Consistent Estimation of Longitudinal Censored Demand Systems

by

Chad D. Meyerhoefer
Agency for Healthcare Research and Quality
Rockville, Maryland

Christine R. Ranney
Department of Applied Economics and Management, Cornell University
Ithaca, New York

David E. Sahn
Department of Economics and Division of Nutritional Sciences,
Cornell University
Ithaca, New York

Selected Paper prepared for presentation at the American Agricultural Economics Association Annual Meeting, Denver, Colorado, August 1-4, 2004

Correspondence to: Chad D. Meyerhoefer, Agency for Healthcare Research and Quality, 540 Gaither Rd., Rockville, MD 20850. Phone: (310) 427-1664. Fax: (301) 427-1276. E-mail: cmeyerhoe@ahrq.gov

This research was conducted while Chad D. Meyerhoefer was a graduate research assistant in the Department of Applied Economics and Management, and was supported in part by a grant from the Mario Einaudi Center for International Studies at Cornell University. The views expressed in this paper are those of the author, and no official endorsement by the Agency for Healthcare Research and Quality or the Department of Health and Human Services is intended or should be inferred.

Consistent Estimation of Longitudinal Censored Demand Systems

Abstract

In this paper we derive a joint continuous/censored demand system suitable for the analysis of commodity demand relationships using panel data. Unobserved heterogeneity is controlled for using a correlated random effects specification and a Generalized Method of Moments framework used to estimate the model in two stages. While relatively small differences in elasticity estimates are found between a flexible specification and one that restricts the relationship between the random effect and budget shares to be time invariant, larger differences are observed between the most flexible random effects model and a pooled cross sectional estimator. The results suggest the limited ability of such estimators to control for preference heterogeneity and unit value endogeneity leads to parameter bias.

Keywords: Censored Demand System, Almost Ideal Demand System, GMM, Random Effects

JEL Classifications: C33, C34, D12

Introduction

Our understanding of how public policy instruments such as taxes, subsidies, and social programs impact consumer behavior has been greatly enhanced by the expanding availability of comprehensive microeconomic data, yet full exploitation of the data for policy analysis is often hampered by the arduous econometric techniques required to extract vital information. In particular, the high proportion of zero expenditure levels for individual commodities makes it difficult to estimate large, theoretically consistent disaggregated consumer demand models. The two principle reasons for zero expenditures in microeconomic data are households at a corner solution for the commodity in question, and limited survey periods leading to infrequency of purchase (IFP) errors. Because of the basis for the former in economic theory and the recent proliferation of survey data designed to mitigate the latter, most of the econometric techniques developed thus far are designed to model economic non-consumption.

Much of the recent empirical research on censored demand systems has focused on developing computationally feasible estimation techniques that circumvent the “curse of dimensionality” associated with the theoretically consistent models proposed by Wales and Woodland and Lee and Pitt (1986, 1987). For example, Shonkwiler and Yen develop an improved two-step approach that is general enough to model IFP errors as well as other processes generating zero expenditures. Nonetheless, its application to corner solutions has been criticized by Arndt, Lui, and Preckel for an inability to account for the role of reservation prices. Instead, Arndt proposes the use of maximum entropy (ME) techniques to address this shortcoming and generate a simpler framework for the imposition of coherency conditions. Limiting this estimator’s feasibility, however, is the fact that its asymptotic properties are unknown in non-linear applications such as the censored demand problem.

More recently, Perali and Chavas have developed a consistent approach to the problem based on generalized method of moments (GMM) techniques, while Yen, Lin, and Smallwood formulate a quasi-maximum likelihood approach they claim is more efficient in small to moderately sized samples. Although all of the above approaches provide a means of obtaining consistent estimates of disaggregated demand models, they are designed for cross sectional data, which suffers from a number of shortcomings. Chief among these are the limited ability to control for heterogeneous preferences and lack of significant real price variation.

Therefore, we develop a methodology for consistently estimating large, theoretically plausible longitudinal censored demand systems using a GMM framework similar to that employed by Perali and Chavas. The estimator is able to exploit the greater price, expenditure, and demographic variability of panel data, and provides a means to reduce bias through more effective controls for household-level heterogeneity and unit value endogeneity. In order to determine the sensitivity of price and income elasticities from censored demand systems to the presence of unobserved heterogeneity, we first implement the longitudinal estimator on a three-year panel data set from Romania and then compare the elasticity estimates to those that result when a more restrictive random effects specification is assumed and when the panel is pooled to create a large cross section.

Specification and Estimation

Theoretical and Empirical Specification

In accordance with the random utility hypothesis (RUH, McFadden), define the direct utility function as $U(q_{jt}, \varepsilon_{jt}; a_{jt}, c_j)$, where $t = 1,...,T$ indexes time periods, $j = 1,...,J$ indexes households, $q_{jt} = (q_{1jt},...,q_{Njt})'$ is a vector containing household *j*'s demand levels for the N commodity groups in time period t, $\varepsilon_{jt} = (\varepsilon_{1jt},...,\varepsilon_{Njt})'$ is a vector of random disturbances distributed $N(0,\sigma_{\varepsilon}^2)$, $a_{jt} = (a_{1jt},...,a_{Ljt})'$ is a vector of L household demographic variables (not all of which are time varying), and c_j is a time invariant household specific effect representing unobserved heterogeneity across households.[1] If it is further assumed $U(\cdot)$ represents a preference ordering of the PIGLOG class, then consumer maximization of utility leads to the familiar cost function corresponding to Deaton and Muellbauer's Almost Ideal Demand System (AIDS);

$$\begin{aligned}\log c(u,p,\varepsilon;a,c) &= \alpha_{0t} + \sum_k \alpha_{kt} \log p_{kt} + \tfrac{1}{2}\sum_k\sum_i \gamma_{ki}^* \log p_{kt} \log p_{it} \\ &+ \sum_k\sum_l \eta_{klt} \log p_{kt} a_{ljt} + u_{jt}\beta_0 \prod_k p_{kt}^{\beta_k} + \sum_k \delta_{kt} \log p_{kt} c_j + \sum_k \log p_{kt}\varepsilon_{kjt}\end{aligned}, \qquad (1)$$

where u_{jt} is a reference level of utility and p_{kt} is the price of good k in time t. Since the household specific effect is akin to a collection of unobserved demographic variables, it is included in the empirical specification via demographic translating (Pollack and Wales) like the observed demographics. The random disturbance terms are also translated into the cost function to maintain consistency with the RUH.

Inverting (1) to obtain the indirect utility function and applying Roy's Identity produces the following Marshallian uncompensated demand functions in budget share form:

$$s_{njt} = \alpha_{nt} + \sum_l \eta_{nlt} a_{ljt} + \sum_i \gamma_{ni} \log p_{it} + \beta_n\left(\log x_{jt} - \log g(P,\cdot)\right) + \delta_{nt} c_j + \tilde{\varepsilon}_{njt} \qquad (2)$$

where

$$\begin{aligned}\log g(P,\cdot) &= \alpha_{0t} + \sum_k \alpha_{kt} \log p_{kt} + \tfrac{1}{2}\sum_k\sum_i \gamma_{ki}^* \log p_{kt} \log p_{it} + \\ &\sum_k\sum_l \eta_{klt} \log p_{kt} a_{ljt} + \sum_k \delta_{kt} \log p_{kt} c_j\end{aligned}, \qquad (3)$$

$n = 1,..,N$ indexes the commodity groups or individual goods, $\gamma_{ki} = \tfrac{1}{2}(\gamma_{ki}^* + \gamma_{ik}^*)$, and $\tilde{\varepsilon}_{njt} = \varepsilon_{njt} - \beta_n \sum_k \log p_{kt} \varepsilon_{kjt}$.

The most flexible specification of equations (2) and (3) possible allows all of the estimable parameters to vary over time. For large, comprehensive demand systems, however, it is unlikely the resulting parameter set could be precisely estimated, and economic conditions may not require such parameter flexibility. The estimation approach detailed in the next section allows us to focus on a sub-set of the estimable parameters and leave the others unrestricted. Because there are no historical events during the sample period that suggest structural change in demand patterns, we assume that the coefficients on the economic variables (prices and total expenditure) are stable and time invariant. Nonetheless, the intercept of each share equation is allowed to vary over time to capture changes on macroeconomic conditions that may influence the structure of demand.

Since the observed demographic variables are not of primary interest and included in the model only as controls, their coefficients are left unrestricted. Indeed, little is know about the temporal relationship between demand patterns and measured demographics, and there are many situations warranting this flexibility. Similarly, the household specific effect contains a time varying coefficient, leading to a more flexible specification than is typically found in applied work, where the fixed effects specification is frequently used to account for unobserved heterogeneity in linear models. Fixed effects implicitly constrains $\delta_{nt} = 1 \ \forall \ n, t$, but if this restriction is invalid and the fixed effect is correlated with the model's regressors, parameter estimates of the slope coefficients will be biased. One of the advantages of the GMM approach used below is that it allows explicit testing of such restrictions.

Another common method for modeling unobserved heterogeneity using panel data is the random effects approach, which treats c_j as a component of the disturbance term and uses GLS to estimate the model. In order for random effects estimators to produce unbiased estimates, the random effect must be orthogonal to model's regressors, an assumption that cannot be made in general. Rarely do surveys contain the exogenous market prices called for in theory, rather, prices are often computed as unit values, where the household's expenditures on a certain item are divided by the physical quantity purchased. These unit values are correlated to the household's preferences for goods of different quality, and consequently, with the household specific effect. Furthermore, it is possible that c_j is correlated with the observable demographic variables in the model.

The nonlinear methods required to estimate censored demand equations lead to additional issues that must be addressed when applying fixed or random effects models, which are summarized by Jakubson (1988) in the context of labor supply. Although fixed effects estimation places no distributional requirements on the form of the unobserved heterogeneity, it is consistent only when the time series dimension of the panel is large. By contrast, random effects requires one assume the household specific effect follows a specified distribution, but is consistent in short panels. Because the data series used in our analysis contains only three time periods, consistency of the parameter estimates can only be achieved through the random effects approach. However, we find that single equation Hausman tests (Greene, p.576) conducted on the non-censored equations reject the null hypothesis of orthogonality of the random effect with the regressors.

In order to incorporate the correlation of the random effect with the regressors into the estimating equation, we employ a specification developed by Jakubson (1988) for single equation Tobit estimation on panel data, based of previous work by Chamberlain in the linear (1982) and probit context (1984). This correlation is modeled as a linear projection of c_j on all the right hand side variables:

$$c_j = \sum_l \sum_t \lambda^1_{lt} a_{ljt} + \sum_k \sum_t \lambda^2_{kt} \log p_{kt} + \sum_t \lambda^3_t \log x^D_{jt} + \upsilon_j , \tag{4}$$

where υ_j is assumed to be independent of both the exogenous regressors and $\tilde{\varepsilon}_{njt}$, x^D_{jt} is expenditure deflated by an appropriate price index, and υ_j is distributed $N(0, \sigma^2_\upsilon)$. For notational convenience, define $x'_t = \left\langle a'_t \mid \log p'_t \mid \log x^D_t \right\rangle$ as a row vector of length $(L + N + 1)$ that includes all the regressors in (2) less the intercept.[2] Jakubson notes there are certain cases in which the assumption of independence between υ_j and $\mathbf{x}' = \left\langle x'_1, ..., x'_T \right\rangle$ may be invalid. For example, since the effect of the regressors outside the sampling period is contained in υ_j, if $\mathbf{x}'$ exhibits strong serial correlation, the independence assumption is violated. When the expression in (4) is used to integrate the household specific effect out of the demand equations, the resulting demand system disturbances are normally distributed, heteroscedatic within each equation, and correlated across equations through both the $\varepsilon' s$ and υ.[3]

In order to linearize the above budget share equations and reduce the potential for severe multicollinearity between the AIDS price index and the rest of the specification, we replace (2) with a scale-invariant log linear Laspeyres index, which has been shown by Moschini and Buse to have good approximation properties. This index is equivalent to the geometrically weighted average of prices $\log P^G_t = \sum_k s_{k0} \log p_{kt}$ when s_{k0} is calculated for some base level. Following substitution of the price index and random effect specification into (1), the reduced form linearized AIDS model (LAIDS) can be written as

$$s_{njt} = \alpha_{njt} + x'_{j1}\pi_{n1} + x'_{j2}\pi_{n2} + ... + x'_{jT}\pi_{nT} + u_{njt} \tag{5}$$

where $\pi_{nt} = (\pi'_{n1}, ..., \pi'_{nT})'$ is the reduced form parameter vector of demand equation *n* in time period *t*. Note that the regressors from all time periods enter the reduced form demand equations through their correlation with the random effect. If the *N* demand equations are partitioned into a subset N_1 containing the uncensored equations, and a subset N_2 containing censored equations, then the system of demands in N_1 can be estimated consistently via equation-by-equation OLS.

The demands in N_2 are specified as

$$s_{njt} = \begin{cases} \alpha_{njt} + x'_{j1}\pi_{n1} + x'_{j2}\pi_{n2} + ... + x'_{jT}\pi_{nT} + u_{njt} & \text{if RHS} > 0 \\ 0 & \text{otherwise} \end{cases}, \tag{6}$$

and estimated efficiently as a system of correlated Tobit equations. Since joint estimation requires the evaluation of N_2T dimension normal integrals, which is infeasible for large N_2T, a consistent approach is adopted to obtain the reduced form parameters using equation-by-equation Tobit estimation. Without accounting for the heteroscedasticity in u_{nt}, however, these parameter estimates will be biased and inconsistent (e.g., Pudney, p.148), so a modification to the conventional Tobit is necessary. A fairly general way of modeling the heteroscedasticity is to specify $E(u_{njt}^2) = \sigma_{nt}^2(w) = \sigma_{nt}^2 \exp(w'_{jt}\zeta_{nt})^2$, where w_{jt} is a vector of length *R* of exogenous variables responsible for unequal dispersion of the individual error terms, ζ_{nt} is a *R*-vector of estimable parameters, and σ_{nt}^2 is an estimable common parameter in the covariance matrix.

Stacking the equations in (5) and (6) over time sequentially by good defines a system of *NT* continuous/censored demand equations with correlated disturbances and the $NT \times (L + N + R + 3)T$ reduced form coefficient matrix:

$$\mathbf{\Pi} = \begin{bmatrix} \mathbf{\Pi_1} \\ \vdots \\ \mathbf{\Pi_N} \end{bmatrix} \tag{7}$$

where

$$\mathbf{\Pi}_n = \left\langle \alpha_n \mid \boldsymbol{\eta}_{nL_1} \mid \left\langle \mathbf{diag}\{\eta_{n1t}\} \cdots \mathbf{diag}\{\eta_{nL_2t}\} \mid \gamma_{n1}\mathbf{I}_T \cdots \gamma_{nN}\mathbf{I}_T \mid \beta_n\mathbf{I}_T + \delta_n\lambda' \right\rangle \mid \boldsymbol{\zeta}_n \mid \sigma_n \right\rangle, \tag{8}$$

α_n is a $T \times 1$ vector of intercepts, $\boldsymbol{\eta}_{nL_1}$ is a $T \times L_1$ matrix of coefficients on the L_1 time invariant observable demographic variables, $\mathbf{diag}\{\eta_{nlt}\}$ are $T \times T$ matrices corresponding to the coefficients on the L_2 time varying observable demographic variables, $\mathbf{I}_T$ is a $T \times T$ identity matrix, δ_n is a $T \times 1$ vector of parameters multiplying the household specific effect, and $\lambda' = (\lambda_{11}^1,...,\lambda_{LT,}^1 \lambda_{11}^2,...,\lambda_{NT}^2, \lambda_1^3,...,\lambda_T^3)$ is a $1 \times (L+N+1)T$ vector of parameters from the correlated random effect specification, $\boldsymbol{\zeta}_\mathbf{n}$ is a $T \times R$ matrix of parameters in the heteroscedastic error specification, and σ_n is a $T \times 1$ vector variance parameters.[4] While (8) represents the hypothesized structure of the underlying system, other specifications are possible and will be tested against this one is the next section. Finally, note that the δ parameters are only identified up to a scale factor, requiring the following normalization in the first time period: $\delta_{n1} = 1 \ \forall n$.

One advantage of the GMM estimator developed below is that it allows the dimensions of the estimation problem to be reduced by focusing on a subset of parameters while leaving the others unrestricted (Chamberlain, 1984). Since the primary objective of this study is to calculate price and expenditure elasticities for the censored and uncensored commodities, we need only identify the coefficients of prices and total expenditure and the univariat variance parameters for the censored equations. Therefore, let $\mathbf{\Pi}^*$ be the $NT \times (N+R+2)T$ reduced from coefficient matrix that excludes the columns containing the demographic coefficients and intercepts, and transform it into vector of length NTK as $\pi = vec(\mathbf{\Pi}'^*)$, where $K = N + R\left(1 - \frac{N_1}{N}\right) + 2$ and the zeros in the ζ parameter sub-matrix have been removed from the π vector.

Generalized Method of Moments Estimation Framework

It is possible to derive a consistent asymptotically normal efficient estimator based on the marginal distributions of the data in cases where the joint likelihood function can be written down in theory, but not calculated directly. This approach, developed by White and generalized by Jakubson (1998), called quasi-maximum likelihood estimation (QMLE) relies on a method of moments framework to approximate joint ML.[5] QMLE can be broken down into two stages, with the first involving consistent estimation of the reduced form parameters using OLS on the non-censored equations and heteroscedastic Tobit estimation on the censored equations. The second stage entails using minimum distance techniques (Malinvaud) to impose restrictions on the reduced form parameter estimates, including those necessary to identify the structural parameters and correlated random effect, and demand theory restrictions such as homogeneity and symmetry.[6]

A critical piece of the minimum distance estimator is the metric used to measure the distance between the sample and population moments. It is widely agreed the proper norm is the inverse covariance matrix of $\hat{\mathbf{\Pi}}^*$ (Jakubson, 1986), however, this matrix must be calculated taking into account the fact that $\hat{\mathbf{\Pi}}^*$ is estimated from the marginal distributions of the time period and good-specific demand equations and not through the joint likelihood function. A detailed derivation of this $NTK \times NTK$ covariance matrix is given in Meyerhoefer (2002), where it is shown to take the form $\mathbf{\Omega} = \mathbf{D}_1^{-1}\mathbf{D}_2\mathbf{D}_1^{-1}$. If $S_j = (S'_{1j1},..., S'_{NjT})'$ denotes the vector of univariate scores for all NT equations, and $\mathbf{H}_{njt}$ the univariate hessian for demand equation n in time period t, then $\mathbf{D}_1^{-1} = \mathbf{diag}\{E(\mathbf{H}_{1j1})^{-1},..., E(\mathbf{H}_{NjT})^{-1}\}$ and $\mathbf{D}_2 = E(S_j S'_j)$. A consistent estimator of $\mathbf{\Omega}$ is obtained by replacing the population moments by their sample counterparts. The minimum distance estimator can then be constructed as

$$\min \mathbf{D}(\psi) = [\hat{\pi} - h(\psi)]'\hat{\mathbf{\Omega}}^{-1}[\hat{\pi} - h(\psi)], \qquad (9)$$

where ψ is a Q-vector of structural parameters ($Q< NTK$) and $h(\cdot)$ is a non-linear function mapping ψ into π. This function is used to impose the demand theory restrictions of symmetry and homogeneity on the reduced form and identify the parameterized random effect. It's Jacobian $\partial h(\psi) / \partial \psi'$, has full column rank equal to Q. Under the null hypothesis that the restrictions imposed by $h(\cdot)$ are correct, $J\mathbf{D}(\hat{\psi})$ is a chi-squared distributed random variable with df = $NTK - Q$. This Wald statistic can be used to formulate tests (nested and non-nested) of the underlying specification of structural parameters.

Data and Results

Data used in the estimation of the joint continuous/censored demand system are drawn from the nationally and regionally representative 1994-96 Romanian Integrated Household Survey (RIHS). The RIHS contains three individual cross sections composed of 24,523 households in 1994, 31,558 households in 1995, and 32,013 households in 1996, as well as an embedded panel data set of 6,940 households. Although we estimate the censored demand system only on the panel of households, the entire cross sections are used to compute cluster prices. Monthly market prices are approximated in each of the survey's forty-seven 'judets' (counties) by the median unit value calculated from the sample of purchasing households, and deflated using a composite food, nonfood, and services CPI. In rare cases where no households in a given judet purchase a commodity in the specified month, the median unit value is computed across a larger region and/or longer time period.[7]

When unit values are used to approximate market prices they are susceptible to endogeneity bias due to measurement error and quality effects, a deficiency that has been addressed by several studies in the context of uncensored equation systems (Deaton; Crawford, Laisney, and Preston). Our use of median unit values computed at the judet level to approximate prices has the potential to reduce measurement error, provided the number of households in each county is sufficiently large (Deaton, p. 294). Indeed, Kedir has found evidence using a much smaller urban data sample from Ethiopia that the difference between uncorrected and measurement error corrected own-price elasticity estimates seems to diminish, while the quality correction becomes relatively more important, as cluster size increases. However, the fact that the medians are computed over the sample of purchasing households leads to the possibility of selection bias, which we do not correct.[8] One advantage of our model over cross sectional estimators is that it provides a reasonable way to control for the endogeneity of unit values due to quality effects through their correlation with the random effect.

Total consumption expenditure is computed by aggregating information on food, nonfood goods and services, collected over a one-month period, or a retrospective one-year time frame in the case of durables. For many households, especially in rural areas, a significant share of food consumption is derived from own production, in-kind payments, and gifts. These are valued at household specific open market price if the household purchases some of the own-consumed product in the market, and the regional market price if the household makes no market purchases of the product. Monetized home consumption is then added to purchased food, nonfood goods, services, and the flow of services from durable goods (based on a constant ten-year depreciation schedule) to create the total consumption expenditure variable.

The RIHS contains a wealth of demographic information that is exploited to control for heterogeneity across households. These include eight regional locators, four seasonal indicators, and the following household composition variables: The number of young children in the household between the ages of zero and four, the number age five through seventeen, and the number of adults eighteen years of age or older. In addition, characteristics of the household head are used as household level preference controls, including the head's age, an indicator of whether the head is female, and four dummy variables denoting educational attainment at either the primary level, lower secondary or technical school, upper secondary, or university/college level.

Table 1 lists the average budget shares and percentage of zero expenditures for each commodity group in the demand system. The grouping of goods in the model is primarily policy driven, as commodities subject to differential value added (VAT) or excise tax rates during Romania's transition are all treated separately. Nevertheless, every attempt was made to place goods that are close substitutes in the same group whenever possible, in accordance with the composite commodity theorem. The fact that the budget shares of each commodity vary little from 1994 through 1996 lends credence to our assertion that the structure of commodity demand in Romania was stable during this period.[9]

The degree of censoring is naturally much higher for the individual commodities (with the exception of bread) than larger commodity groups, which are also generally composed of necessities and staple foods. As noted by Perali and Chavas as well as Pudney, instances of zero expenditure levels due to non-consumption are more likely in developing countries than wealthier societies. The same is true of transition countries, such as Romania, where many households live below the poverty line and the removal of communist-era price subsidies has lead to large real price increases during the transition period.[10] In addition, the survey period of the RIHS is long enough to make the possibility of systematic IFP errors in the data remote, so most of the observed zero expenditure levels are attributable to economic non-consumption.

Specification Tests

Although the theoretical derivation of the censored demand equations from a random utility function implies the error terms of the estimating equations are heteroscedastic, it is advisable to confirm the implications of the theory empirically before corrective action is taken. Following the approach detailed in Greene (p.914), we construct a Lagrange multiplier (LM) statistic under the assumption that the unequal dispersion of error terms is related to household size and the log of total expenditures. The tests indicate the regression disturbances are heteroscedastic in all of the equations expect that of gasoline and diesel fuel, so a conventional rather than heteroscedastic Tobit model is specified for this commodity group.

It is also possible to test whether the data generating process is consistent with more parsimonious specifications of the random effect. For example, fixed effect models typically make the implicit assumption that $\delta_{nt} = 1 \ \forall n, t$, while most nonlinear applications of the random effects approach impose the additional restriction that all the λ parameters are equal to zero. These nested specifications are tested by subtracting the distance function of the incrementally restricted model (A) from that of the less restricted model (B). The resulting test statistic $JD(\hat{\boldsymbol{\psi}}_{\text{B}}) - JD(\hat{\boldsymbol{\psi}}_{\text{A}})$ follows a chi-squared distribution with df = $df_B - df_A$.

Restricting the impact of the random effect to be constant over time leads to the test statistic $\chi^2_{(24)} = 1121$, which is considerably larger than the critical value 36 at the 5% level of significance. Likewise, the restriction that the random effect is orthogonal to the regressors in the model is also soundly rejected at the 5% level of significance. In that case the test statistic is $\chi^2_{(63)} = 1379$ and critical value 83.[11] Therefore, both of the incremental restrictions on the model commonly assumed to hold in other studies are rejected using our data sample.

Elasticity Estimates

Expenditure elasticities for the correlated random effects (CRE) model are reported in Table 2 along with their standard errors.[12] We also report estimates from the CRE model with the δ parameters restricted to unity, and the estimates from a cross sectional (CS) model where the three years of panel data are pooled and the demand system estimated without a random effect. The percentage change in the magnitude of expenditure elasticities between full CRE and restricted CRE are reported to demonstrate the potential bias associated with more restrictive estimators that do not allow the impact of the household specific effect to vary over time, such as the conventional fixed effects specification. Likewise, differences between the CS and CRE model can be primarily attributed to biases induced by an inability to control for household heterogeneity in preferences (omitted variable bias). Since this is not a Monte Carlo study the observed biases are not generalizable, rather, the results provide an indication of the expected difference in elasticities estimated using a typical household panel.

In general, the CRE expenditure elasticities are consistent with prior expectations and show the staple foods bread and grain are fairly unresponsive to income changes, while luxuries such as gasoline, diesel fuel, and other nonfood goods are highly responsive. Restricting the impact of the random effect to be time invariant leads, for the most part, to elasticities that under-estimate those of the more flexible specification, by nearly 5 percent on average.[13] In contrast, most of the CS estimates exceed those from the CRE model, with the magnitude of the divergence surpassing 20 percent in the case of bread, fruits and vegetables, coffee, and the meat, dairy, oils, and fats groups. In fact, the average differential between CRE and CS elasticities is over three times that of the restricted CRE model at 16 percent.

Most of the own-price elasticities associated with the three models reported in Table 3 are also within the expected magnitudes. However, we were surprised to find the grains elasticity above unity, and the own-price responsiveness of beer is higher in Romania than has been documented for other countries. Nonetheless, the other alcohol elasticities are similar to those found elsewhere in the commodity demand literature (Leung and Phelps; Smith). The tobacco elasticity is larger than estimates for the U.S. and U.K., but falls within the -0.6 to -0.8 range reported for less developed countries (Chaloupka and Jha).

We find clear differences in own-price elasticities between the CRE model and both the restricted CRE and CS models, although there is no clear pattern of over- or under-estimation in this case. The restricted CRE estimates deviate from the more flexible specification by 7 percent, due in part to the large over-estimation of the own-price responsiveness of tobacco. The deviation in CS own-price elasticities from the CRE model, at approximately 12 percent, is somewhat less than observed for the expenditure elasticities. The largest differential occurs for wine, which is over-estimated by the CS model by 29 percent.

When the CS cross-price elasticities are compared to those generated by the CRE model, it is also changes in the price of wine that lead to the greatest elasticity differentials. The CRE and CS estimates for all of the commodity groups are reported in Table 4 with their standard errors. While the overall median differential between the two estimators is 140 percent, changes in the wine price generate demand responses in the CS model that differ by 389 percent from the CRE model. Since some of the cross-price elasticities are imprecisely estimated, differences in degrees of freedom between the estimators and sample variability play a greater role in the comparison of specifications than they do for expenditure and own-price elasticities. However, there are a variety of sizable differences in the cross-price effects even for statistically significant elasticities.

Summary and Conclusions

This study develops a framework to exploit the rich information content of longitudinal data in the estimation of large, disaggregated demand systems. Censoring of the dependent variables makes maximum likelihood estimation of these systems difficult with cross sectional data and infeasible for panels with even a small number of time periods. Therefore, a consistent and asymptotically efficient GMM estimator is used to identify the parameters of an empirical specification consistent with the random utility hypothesis and flexible enough to nest a variety of different models of household heterogeneity. First, estimates of reduced form parameters are obtained from linear regressions and non-linear heteroscedastic Tobit models. The minimum distance estimator is then used to identify the underlying structural parameters, impose economic restriction on the model, and test for more restrictive specifications of the household specific effect. The most appropriate model allows the impact of the household specific random effect to vary over time, a generalization rarely tested for in the applied literature.

When the resulting elasticity estimates are compared to those from a more restrictive correlated random effects model where the household specific effect is assumed to be time invariant, average differences in the expenditure and own-price elasticities are found to be 5 and 7 percent. This suggests the bias associated with specifications that allow the random/fixed effect to be freely correlated with the regressors, but do not allow for time dependency, may not be substantial. However, when the more flexible specification is compared to a cross sectional model estimated on pooled data, average differences in expenditure and own-price elasticities are between 12 and 16 percent. In addition, substantial differences in cross-price elasticities are found, suggesting that the inability to control for heterogeneous preferences and unit-value endogeneity in cross sectional data can lead to more serious parameter bias.

Notes

[1] Further, assume that $U(\cdot)$ is strongly separable over time, monotonic, and strictly quasi-concave in q.

[2]To avoid confusion in the notation, total expenditures will always be referred to in logarithmic form as $\log x_{jt}$, while the vector x_t' is as defined above.

[3] Chavas and Segerson have shown heteroscedasticity in share equation disturbances to be a general property of all specifications derived from a random objective function.

[4] Note that for the uncensored equations $\zeta = 0$.

[5] The term "quasi-maximum likelihood" has become more general since its use in the White reference. While our QLME approach falls into the class of GMM estimators, Yen, Lin, and Smallwood's QMLE does not. The consistency of this class of estimators was established by Hansen.

[6] Although the observed budget shares add up, the latent shares need not, so we do not impose the adding-up on the system. This should have little impact on the price coefficients since they sum to zero across equations by default once symmetry and homogeneity have been imposed.

[7] The only commodity whose price cannot be computed from survey data is tobacco. Therefore, we use the monthly national tobacco CPI derived by the Romanian National Institute for Statistics.

[8] Dong, Shonkwiler, and Capps have developed a method to deal with this issue when unit values are used in lieu of prices. Nonetheless, incorporating their methodology into our model would be technical challenging, and is left as an area of future research.

[9] The only exception is the large drop in the gasoline and diesel fuel budget share in 1995, which coincides with one of Romania's coldest winters for a century and the strong possibility of fuel rationing.

[10] Headcount estimates from Meyerhoefer (2001) put the percentage of the population living in poverty in 1994-96 between 25 and 30 percent, depending on the method used to compute the poverty line.

[11] Although these tests were conducted conditional on the joint imposition of symmetry and homogeneity, the demand theory restrictions (taken together) are rejected by the data. Conducting the tests without the prior imposition of symmetry and homogeneity produces test statistics of 1159 and 1383, respectively, which also lead to rejection.

[12] All of the reported standard errors were computed using the delta method, which was solved analytically or numerically by means of a finite differences method.

[13] Imposing equality on the time period specific disturbance variances from the gasoline and diesel fuel equations leads to estimation problems in the $CRE^{\delta=1}$ model. Therefore, we estimated the model while restricting the disturbance variance to the arithmetic average of the time period specific estimates. As a result, the gasoline and diesel fuel elasticities for CRE and $CRE^{\delta=1}$ are not directly comparable.

References

Arndt, C. "Demand for Herbicide in Corn: An Entropy Approach Using Micro-Level Data." *Journal of Agricultural and Resource Economics* 24 (1999):204-221.

Arndt, C., S. Liu, and P. V. Preckel. "On Dual Approaches to Demand Systems Estimation in the Presence of Binding Quantity Constraints." *Applied Economics* 31 (1999):999-1008.

Buse, A. "Testing Homogeneity in the Linearized Almost Ideal Demand System." *American Journal of Agricultural Economics* 80 (1998):208-20.

Chaloupka, F. J. and P. Jha. *Curbing the Epidemic: Governments and the Economics of Tobacco Control*. Washington, D.C.: The World Bank, 1999.

Chamberlain, G. "Multivariate Regression Models for Panel Data." *Journal of Econometrics* 18 (1982):5-46.

_____. "Panel Data", Chap. 22 of *Handbook of Econometrics*, vol. 2, Z. Griliches and M. Intriligator, eds., Amsterdam: North Holland, 1984.

Chavas, J. P. and K. Segerson. “Stochastic Specification and Estimation of Share Equation Systems.” *Journal of Econometrics* 35 (1987):337-58.

Crawford, I., F. Laisney, and I. Preston. “Estimation of Household Demand Systems with Theoretically Compatible Engel Curves and Unit Value Specifications,” *Journal of Econometrics* 114 (2003):221-241.

Dahl, C. and T. Sterner. “Analysing Gasoline Demand Elasticities: A Survey.” *Energy Economics* 13 (1991):203-210.

Deaton, A. *The Analysis of Household Surveys: A Microeconometric Approach to Development Policy*. Baltimore: The Johns Hopkins University Press for the World Bank, 1997.

Deaton, A. and J. Muellbauer. *Economics and Consumer Behavior*. Cambridge: Cambridge University Press, 1980.

Greene, W.H. *Econometric Analysis,* 4th ed. New Jersey: Prentice Hall, 2000.

Hanson, L. P. “Large Sample Properties of Generalized Method of Moments Estimators.” *Econometrica* 50 (1982):1029-54.

Jakubson, G. “The Sensitivity of Labor-Supply Parameter Estimates to Unobserved Individual Effects: Fixed- and Random-Effects Estimates in a Nonlinear Model Using Panel Data.” *Journal of Labor Economics* 6 (1988):302-29.

_____. “Lecture Notes for ILRLE 741; Fall 1998.” Unpublished, Cornell University, 1998.

Kedir, A.M. “Some Issues in Using Unit Values as Prices in the Estimation of Own-Price Elasticities: Evidence from Urban Ethiopia.” CREDIT Research Paper No. 01/11, University of Nottingham, 2001.

Lee, L.-F., and M. M. Pitt. “Microeconometric Demand Systems with Binding Nonnegativity Constraints: The Dual Approach.” *Econometrica* 54 (1986):1237-42.

_____. “Microeconometric Models of Rationing, Imperfect Markets, and Non-Negativity Constraints.” *Journal of Econometrics* 36 (1987):89-110.

Leung, S. F., and C. E. Phelps. “My Kingdom for a Drink . . .? A Review of Estimates of the Price Sensitivity of Demand for Alcoholic Beverages.” *Economics and the Prevention of Alcohol-Related Problems*. M. E. Hilton and G. Bloss, eds., NIAAA research Monograph No. 25, NIH Pub. No. 93-3513. Bethesda, MD: National Institute on Alcohol Abuse and Alcoholism, 1993.

Meyerhoefer, C. D. “An Analysis of Poverty, Inequality, and Consumer Behavior in Romania With Implications for Tax Policy.” MS Thesis, Cornell University, 2001.

_____. “The Econometrics of Non-Standard Structural Demand Modeling: Applications to Transition Country Data.” PhD Dissertation, Cornell University., 2002.

Malinvaud, E. *Statistical Methods of Econometrics.* Amsterdam: North Holland, 1970

Moschini, G. "Units of Measurement and the Stone Index in Demand Systems Estimation." *American Journal of Agricultural Economics* 77 (1995):63-68.

Perali, F. P. and J. P. Chavas. “Estimation of Censored Demand Equations.” *American Journal of Agricultural Economics* 82 (2000):1022-1037.

Pollack, R. and T. J. Wales. *Demand System Specification and Estimation.* New York: Oxford University Press, 1992.

Pudney, S. *Modelling Individual Choice: The Econometrics of Corners, Kinks and Holes*. New York: Basil Blackwell Inc., 1989.

Shonkwiler, J. S., and S. T. Yen. “Two-Step Estimation of a Censored System Equations.” *American Journal Agricultural Economics* 81 (1999):972-82.

Smith, Zoe. “The Revenue Effect of Changing Alcohol Duties.” London: Institute for Fiscal Studies, Briefing Note No. 4, 1999.

Yen, S. T., B-H Lin, and D. M. Smallwood. “Quasi- and Simulated-Likelihood Approaches to Censored Demand Systems: Food Consumption by Food Stamp Recipients in the United States.” A*merican Journal of Agricultural Economics* 85 (2003):458-491.

Wales, T. J., and A. D. Woodland. “Estimation of Consumer Demand Systems with Binding Non-Negativity Constraints.” *Journal of Econometrics* 21 (1983):263-85.

White, H. “Maximum Likelihood Estimation of Misspecified Models.” *Econometrica* 50 (1982):125.

Table 1. Average Budget Shares and Degree of Censoring

	Average Budget Share			% of Zero Budget Shares		
Commodity	94	95	96	94	95	96
Bread	7.2	6.8	7.0	2.4	0.6	0.6
Grains	3.3	2.8	3.2	1.9	0.7	1.2
Fruits, Vegetables	12.6	15.7	14.7	0.2	0.1	0.1
Meat, Dairy, Oils, Fats	26.0	27.0	27.3	0.1	0.0	0.0
Other foods	7.8	8.3	8.4	0.2	0.0	0.0
Coffee	1.2	1.3	1.2	50.8	45.3	44.0
Beer	0.6	0.7	0.6	73.4	69.8	72.6
Wine	1.8	2.0	2.2	56.8	56.0	57.1
Liqueur	1.1	1.1	1.1	57.8	51.9	53.4
Tobacco products	1.4	1.3	1.5	62.9	64.1	66.3
Gasoline, Diesel fuel	0.1	0.04	0.1	86.1	85.6	85.0
Nonfoods	36.4	32.9	32.1	1.1	1.1	1.0

Table 2. Expenditure Elasticities (Standard Errors in Parenthesis)

Commodity n	CRE	$CRE^{\delta=1}$	CS	%Δ $CRE^{\delta=1}$ from CRE	%Δ CS from CRE
Bread	0.339	0.315	0.465	-7.1	37.2
	(0.009)	(0.009)	(0.011)		
Grains	0.441	0.404	0.453	-8.4	2.7
	(0.013)	(0.013)	(0.016)		
Fruits, Vegetables	0.633	0.621	0.771	-1.9	21.8
	(0.007)	(0.006)	(0.006)		
Meat, Dairy, Oils,	0.653	0.655	0.807	0.3	23.6
Fats	(0.007)	(0.005)	(0.006)		
Other Foods	0.759	0.757	0.880	-0.3	15.9
	(0.010)	(0.009)	(0.011)		
Coffee	0.753	0.732	0.926	-2.8	23.0
	(0.023)	(0.022)	(0.026)		
Beer	0.851	0.824	0.976	-3.2	14.7
	(0.041)	(0.038)	(0.033)		
Wine	0.877	0.820	0.891	-6.5	1.6
	(0.035)	(0.035)	(0.033)		
Liqueur	0.804	0.736	0.760	-8.5	-5.5
	(0.029)	(0.029)	(0.028)		
Tobacco Products	0.939	0.840	0.822	-10.5	-12.5
	(0.031)	(0.029)	(0.028)		
Gasoline, Diesel	1.811	2.291	2.048	26.5	13.1
Fuel	(0.073)	(0.018)	(0.069)		
Nonfoods	1.670	1.666	1.436	-0.2	-14.0
	(0.006)	(0.006)	(0.006)		
*Excludes Gasoline and Diesel Fuel			**Average**	4.5*	15.5

Table 3. Own-Price Elasticities (Standard Errors in Parenthesis)

Commodity n	CRE	$CRE^{\delta=1}$	CS	%Δ $\lvert CRE^{\delta=1}\rvert$ from |CRE|	%Δ |CS| from |CRE|
Bread	-0.482	-0.489	-0.481	1.5	-0.2
	(0.023)	(0.023)	(0.030)		
Grains	-1.039	-1.000	-1.190	-3.8	14.5
	(0.044)	(0.045)	(0.058)		
Fruits, Vegetables	-0.922	-0.901	-0.718	-2.3	-22.1
	(0.021)	(0.020)	(0.021)		
Meat, Dairy, Oils,	-0.717	-0.660	-0.606	-7.9	-15.5
Fats	(0.028)	(0.028)	(0.026)		
Other Foods	-0.964	-0.915	-1.031	-5.1	7.0
	(0.032)	(0.032)	(0.038)		
Coffee	-0.955	-0.998	-1.083	4.5	13.4
	(0.034)	(0.034)	(0.030)		
Beer	-1.246	-1.207	-1.297	-3.1	4.1
	(0.101)	(0.099)	(0.081)		
Wine	-1.195	-1.100	-1.536	-7.9	28.5
	(0.053)	(0.053)	(0.046)		
Liqueur	-1.140	-1.151	-1.137	1.0	-0.3
	(0.053)	(0.055)	(0.053)		
Tobacco Products	-0.666	-0.900	-0.569	35.1	-14.6
	(0.146)	(0.145)	(0.082)		
Gasoline, Diesel	-0.812	-0.732	-0.768	-9.9	-5.4
Fuel	(0.043)	(0.026)	(0.036)		
Nonfoods	-0.994	-0.953	-0.837	-4.1	-15.8
	(0.008)	(0.007)	(0.007)		
*Excludes Gasoline and Diesel Fuel			**Average***	6.9	11.8

Table 4. Price Elasticity Matrices (Standard Errors in Parenthesis)

	Bread		Grains		Fruits, Vegetables		Meat, Dairy, Oils, Fats	
	CRE	**CS**	**CRE**	**CS**	**CRE**	**CS**	**CRE**	**CS**
Bread	-0.482	-0.481	0.079	0.166	0.011	0.117	0.018	-0.385
	(0.023)	(0.030)	(0.013)	(0.017)	(0.021)	(0.023)	(0.037)	(0.040)
Grains	0.171	0.373	-1.039	-1.190	0.161	0.277	-0.023	-0.627
	(0.029)	(0.038)	(0.044)	(0.058)	(0.035)	(0.039)	(0.067)	(0.074)
Fruits, Vegetables	-0.015	0.036	0.029	0.050	-0.922	-0.718	0.121	-0.087
	(0.010)	(0.011)	(0.008)	(0.008)	(0.021)	(0.021)	(0.024)	(0.022)
Meat, Dairy, Oils,	-0.017	-0.125	-0.009	-0.084	0.062	-0.052	-0.717	-0.606
Fats	(0.010)	(0.011)	(0.008)	(0.009)	(0.013)	(0.012)	(0.028)	(0.026)
Other Foods	0.006	0.064	0.032	0.030	0.194	0.162	0.060	0.161
	(0.018)	(0.023)	(0.015)	(0.019)	(0.024)	(0.027)	(0.040)	(0.043)
Coffee	-0.107	-0.165	0.111	0.084	-0.082	-0.034	0.120	-0.095
	(0.038)	(0.037)	(0.023)	(0.024)	(0.053)	(0.047)	(0.079)	(0.070)
Beer	-0.066	-0.174	-0.334	0.107	-0.355	0.035	0.533	0.327
	(0.075)	(0.065)	(0.060)	(0.056)	(0.095)	(0.073)	(0.153)	(0.116)
Wine	-0.077	0.121	-0.028	-0.065	-0.144	0.086	-0.156	0.016
	(0.029)	(0.023)	(0.018)	(0.015)	(0.045)	(0.033)	(0.061)	(0.045)
Liqueur	0.018	-0.204	-0.040	-0.068	-0.036	-0.268	-0.101	0.405
	(0.047)	(0.048)	(0.036)	(0.039)	(0.066)	(0.056)	(0.100)	(0.091)
Tobacco Products	-0.122	0.225	0.356	0.504	-0.110	-0.531	-0.607	-0.176
	(0.060)	(0.045)	(0.049)	(0.036)	(0.078)	(0.056)	(0.134)	(0.085)
Gasoline, Diesel	-0.051	-0.071	-0.057	-0.029	0.099	-0.087	-0.373	-0.313
Fuel	(0.024)	(0.021)	(0.015)	(0.014)	(0.036)	(0.031)	(0.054)	(0.047)
Nonfoods	-0.087	-0.089	-0.043	-0.038	-0.131	-0.120	-0.269	-0.072
	(0.002)	(0.002)	(0.001)	(0.002)	(0.004)	(0.004)	(0.006)	(0.003)
Median %Δ	257.1		70.0		159.7		168.3	

Table 4. Continued

	Other Foods		Coffee		Beer		Wine	
	CRE	CS	CRE	CS	CRE	CS	CRE	CS
Bread	0.041	0.108	-0.019	-0.039	-0.001	-0.036	-0.006	0.105
	(0.021)	(0.026)	(0.009)	(0.010)	(0.017)	(0.019)	(0.012)	(0.014)
Grains	0.110	0.113	0.072	0.067	-0.158	0.083	-0.002	-0.066
	(0.038)	(0.050)	(0.013)	(0.015)	(0.030)	(0.037)	(0.017)	(0.021)
Fruits, Vegetables	0.120	0.101	-0.005	0.001	-0.028	0.017	-0.009	0.048
	(0.014)	(0.006)	(0.006)	(0.006)	(0.010)	(0.011)	(0.009)	(0.010)
Meat, Dairy, Oils,	0.027	0.055	0.013	-0.002	0.044	0.037	0.004	0.023
Fats	(0.012)	(0.013)	(0.005)	(0.005)	(0.009)	(0.009)	(0.006)	(0.007)
Other Foods	-0.964	-1.031	-0.001	-0.013	-0.044	-0.048	0.062	0.072
	(0.032)	(0.038)	(0.011)	(0.012)	(0.017)	(0.019)	(0.013)	(0.016)
Coffee	-0.020	-0.070	-0.955	-1.083	0.002	0.031	0.055	0.269
	(0.050)	(0.048)	(0.034)	(0.030)	(0.038)	(0.036)	(0.033)	(0.033)
Beer	-0.279	-0.241	-0.006	0.027	-1.246	-1.297	0.212	0.087
	(0.091)	(0.076)	(0.042)	(0.034)	(0.101)	(0.081)	(0.061)	(0.050)
Wine	0.114	0.097	-0.156	0.122	0.114	0.041	-1.195	-1.536
	(0.037)	(0.031)	(0.020)	(0.016)	(0.033)	(0.025)	(0.053)	(0.046)
Liqueur	0.060	-0.205	-0.006	-0.021	0.229	0.148	-0.007	0.100
	(0.063)	(0.062)	(0.027)	(0.025)	(0.048)	(0.045)	(0.038)	(0.036)
Tobacco Products	-0.045	-0.234	-0.002	-0.011	-0.180	-0.233	0.193	0.157
	(0.077)	(0.057)	(0.035)	(0.025)	(0.063)	(0.045)	(0.047)	(0.041)
Gasoline, Diesel	-0.228	-0.116	-0.050	-0.043	0.105	0.030	-0.128	-0.227
Fuel	(0.027)	(0.025)	(0.015)	(0.013)	(0.025)	(0.021)	(0.033)	(0.034)
Nonfoods	-0.093	-0.228	-0.013	-0.003	-0.002	-0.002	-0.019	-0.035
	(0.003)	(0.006)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)
Median %Δ	103.7		120.0		64.0		389.1	

Table 4. Continued

	Liqueur		Tobacco Products		Gasoline, Diesel Fuel		Nonfoods	
	CRE	**CS**	**CRE**	**CS**	**CRE**	**CS**	**CRE**	**CS**
Bread	0.020	-0.056	-0.034	0.132	0.005	0.004	0.030	-0.099
	(0.012)	(0.016)	(0.025)	(0.024)	(0.008)	(0.007)	(0.010)	(0.010)
Grains	-0.012	-0.039	0.352	0.625	-0.021	0.005	-0.052	-0.074
	(0.022)	(0.029)	(0.045)	(0.042)	(0.011)	(0.010)	(0.015)	(0.016)
Fruits, Vegetables	0.007	-0.035	-0.010	-0.137	0.037	0.011	0.041	-0.059
	(0.009)	(0.009)	(0.016)	(0.014)	(0.005)	(0.005)	(0.009)	(0.008)
Meat, Dairy, Oils,	0.004	0.045	-0.054	-0.021	-0.012	-0.002	0.004	-0.075
Fats	(0.007)	(0.008)	(0.015)	(0.012)	(0.004)	(0.004)	(0.007)	(0.006)
Other Foods	0.025	-0.052	-0.005	-0.106	-0.046	-0.008	-0.078	-0.112
	(0.015)	(0.018)	(0.028)	(0.026)	(0.007)	(0.007)	(0.012)	(0.011)
Coffee	-0.001	-0.021	0.002	-0.022	-0.052	-0.034	-0.094	-0.024
	(0.030)	(0.029)	(0.060)	(0.048)	(0.020)	(0.015)	(0.029)	(0.025)
Beer	0.278	0.170	-0.339	-0.449	0.160	0.039	-0.165	-0.166
	(0.058)	(0.049)	(0.118)	(0.080)	(0.036)	(0.022)	(0.051)	(0.036)
Wine	0.027	0.051	0.115	0.128	-0.004	-0.109	0.185	-0.317
	(0.025)	(0.020)	(0.048)	(0.036)	(0.026)	(0.018)	(0.040)	(0.031)
Liqueur	-1.140	-1.137	-0.036	0.023	-0.105	-0.001	-0.228	-0.051
	(0.053)	(0.053)	(0.074)	(0.059)	(0.025)	(0.017)	(0.036)	(0.027)
Tobacco Products	-0.023	0.017	-0.666	-0.569	0.005	-0.088	-0.057	-0.099
	(0.047)	(0.036)	(0.146)	(0.082)	(0.026)	(0.020)	(0.037)	(0.031)
Gasoline, Diesel	-0.094	-0.011	-0.004	-0.157	-0.812	-0.768	-0.218	-0.255
Fuel	(0.021)	(0.018)	(0.032)	(0.034)	(0.043)	(0.036)	(0.058)	(0.052)
Nonfoods	-0.013	-0.002	-0.007	-0.016	0.001	0.005	-0.994	-0.837
	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)	(0.003)	(0.008)	(0.007)
Median %Δ	225.0		163.9		83.3		74.5	