food purchases by urban Mexican households during August-September, 1998. We adopt a method where prices are scaled in a manner that an estimate of a single household food adult equivalent is estimated. This is in contrast to previous analyses where food-specific scaling functions were estimated (Gould, Cox and Perali, 1991).

A Model of the Role of Household Composition

We assume that household at-home food demand is separable from the demand for other goods. Additionally we assume that utility obtained from at-home food purchases can be represented by an indirect utility function (V) which represents the maximum equally distributed utility for each household member:

$$V = V(p, M \mid c) = \max[U(x;c) \mid p'x \le M], \tag{1}$$

where U is the household's utility function, x is a (K x 1) vector of purchased food amounts with corresponding price vector p, c is a vector of demographic characteristics, and M is the household's food budget. Thus, V represents the level of per capita utility which, if shared by each household member, would yield the same aggregate well-being as the actual distribution of utility within the household (Phipps, 1998). An equivalence scale (d) can then be defined using the above indirect utility function:

$$V = V(p, M \mid c) = V(p, M/d \mid c^R), \tag{2}$$

where c^R is the vector of characteristics of an arbitrary reference household. Given (2), members of a household with characteristic vector c, facing prices p and with household income (expenditure) M experience the same utility level as the reference household facing the same prices but with income (M/d).

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

$$d = E(V, p \mid c) / E(V, p \mid c^R) = d(V, p \mid c). \tag{3}$$

Phipps(1998) notes that such equivalence scales are of interest in that they allow for interhousehold comparisons of utilities and a determination of income levels at which members of households with different characteristics, such as the age or gender composition of household members, are equally well off. If these equivalence scales are to be independent of the utility level at which these comparisons are made, then preferences must satisfy *independence of base* (IB) and/or *equivalence scale exactness* (ESE).[3] Lewbel(1989) describes the general restrictions on cost and social welfare functions required for the estimation of IB equivalence scales.

[3] The assumption of equivalence scale exactness implies that this measure is only a function of the demographic

Blackorby and Donaldson (1993) show that in order to recover exact equivalence scales from demand behavior it is necessary that the preferences not take a PIGLOG form (Muellbauer, 1975).

Given (3), one needs to specify a functional form for the equivalence scale measure. That is, define the equivalence of the reference household, V^R, such that

$$V(p,\ M \mid c) = V^R\left(p, M / d(c, p)\right). \tag{4}$$

We can apply Roy's identity to the above indirect utility function to generate a system of demand equations. These demand equations will be functions of prices, income and demographic characteristics implying that the parameters of the equivalence scale, $d(c, p)$, can be obtained via estimation of these demand equations (Blackorby and Donaldson, 1993).

In our analysis of food expenditures and similar to Phipps (1998), we assume our reference household's indirect utility (V) can be represented by the following nonhomothetic translog function (Christensen, Jorgensen and Lau, 1975)

$$\log V(p, M) = \alpha_0 + \sum_{i=1}^{K} \alpha_i \log(p_i / M) + \frac{1}{2}\sum_{i=1}^{K}\sum_{j=1}^{K} \log(p_i / M)\log(p_j / M), \tag{5}$$

where p_i's are elements of the price vector p and α_0, α_i's and β_{ij}'s are unknown parameters. Preference of a non-reference household can be obtained by following the procedure in (4), that is, by deflating household income by the equivalent scale:

$$\log V(p, M) = \alpha_0 + \sum_{i=1}^{K} \alpha_i \log(p_i / M^*) + \frac{1}{2}\sum_{i=1}^{K}\sum_{j=1}^{K} \log(p_i / M^*)\log(p_j / M^*), \tag{6}$$

where $M^* = M / d(c, p)$. For our empirical implementation, the scale function $d(c, p)$ is specified as

characteristics and prices and is independent of the level of utility.

$$\log d(c, p) = \sum_{d=1}^{D} d_d c_d + \sum_{\ell=1}^{K-1} \sum_{s=1}^{S} g_{\ell s} z_s \log(p_\ell / p_n), \tag{7}$$

where z_s represents the number of other household members in the sth age group than represented by the base household, c_d is the dth demographic characteristic other than member category counts, and the δ_k's and $\gamma_{\ell s}$'s are parameters to be estimated. In (7), the scale function is expressed in terms of the price ratios p_ℓ / p_n to guarantee the relevant homogeneity in the utility function (6).

Applying Roy's identity to the indirect utility function (6), the translog demand system becomes

$$w_i = \frac{\alpha_i + \sum_{i=1}^{K} \beta_{ij} v_j}{-1 + \sum_{\ell=1}^{K} \sum_{j=1}^{K} \beta_{\ell j} v_j}, \qquad (i = 1, 2, \cdots, K), \tag{8}$$

where $v_j = [p_j d(c, p) / M]$. Homogeneity is guaranteed by use of the normalized prices p_j / M in (5) and (6), while symmetry and adding up are guaranteed by the following parametric restrictions:

$$\beta_{ij} = \beta_{ji}$$

$$\sum_{i=1}^{K} \alpha_i = -1; \sum_{i=1}^{K} \gamma_{is} = 1 \ \forall \ s. \tag{9}$$

Phipps(1998) uses the above to examine expenditure patterns of Canadian two-adult households when children less than 18 years of age are present in the household. We extend this analysis by (i) focusing on the demand for specific foods and (ii) examining whether there are indeed differences in the impacts of additional household members on food expenditures where these members are differentiated by age. This is especially important given that our empirical application is concerned with the food purchase behavior of Mexican households and a large proportion of these households have relatively large numbers of extended family members eating out the same household food supply.

Accounting for Censoring of Household Food Expenditures

As noted in Table 1, the data used in this analysis is obtained from a weekly survey of food expenditures of Mexican households. One advantage of the use of this survey data is that detailed demographic information collected in these surveys allow for the treatment of heterogeneous preferences and estimation of an endogenous equivalent scale. The use of household-level data for demand analysis is often complicated by the censoring of commodity purchases for a large proportion of the sample. This problem of limited dependent variables is particularly notable when analyzing a set of disaggregated products.

There exist a number of methodologies that allow for the estimation of demand systems where the dependent variables are censored. Starting with Amemiya (1974), a number of alternative procedures have appeared in the literature. Wales and Woodland (1983) construct the likelihood function for a demand system based on the Kuhn-Tucker conditions of constrained utility maximization. Lee and Pitt (1986, 1987) and Lee (1993) suggest a dual approach to this procedure, utilizing the indirect utility function and the concept of virtual prices. These estimators all feature multiple probability integrals in the likelihood function, which have hindered their applications to disaggregate products with a large number of zeros.

Recent developments in simulation estimation have provided a solution to this complicated problem (Börsch-Supan and Hajivassiliou, 1993; Geweke, 1991; Keane, 1993). By simulating the multivariate normal probabilities in the likelihood function, the procedure provides a practical alternative to numerical evaluation of these probability integrals. A censored demand system application of the simulation approach can be found in Kao, Lee and Pitt (2001). A review of other applications can be found in Mariano, Schuermann and Weeks (2000).[4]

As an alternative to the problem of having to evaluate high dimensioned distributions, one can approximate the multivariate likelihood function with a sequence of bivariate specifications. This parsimonious approach has been attempted in multivariate probit estimation but until recently has received little attention in the censored system literature (Avery, Hansen and Hotz, 1983; Avery and Hotz, 1985). This procedure has been applied to the case of censored system of linear equations in Harris and Shonkwiler (1997) and Yen and Lin (2002). We incorporate this dimension-reduction alternative in our analysis of Mexican food expenditures where we develop a demand system that accounts for censored commodity expenditures.

Unlike time-series studies, in which cross-price effects are often plagued by collinearity, the use of cross-sectional data offers an obvious advantage for deriving better cross-price elasticity estimates. A number of two-step estimation procedures have appeared in the literature where the objective is the estimation of a demand system characterized by significant expenditure censoring (Heien and Wessells, 1990; Perali and Chavas, 2000; Shonkwiler and Yen, 1999). The Shonkwiler and Yen (1999) and Perali and Chavas (2000) system estimators are both consistent but suffer in efficiency. This study aims at filling an important gap in the empirical demand literature, by addressing censoring in cross-sectional data without the shortcomings of existing two-step estimators. This is accomplished by our adoption of a new quasi maximum-likelihood (QML) procedure in which multiple probability integrals are avoided by using a procedure where the sample likelihood function is approximated via the use of a series of bivariate probability density functions (pdf's) and cumulative distribution functions (cdf's).

[4] Earlier applications of censored system estimators featured up to three-level integrations in the likelihood function (Gould, 1996; Lee and Pitt, 1987; Wales and Woodland, 1983; Yen and Roe, 1989).

We can denote the vector of all demand parameters as θ and the ith deterministic expenditure share as $s_i(\theta)$. To complete the system specification, we append a stochastic error term ε_i to each equation:

$$w_i^* = s_i(\theta) + \varepsilon_i\,, \quad \left(i = 1, 2, \cdots, K \right). \tag{10}$$

This stochastic structure is consistent with the additive general error model of McElroy (1987). We can account for the non-negativity of food purchases by relating observed shares (w_i) to their latent counterparts:

$$w_i = \max\{w_i^*, 0\}, \ \left(i = 1, 2, \cdots K \right). \tag{11}$$

Note that while the adding-up conditions hold with restrictions (9) in the absence of censoring, the censoring mechanism (11) implies that adding up do not hold when censoring is present. To guarantee adding-up of the system, we take a parsimonious approach of estimating a system of the first $n - 1$ equations and then deriving demand for the last (nth) good as residual demand. Without loss of generality, we consider a regime in which the first ℓ goods are consumed, with observed (K–1)-vector $w = [w_1^*, w_2^*, \cdots, w_\ell^*, 0, 0, \cdots, 0\,]'$. We can assume the error vector is distributed as (K–1)-dimensioned normal variable with zero mean and a positive definite contemporaneous covariance matrix Σ. The error vector can be partitioned where the error terms for purchased goods appear first: $e = [\varepsilon_1, \varepsilon_2, \cdots, \varepsilon_\ell \mid \varepsilon_{\ell+1}, \varepsilon_{\ell+1}, \cdots, \varepsilon_{K-1}]' = e[e_1', e_2\,]'$. The regime switching condition (11) can then be represented as

$$e_2 \le u \equiv [-s_{\ell+1}(\theta), -s_{\ell+2}(\theta), \cdots, -s_{K-1}(\theta)\,]', \tag{12}$$

and the likelihood contribution for this regime is

$$L_c(w) = f(e_1) \int_{\{e_2:\, e_2 \le u\}} g(e_2 \mid e_1)\, de_2, \tag{13}$$

where $f(e_1)$ is the marginal pdf of e_1 and $g(e_2 | e_1)$ is the conditional pdf of e_2 given e_1. The sample likelihood function is the product of the likelihood contribution (13) across the sample.

One difficulty in full-information maximum likelihood lies in evaluation of the multiple dimension probability integral in (13), which is difficult when the number of censored purchases is large. To overcome the computational complexity we use the QML procedure discussed below.

Description of the Quasi-Maximum Likelihood (QML) Algorithm

Any likelihood function based procedure has a corresponding quasi-likelihood generalization (Heyde, 1997, p.10). The procedure avoids evaluation of multiple probability integrals by maximizing the product of a sequence of bivariate Tobit likelihood functions. We can standardize the *i*th and *j*th expenditure shares by $z_i = (w_i - s_i(\theta))/\sigma_i$ and $z_j = (w_j - s_j(\theta))/\sigma_j$. The bivariate Tobit likelihood function for these two share equations can then be represented as

$$\begin{aligned} L_{ij} = & \prod_{w_i=0,\, w_j=0} \Psi(z_i, z_j, \rho_{ij}) \prod_{w_i>0,\, w_j>0} \sigma_i^{-1}\sigma_j^{-1}\psi(z_i, z_j, \rho_{ij}) \\ & \times \prod_{w_i=0,\, w_j>0} \sigma_j^{-1}\phi(z_j)\,\Phi\Big((z_i - \rho_{ij} z_j)/(1-\rho_{ij}^2)^{1/2}\Big) \\ & \times \prod_{w_i>0,\, w_j=0} \sigma_i^{-1}\phi(z_i)\,\Phi\Big((z_j - \rho_{ij} z_i)/(1-\rho_{ij}^2)^{1/2}\Big), \quad \big(i, j = 1,2,\cdots,(K-1); i \neq j\big), \end{aligned} \tag{14}$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ are univariate standard normal pdf and cdf, and $\psi(\cdot,\cdot,\cdot)$ and $\Psi(\cdot,\cdot,\cdot)$ are the bivariate standard normal pdf and cdf, respectively. Adding an observation subscript t to the bivariate Tobit likelihood, L_{ijt}, the quasi-likelihood function for a sample of N observations is

$$L = \prod_{t=1}^{N} \prod_{i=1}^{K-2} \prod_{j=i+1}^{K-1} L_{ijt}\,. \tag{15}$$

Cross-equation correlation is accommodated by products of pairwise bivariate Tobit likelihoods in (14), and parametric demand restrictions can be imposed as usual.

As in other limited dependent variable models, censoring of the dependent variables should be accommodated when calculating demand elasticities. For commodity *i*, because the probability of a positive observation is $\Pr(w_i > 0) = \Phi(s_i(\theta)/\sigma_i)$ and the conditional mean of share is $E(w_i \mid w_i > 0) = s_i(\theta) + \sigma_i\phi(s_i(\theta)/\sigma_i)/\Phi(s_i(\theta)/\sigma_i)$, the corresponding unconditional mean is

$$E(w_i) = \Phi(s_i(\theta)/\sigma_i)\, s_i(\theta) + \sigma_i\phi(s_i(\theta)/\sigma_i)\ . \qquad (16)$$

Unconditional demand elasticities can be obtained by differentiating (16).

The Mexican Household Purchase Data Set

Data used to examine household food demand in Mexico were obtained from the 1998 Encuesta Nacional de Ingreso y Gastos del Hogar (ENIGH) collected between Aug.-Nov. 1998. This is a nation-wide survey encompassing Mexico's 32 states. Surveyed households maintained weekly diaries of expenditures on a detailed set of food and non-food items. Household members record their food purchases according to disaggregated set of food categories including not only expenditures but also quantities purchased. A detailed set of household and member characteristics are also collected.

To avoid problems with respect to the valuation of home produced goods, we limited our current analysis to households that resided in towns with a population greater than 15,000 persons. We also excluded households that did not purchase any food for at-home consumption during the survey week. As noted in the above discussion of equivalence scales, we need to identify a base household type. Similar to Phipps (1998), we limit our analysis to households with both a male and female head present and in which at least one of these heads is between the age of 18 and 65. Given the above, our final sample size was 4,064 households. The sample statistics described in Table 1 was obtained from this data set.

Table 2 provides an overview of household size and composition of our sample. Mean household size, given that we limit our analysis to two-parent households, was 4.5 with an average 1.9 children under the age of 18. More than two thirds of the households had children present. The extended nature of Mexican households is evidenced by the fact that 38% of the sample households had at least one other adult present in the household. Approximately 25% of the households had 6 or more members.

In the scaling function estimated for this analysis we included 3 age classifications to describe the composition of non-head members: less than 5 years of age, 5 to 17 years of age and other adults. Besides the count of the number of household members in these age categories, (e.g. the z variables shown in (7)), we also include as other demographic variables three variables which correspond to the percent of household members represented by these age groups. These percentage variables are used within the c variables shown in (7). On average, 11% of household members are under the age of 5, more than a quarter are between 5 and 17 and slightly less than 13% are non-head adults.

Table 2 also provides a summary of other demographic characteristics used in the scaling function. These included the percent of female adult members that work outside the home (PFALF) and 7 regional dummy variables. Slightly less than 40% of the female adult members were found to work outside the home. We included this variable to reflect the opportunity costs of food preparation and the implications of these costs on food choices and on endogenous food quality decisions.

Estimated Structure of Food Demand in Urban Mexican Households

We estimated the parameters of the censored translog demand system using the likelihood function represented in (15) and the share equations in (8). The 9-equation system consisting of expenditures on: beef, pork/processed meat, poultry, fish/shellfish, beans/grains, vegetables, fruits, cheese, and non-alcoholic beverages.[5] Optimization was carried out through the application of the BHHH algorithm in the MAXLIK (5.0) routines contained within the GAUSS software system. To increase computational speed, analytical gradients were used. Parameter standard errors were estimated using a heteroscedasticity-consistent covariance matrix (White, 1982).

Given our 9-equation system and the above demographic characteristics, 123 parameters were estimated. To summarize the statistical significance of these parameter estimates, at the 5% level of significance, all estimated coefficients associated with the demographic variables (δ's) and all error standard deviations (σ's) are significant, as are 22 of the 28 error correlation coefficients (ρ_{ij}'s). In addition, all but one of the constant terms (α_i's), 14 of the 24 $\gamma_{\ell s}$'s coefficients, and 35 of the 45 quadratic price coefficients (β_{ij}'s) are significant at the 5% level of significance. Overall, about 75% of the estimated coefficients are significant at the 5% level of significance, and about 65% are significant at the 1% level of significance.[6]

From the estimated coefficients, unconditional price (compensated and uncompensated) and expenditure elasticities are obtained by differentiating the unconditional expected value of expenditure share shown in (16). The resulting uncompensated price and expenditure elasticities are presented in Table 3. All of the own-price elasticities are negative and we find evidence of

[5] We combined the pork and processed meat, the beans and grains, and the milk and other non-alcoholic beverages categories so as to reduce model size.

[6] To save space we do not present the parameter estimates here. A copy of these estimates can be obtained from the

mainly gross complements among commodities. Dong, Gould and Kaiser (2002) use the same data as used in this analysis to estimate a complete food system based on the AIDS structure. In their analysis they use the numerically intensive Amemiya-Tobin approach to the estimation of a censored system. Their approach requires simulation of multi-dimensional truncated distributions requiring much greater computation time than our QML procedure. In the last row of Table 3, we provide a summary of the estimated own-price elasticities obtained by Dong, Gould and Kaiser (2002). Comparing these elasticities with those obtained using our QML procedure we find a very close correspondence. The similarity in these two sets of results is important given the relative computational speed of the estimation methods.

Compensated unconditional price elasticities are presented in Table 4. The results show that all compensated own-price elasticities are negative and well under unity. Whereas the uncompensated cross-price elasticities suggested that complementarity dominates, these estimated compensated cross-price elasticities suggest a mixture of net substitutes and net complements among the commodities considered. Our results are comparable to those reported in the literature. In a recent analysis of Mexican meat demand based on an earlier version of the data used here, Golan, Perloff and Shen (2001) obtained similar own-price elasticities as obtained here with the exception of the seafood category. For example they obtain compensated own-price elasticity estimates of –0.60, –0.42, –0.71, –0.40 and –2.09 for beef, pork, processed meats, poultry and seafood, respectively. They also find evidence of complimentarily between the demands for seafood and other meats as was reported here. For both the beans/grains and non-alcoholic beverage category we find a substitute relationship with respect to the demand for other foods with changes in their own price.

Using the mean values of prices, expenditures and other demographic characteristics, we

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authors upon request.

evaluate the impact of having an additional household member when compared to our two-person, no children reference household.[7] Given our age breakdown our estimated adult equiv scales are 1.07 for a child aged < 5 and 1.13 for one aged 5–17. These results are a bit low but rather reasonable when compared with those reported in other analyses. In an analysis of the impact of children on the costs of food, clothing, shelter and transportation by Canadian households, Phipps(1998) found that compared to a childless couple, the addition of one child to the household resulted in a relative equivalence scale value of children of 1.16. Phipps and Garner (1994) estimate food equivalence scales for Canada and the U.S. using a series of Engel curves. Unfortunately, they examine the impact of household size on food expenditures regardless of whether these additional members are adults or children. With a two-person household as a base, they obtain relative food equivalence values of 1.33 and 1.36 for 3-person U.S. and Canadian households, respectively (p.10-11). Similarly, Blaylock (1991) presents food equivalence values for different size households regardless of age of additional members. Using a 2-person household as a base, he obtains a relative equivalence measure of 1.22 for a 3-person household.

Our result with respect to the impact of another adult on household food expenditures is of concern. We obtained a relative equivalence scale value of 1.10 . Our conjecture was that this low value might be due to the increased utilization of food-away-from home as a food source for households with other adult members. That is, our present analysis is limited to expenditures for food at-home (FAH). Food expenditures that occur away from home (FAFH) are not accounted for this analysis. Any increase in the use of FAFH versus FAH will result in relative expenditures and may lead to lower equivalence scale estimates. Households in our sample

[7] The relative equivalence scale values are calculated as the ratio of the equivalence scales for a particular household composition to our base 2-person childless household using the mean values of all household variables and prices

spent on average, 16.9% of their weekly total food expenditures on FAFH. We in fact found a negative relationship between household size and FAFH expenditures. We were therefore surprised by the very low other adult impacts. We are unsure as to the reason why.

Areas of Future Research

In this analysis we have estimated a disaggregated food demand system through the use of a method which does not require the evaluation of multi-dimensional probability integrals. With respect to estimated price and expenditure elasticities we obtain reasonable results when compared to previous analyses. Our experience however with the incorporation of the endogenous equivalence scales is less than satisfactory and this research should be considered a work in progress in this regard. First, we generated relatively low estimated impacts of having non-head adults in the household. Second, and more importantly, for all age groups we obtained unreasonable estimates of large scale economies when additional household members of a particular age group are present. Upon reflection, the functional form used and the adoption of the percent of household members represented by non-head members may be the reason for the poor scaling results. We are investigating the impact of changes to the functional form used to estimate the scaling function parameters in terms of our endogenous scale values. The difficulty we have in obtaining reasonable endogenous scale values is surprising given the success achieved by others in using the approached used in this analysis. The implications of our QML approach on these estimates need to be more fully understood.

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except for the composition-related variables.

Table 1. Overview of Weekly Mexican Per Capita Food Purchases

Commodity	Mean Per Capita Expenditure (Peso)	Mean Expend-iture Share	% of House-holds Purchasing	Mean Per Capita Expenditure by Purchasing Households (Peso)	Std. Dev. of Per Capita Expenditure by Purchasing Households (Peso)
Total food at home	54.6	100.0	100.0	54.6	32.1
Beans	2.0	3.6	53.9	3.7	11.2
Cheese	2.0	3.6	47.0	4.1	3.7
Fruits	3.2	5.8	14.5	4.9	5.1
Grains	10.7	19.5	98.2	10.8	7.0
Fluid milk	6.7	12.2	81.7	8.2	6.7
Beverages	5.5	10.1	77.7	7.1	5.9
Vegetables	6.1	11.1	89.8	6.7	5.1
Beef	7.7	14.1	71.9	10.7	7.9
Pork	2.0	3.6	28.6	6.9	5.0
Poultry	4.5	8.2	62.8	7.1	4.9
Processed meat	3.1	5.7	57.8	5.3	4.8
Fish/Shellfish	1.5	2.7	22.9	6.4	6.6

Source: 1998 ENIGH, Urban Households, Male/Female Adult Heads present and have positive food-at-home expenditures.

Table 2. Household Composition and Other Characteristics

Household Composition

Household Size Mean=4.6, S.D.=1.8		Children < 5 yrs. Mean=0.5, S.D.=0.73		Children 5-17 yrs. Mean=1.4, S.D.=1.33		Non-Head Adults Mean=0.7, S.D.=1.2	
Category	%	Category	%	Category	%	Category	%
2	8.1	0	32.5	0	60.4	0	62.5
3	17.7	1	25.8	1	29.4	1	17.5
4	27.7	2	24.0	2	8.9	2	11.1
5	23.0	3	11.1	3	1.1	3	5.9
6	12.2	4	4.3	4	0.2	4	2.0
7	5.8	5	1.3	5	0.0	5	0.7
>7	5.5	>5	0.9	>5	0.0	>5	0.3

Exogenous Variables

Variable	**Description**	**Mean**	**S.D.**
PFALF	Percent of Female Members in the Labor Force (%)	38.1	45.0
PER<5	Percent of Household Members < 5 years old (%)	11.0	15.3
PER5-17	Percent of Household Members 5 -17 years of age (%)	26.2	21.9
PEROTHAD	Percent of Household Members That Are > 17 Years of Age and Not a Head (%)	12.9	18.8
	Regional Dummy Variables (State of Residence)		
DF[a]	Distrito Federal, Estado de Mexico and Metropolitan Areas around Mexico City	32.4	-----
NW	Baja California, Baja California Sur, Sonora and Sinaloa	8.3	-----
NE_NC	Coahuila, Chihuahua, Nuevo Leon and Tamaulipas, Durango, San Luis Potosi, Queretaro and Zacatecas	16.7	-----
WEST	Nayarit, Jalisco, Colima, Guanajuato and Michocacan	19.5	-----
CENTRAL	Aguascalientes, Hidalgo, Morelos, Puebla and Tlaxcala	8.8	-----
SOUTH	Guerrero, Oaxaca and Veracruz	6.1	-----
SE	Yucatan, Tabasco, Quintana Roo, Chiapas and Campeche	8.3	-----

[a] Region DF is used as the base region.

Table 3. Estimated Uncompensated Price Expenditure Elasticities

	Beef	Pork/ PrcMeat	Poultry	Seafood	Beans/ Grains	Veg.	Fruits	Cheese	Beverages	Expend.
Beef	–0.611	–0.241	–0.037	–0.111	–0.185	–0.013	–0.072	–0.135	0.019	1.386
Pork/PrcMeat	–0.356	–0.650	–0.047	–0.118	–0.141	–0.114	–0.023	–0.038	–0.002	1.489
Poultry	–0.076	–0.053	–0.773	–0.276	–0.255	0.029	–0.048	0.037	–0.056	1.472
Seafood	–0.356	–0.269	–0.456	–0.657	0.043	0.051	–0.018	–0.081	0.039	1.704
Beans/Grains	–0.022	0.010	–0.043	0.038	–0.744	–0.023	0.017	0.052	–0.004	0.720
Veg.	0.015	–0.072	0.065	0.118	–0.175	–0.836	–0.213	–0.086	–0.025	1.209
Fruits	–0.184	–0.048	–0.077	0.069	–0.110	–0.378	–0.776	–0.045	–0.015	1.565
Cheese	–0.359	–0.092	0.038	–0.068	0.123	–0.191	–0.066	–0.725	–0.028	1.366
Beverages	0.060	0.072	0.027	0.040	–0.003	0.068	0.084	0.023	–0.977	0.607
DGK, 2002	-0.530	-0.497	-0.780	-0.694	-0.586	-0.794	-0.713	-0.704	-1.060	-----

Note: The last row contains the uncompensated unconditional own price elasticity estimates presented by Dong, Gould and Kaiser, 2002. For the Pork and Processed Meats, Beans and Grains, and Milk and Oth. Bev. categories the average values of those reported in Dong, Gould and Kaiser are presented here.

Table 4. Estimated Compensated Price Elasticities

	Beef	Pork/ PrcMeat	Poultry	Seafood	Beans/ Grains	Veg.	Fruits	Cheese	Beverages
Beef	–0.451	–0.138	0.058	–0.087	0.187	0.132	–0.009	–0.093	0.401
Pork/PrcMeat	–0.184	–0.539	0.055	–0.092	0.260	0.042	0.044	0.006	0.408
Poultry	0.094	0.057	–0.673	–0.250	0.140	0.183	0.018	0.081	0.350
Seafood	–0.160	–0.142	–0.340	–0.627	0.501	0.229	0.059	–0.029	0.509
Beans/Grains	0.061	0.064	0.006	0.050	–0.550	0.052	0.049	0.073	0.194
Veg.	0.155	0.019	0.147	0.139	0.150	–0.709	–0.159	–0.050	0.308
Fruits	–0.003	0.069	0.030	0.096	0.311	–0.215	–0.706	0.002	0.416
Cheese	–0.201	0.010	0.131	–0.044	0.491	–0.048	–0.004	–0.684	0.349
Beverages	0.130	0.117	0.068	0.051	0.160	0.132	0.112	0.041	–0.810

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