Journal of Agricultural and Resource Economics 29(2):276–295

The FAST Method: Estimating Unconditional Demand Elasticities for Processed Foods in the Presence of Fixed Effects

Jason Bergtold, Ebere Akobundu, and Everett B. Peterson

This study estimates a set of unconditional own-price and expenditure elasticities across time for 49 processed food categories using scanner data and the FAST multi-stage demand system with fixed effects across time. Estimated own-price elasticities are generally much larger, in absolute terms, than previous estimates, while our expenditure elasticities are generally much lower. The use of disaggregated product groupings, scanner data, and the estimation of unconditional elasticities likely accounts for these differences. Results of the study suggest providing more disaggregate product-level demand elasticities could aid in the economic analysis of issues relating to industry competitiveness or the impact of public policy.

Key words: demand elasticities, indirect separability, processed foods

Introduction

Economic analyses of issues relating to firm or industry competitiveness and the impact of public policy upon the performance of the food system depend critically upon the existence of reliable and disaggregate elasticity of demand estimates. For example, recently developed methods to estimate welfare loss, based on a variety of oligopoly models, require product- or market-level demand elasticity estimates (Bhuyan and Lopez, 1998; Clarke and Davies, 1982; Gisser, 1986; Peterson and Connor, 1995; Willner, 1989). Furthermore, demand elasticities are crucial in defining relevant product markets and measuring market power in antitrust enforcement activities (Cotterill, 1994; Levy and Reitzes, 1992; Starek and Stockum, 1995). Disaggregated, product-level demand elasticities allow for more meaningful benefit-cost analyses of proposed regulations for the food processing industries.[1] The increasing importance of food processing and marketing activities in the U.S. and global food systems compels future analyses of domestic and international agricultural commodity policies to focus on the demand for processed food

---

Jason Bergtold and Ebere Akobundu are doctoral students, and Everett B. Peterson is associate professor, all in the Department of Agricultural and Applied Economics, Virginia Tech, Blacksburg, Virginia. Helpful comments from Anya McGuirk and two anonymous reviewers are gratefully acknowledged.

Review coordinated by Gary D. Thompson and DeeVon Bailey; publication decision made by DeeVon Bailey.

[1] For example, consider the case of analyzing a new Hazard Analysis and Critical Control Points (HACCP) regulation for a processed food product. The amount of the production cost increase passed on to consumers is determined by the relative magnitude of the supply and demand elasticities. The more elastic consumer demand is for any given product, any change in policy will then result in a smaller price change at the retail level, compared to a more inelastic demand response. So in the case of a production cost-increasing policy or regulation, the loss in consumer surplus from a price increase will be lower when consumer demand is more elastic.

products rather than raw agricultural commodities (Peterson, Hertel, and Stout, 1994). To facilitate these analyses, analysts will need a set of unconditional and disaggregated price and expenditure elasticities for a large group of processed food products.

There have been several barriers to empirically estimating a set of demand elasticities for processed food products. The most obvious is the difficulty in obtaining price and quantity data for a disaggregate set of processed food products. To illustrate this problem, consider the study by Huang (1993), who estimated a complete demand system for 39 food categories and one non-food category. Huang developed a time series of food quantity indices based on disappearance data and food price indices based on components of the consumer price index. The quantity indices are not direct estimates of actual purchases (or consumption) at the retail level. Consequently, the correspondence between the price and quantity indices is not perfect because they are different data series. Furthermore, time-series data can create a problem if the number of time periods observed is not sufficient to estimate a large demand system. In this case, the analyst may be required to aggregate across food products.

One solution to the above data problems is the use of scanner data. This type of data provides an exact correspondence between price and quantity, and yields detailed information on prices and quantities across both time and regions (or cross-sections), which can help solve the degrees-of-freedom problem. However, because scanner data are costly to obtain, only a small (but growing) number of demand analyses have been conducted using scanner data (Capps, 1989; Capps and Lambregts, 1991; Cotterill, 1994; Cotterill and Haller, 1994; Green and Park, 1998; Kinoshita et al., 2001; Maynard, 2000; Nayga and Capps, 1994; Schmit et al., 2000; Wessells and Wallström, 1999). These investigations have focused on small groups of processed food products, such as meat products, beverages, canned salmon and tuna, and dairy products. To date, scanner data have not been used to estimate a set of demand elasticities for a more encompassing group of processed food products.

The main objective of this article is to estimate a set of unconditional price and expenditure elasticities for 49 different processed food categories and one composite good. To alleviate the parametric burden of a large disaggregated demand system, Moschini's (2001) flexible and separable translog (FAST) multistage demand system is used to obtain unconditional own-price and expenditure demand elasticities. Due to our incorporation of panel data, the FAST model is extended to include fixed effects across time.

Data

The data used in this study are from the Information Resources, Inc. (IRI) InfoScan® retail database.[2] The IRI data include prices and total sales for 140 different processed food products for 42 U.S. metropolitan areas from the first quarter of 1988 through the fourth quarter of 1992.[3] The total sales for each metropolitan area is the total amount sold each quarter by all supermarkets in the metropolitan area, and the price is a weighted average price per unit of that particular product. Because it is not possible to

[2] These data were made available to us by an arrangement with Professor Ron Cotterill at the Food Marketing Policy Center, University of Connecticut.

[3] Cotterill and Haller (1994), as well as Wessells and Wallström (1999), have used a subset of these data. The selected metropolitan areas were chosen based on completeness of data.

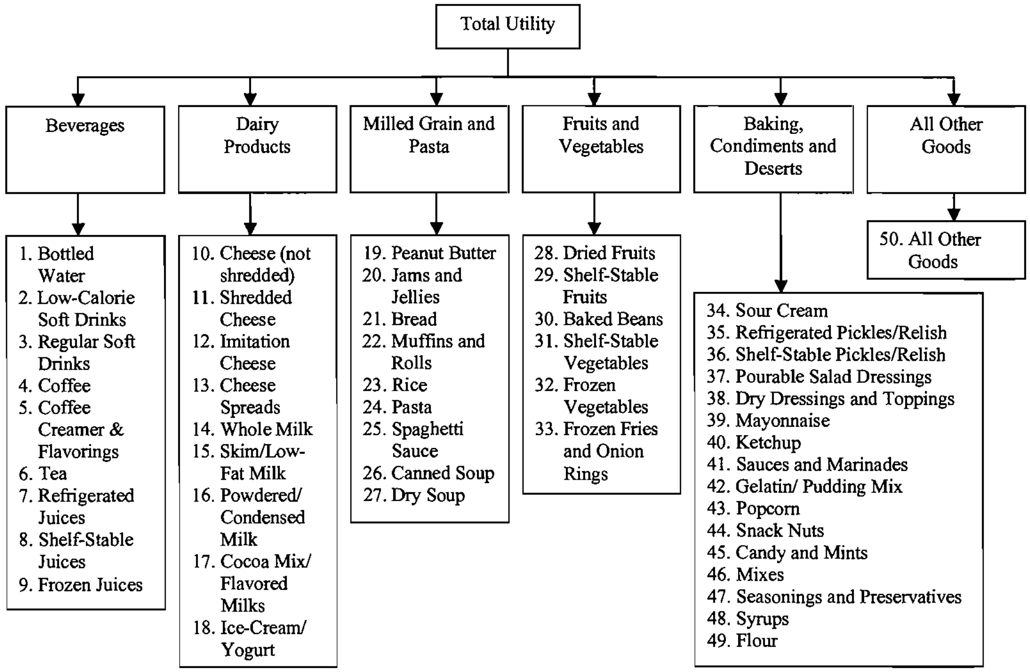

Figure 1. Separable preference structure of representative consumer: 49 aggregated processed food categories and one composite good

estimate a demand system with 140 processed food products, these food products are aggregated into 49 processed food categories based on IRI category definitions. These product categories are shown in figure 1.

One limitation of the IRI data set is that it does not include information on several key food categories, such as fresh meats and fresh fruits and vegetables. This is because supermarkets either did not assign bar codes to these items, or the codes assigned are not uniform during the sample time period. Thus, IRI is unable to provide information on these food product categories. As such, they are included in an "all other goods" composite good in our model. Another data limitation is that IRI collects data only from supermarkets, so food purchases from other retailers, such as convenience stores, are not included.

The IRI price and quantity data are also supplemented with information on median household income and total number of households from the IRI InfoScan® market profiles for each metropolitan area. Given that the data on median household income are on an annual basis and the price and quantity data are on a quarterly basis, the level of median household income is allocated across the four quarters for each year to provide median household income on a quarterly basis. This allocation is accomplished through use of the quarterly data series on "Disposable Personal Income" and "Personal Outlays" available from the Bureau of Economic Analysis (BEA) for the years 1988 to 1992 (U.S. Department of Commerce). Using these series, annual savings rates are calculated for adjusting the annual data on median household income (by subtracting out household savings). The adjusted annual levels of household income are then allocated across quarters using the quarterly percentages calculated from the BEA's "Disposable Personal Income" series.

The "all other goods" composite is a residual good representing expenditures on all goods and services not included in the 49 processed food categories examined in the study. A price index for this residual good is computed using regional consumer price indices (U.S. Department of Labor) for "All Urban Consumers." This consumer price index series is chosen because of the relatively large consumption share of the "all other goods" category. Regional data are available for New York, Philadelphia, Boston, Chicago, Cleveland, Detroit, St. Louis, Dallas/Ft. Worth, Houston, Miami/Ft. Lauderdale, Los Angeles, and San Francisco. For all other regions, the respective composite consumer price index for the Northeast, Midwest, South, and West was utilized.

Descriptive statistics for total sales and average prices for each of the 49 processed food categories are provided in table 1. To illustrate the variability in the panel data set across markets and time, sample standard deviations are calculated across markets and time for each of the processed food categories.

Nonparametric Tests of Utility Maximization

An underlying premise in the estimation of a demand system is that consumer behavior is consistent with the maintained hypothesis of utility maximization. Before estimating a demand system parametrically, it is important to determine if the data to be used are consistent with this hypothesis. Varian (1982) proposed a nonparametric procedure for evaluating whether a set of observed data is consistent with the utility maximization hypothesis by directly testing whether the data satisfy the weak axiom of revealed preference (WARP) and/or the general axiom of revealed preference (GARP). As shown by Diaye, Gardes, and Starzec (2001), if WARP is satisfied, then it can be claimed there exists a utility function which rationalizes that data, but no other conclusions can be drawn about the nature of the utility function. If GARP is also satisfied, then there exists a non-satiated utility function and a demand correspondence that rationalizes the data.

WARP and GARP are tested simultaneously for each metropolitan area employing a variant of Warshall's algorithm (as presented by Varian, 1982) using the normalized prices (in order to lessen the effects of seasonality) and quantities (calculated by dividing total sales by price) from each of the 49 processed food categories. Strict adherence to the rules of nonparametric testing would lead to rejection of the hypothesis that WARP or GARP are satisfied by the data if just one violation is found. Thus, Varian proposed an axiom should be rejected if the violation rate is greater than 5%, where the violation rate is defined as the number of violations of the revealed preference relation being examined divided by the total number of pairs belonging to the revealed preference relation (Diaye, Gardes, and Starzec, 2001). Testing for both WARP and GARP using this rule, the data for three of the original 42 metropolitan areas—Columbus (6.2% violation rate for both tests), Kansas City (8.6% violation rate for both tests), and Portland (8.6% violation rate for both tests)—failed the nonparametric tests and were summarily excluded from the sample, leaving 780 observations in the panel data set.[4]

[4] The metropolitan areas included in the sample are Albany, Atlanta, Baltimore/Washington, Birmingham, Boston, Buffalo/Rochester, Chicago, Cincinnati/Dayton, Cleveland, Dallas/Ft. Worth, Denver, Detroit, Grand Rapids, Hartford/Springfield, Houston, Indianapolis, Los Angeles, Louisville, Memphis, Miami/Ft. Lauderdale, Milwaukee, Minneapolis/St. Paul, Nashville, New York, Oklahoma City, Omaha, Philadelphia, Phoenix/Tucson, Pittsburgh, Raleigh/Greensboro, Sacramento, Salt Lake City, San Antonio, San Diego, San Francisco/Oakland, Seattle/Tacoma, St. Louis, Tampa/St. Petersburg, and Wichita.

Table 1. Sample Means and Standard Deviations for Total Sales and Average Prices, by Product Groupings

	Average Price ($/unit)				Total Sales ($)			
			Std. Dev. of Means (across)				Std. Dev. of Means (across)	
Product Grouping	Pooled Mean	Standard Deviation	Markets	Time	Pooled Mean	Standard Deviation	Markets	Time
Coffee	0.8457	0.1616	0.1324	0.0882	11,135,549	11,795,926	11,829,689	1,028,573
Coffee Creamer and Flavorings	1.7328	0.1783	0.1522	0.0757	661,324	547,440	544,408	72,117
Tea	8.0076	2.1091	1.9446	0.6803	2,081,575	2,407,966	2,390,600	218,878
Bottled Water	0.9983	0.0600	0.0069	0.0271	4,636,961	7,127,086	7,152,379	485,462
Low-Calorie Soft Drinks	3.7292	0.2987	0.2440	0.0871	10,376,526	9,485,445	9,484,894	933,990
Regular Soft Drinks	0.9006	0.1591	0.1428	0.0387	19,604,021	17,015,937	16,975,890	1,797,670
Refrigerated Juices	0.9964	0.0618	0.0030	0.0494	10,423,344	15,491,568	15,566,054	1,153,337
Shelf-Stable Juices	0.9991	0.0563	0.0008	0.4850	14,425,856	16,913,652	16,968,070	1,386,250
Frozen Juices	0.9960	0.0627	0.0028	0.0475	6,642,821	5,519,396	5,548,842	334,281
Refrigerated Pickles and Relish	0.9988	0.1017	0.0020	0.0993	485,566	570,803	570,532	45,809
Shelf-Stable Pickles and Relish	0.9960	0.0607	0.0017	0.0547	3,493,288	3,157,395	3,147,582	381,052
Pourable Salad Dressings	1.0000	0.0803	0.0002	0.0783	3,294,211	3,084,270	3,035,592	542,243
Dry Dressings and Toppings	0.8665	0.2757	0.0475	0.2546	675,399	543,808	540,443	61,123
Mayonnaise	0.6630	0.0944	0.0388	0.0848	3,282,010	3,063,168	3,070,609	284,257
Ketchup	0.7201	0.0737	0.0664	0.0237	1,364,697	1,206,257	1,203,572	121,675
Sauces and Marinades	0.8529	0.1200	0.0238	0.1125	2,513,323	2,158,855	2,087,289	494,755
Sour Cream	1.1519	0.1277	0.1196	0.0290	1,501,821	1,690,018	1,694,568	153,101
Whole Milk	0.2992	0.0314	0.0223	0.0191	10,141,940	11,263,201	11,250,633	629,306
Skim/Low-Fat Milk	0.2756	0.0361	0.0288	0.0191	16,506,631	14,093,536	13,878,606	2,531,526
Powdered/Condensed Milk	0.9948	0.0946	0.0046	0.0832	1,240,180	1,363,586	1,304,845	345,549
Cocoa Mix and Flavored Milks	0.9957	0.0829	0.0041	0.0776	2,008,606	1,938,968	1,674,860	787,423
Ice Cream/Yogurt	0.9869	0.0416	0.0102	0.0187	10,708,396	10,864,883	10,778,967	1,573,946
Cheese (non-shredded)	0.9992	0.0812	0.0009	0.0795	11,382,555	12,407,589	12,362,212	1,372,988
Shredded Cheese	3.5737	0.4102	0.2819	0.2885	2,177,247	1,761,291	1,628,914	579,716
Imitation Cheese	2.5971	0.5474	0.4062	0.2036	91,898	119,944	99,784	26,535

(continued . . .)

Table 1. Continued

Product Grouping	Average Price ($/unit) Pooled Mean	Average Price Standard Deviation	Std. Dev. of Means (across) Markets	Std. Dev. of Means (across) Time	Total Sales ($) Pooled Mean	Total Sales Standard Deviation	Std. Dev. of Means (across) Markets	Std. Dev. of Means (across) Time
Cheese Spreads	0.9975	0.0504	0.0016	0.0424	3,418,286	3,530,889	3,489,768	585,262
Dried Fruits	0.9988	0.0543	0.0019	0.0464	1,614,831	1,826,564	1,793,823	289,980
Shelf-Stable Fruits	0.9307	0.0585	0.0246	0.0485	4,985,008	4,692,063	4,635,957	720,924
Baked Beans	0.5424	0.0757	0.0653	0.0321	1,107,529	828,919	777,465	230,705
Shelf-Stable Vegetables	0.8783	0.2333	0.0386	0.2311	7,811,451	8,082,719	7,782,702	1,774,772
Frozen Vegetables	0.9992	0.0424	0.0005	0.0367	6,119,662	7,375,367	7,379,023	723,566
Frozen Fries and Onion Rings	0.7000	0.0785	0.0420	0.0635	2,283,763	2,007,918	2,003,372	226,308
Bread	1.0000	0.0639	0.0000	0.0560	15,012,560	15,085,067	15,162,453	1,127,889
Muffins and Rolls	0.9981	0.0680	0.0014	0.0577	5,464,413	6,303,311	6,290,252	637,305
Rice	1.2599	0.2986	0.2949	0.0300	3,430,886	4,097,155	4,102,936	361,768
Pasta	0.9321	0.1103	0.1031	0.0287	4,088,161	5,047,888	5,072,262	359,868
Spaghetti Sauce	0.9314	0.0906	0.0843	0.0258	3,513,022	3,761,892	3,748,880	383,305
Peanut Butter	1.8257	0.2054	0.1307	0.1541	2,980,863	2,459,919	2,463,054	241,661
Jams and Jellies	0.9994	0.0651	0.0007	0.0590	2,754,568	2,895,557	2,908,443	232,433
Mixes	0.9983	0.0436	0.0011	0.0329	3,328,600	2,552,430	2,509,950	407,723
Seasonings and Preservatives	0.9983	0.0802	0.0043	0.0700	4,558,537	4,685,780	4,626,443	718,888
Syrups	0.9991	0.0580	0.0008	0.0528	1,746,297	1,613,675	1,598,382	240,637
Flour	0.9884	0.1734	0.0060	0.1639	1,278,964	1,089,218	1,036,151	1,127,889
Canned Soup	0.9127	0.1063	0.0598	0.0874	6,301,093	5,808,765	5,444,426	1,611,846
Dry Soup	0.9906	0.0587	0.0080	0.0200	2,978,058	3,822,765	3,704,676	685,760
Gelatin/Pudding Mix	0.9978	0.0686	0.0011	0.0643	1,823,759	1,621,042	1,617,356	175,556
Popcorn	0.9989	0.0407	0.0023	0.0178	1,877,550	1,539,600	1,525,218	227,107
Snack Nuts	1.0402	0.2019	0.0623	0.1845	2,199,366	2,462,671	2,424,247	370,042
Candy and Mints	1.0017	0.0466	0.0033	0.0414	8,017,229	7,583,452	7,289,926	1,730,964

Model Specification

Following Moschini (2001), the empirical demand model developed for this study is based on the notion of indirect separability. Preferences are indirectly weakly separable in the partition $\hat{I} = \{I^1, \ldots, I^N\}$ if the indirect utility function $V(p/y)$ can be written as

$$V(p/y) = V^0\left[V^1(p^1/y), \ldots, V^N(p^N/y)\right], \tag{1}$$

where $\mathbf{p}^r$ is the vector of prices in the rth group ($r = 1, \ldots, N$), and $V^r(p^r/y)$ are indices dependent only on $\mathbf{p}^r$ and total expenditure (y). It is assumed $V^0(\cdot)$ is continuous, nonincreasing, and quasiconvex, and $V^r(\cdot)$ is continuous, nondecreasing, and quasiconcave, such that $V(p/y)$ retains the general properties of an indirect utility function.

The advantage of indirect separability, compared to direct separability, is that it allows a consistent specification of the unconditional demand functions and conditional demand functions of a weakly separable preference structure. Using Roy's identity, the unconditional (Marshallian) demand functions $q_i(p/y)$ and the conditional demand functions $c_i(p^r/y)$ are defined, respectively, as:

$$q_i(p/y) = -\frac{\dfrac{\partial V^0}{\partial V^r}\dfrac{\partial V^r(p^r/y)}{\partial p_i}}{\displaystyle\sum_{s=1}^{N}\frac{\partial V^0}{\partial V^s}\frac{\partial V^s(p^s/y)}{\partial y}}, \quad i \in I^r \tag{2}$$

and

$$c_i(p^r/y) = -\frac{\dfrac{\partial V^r(p^r/y)}{\partial p_i}}{\dfrac{\partial V^r(p^r/y)}{\partial y}}, \quad i \in I^r. \tag{3}$$

Explicit forms for equations (2) and (3) can be obtained once functional forms are specified for $V^0(\cdot)$ and $V^r(\cdot)$. Moschini derives the first-stage group share equations and second-stage conditional share equations using equations (2) and (3) via the following relationship:

$$q_i(p/y) = \frac{y_r(p/y)}{y}c_i(p^r/y), \quad i \in I^r,$$

where

$$y_r(p/y) = \sum_{i \in I^r} p_i q_i,$$

the within-group expenditure allocation for partition I^r.

Moschini adopts the translog specification of Christensen, Jorgenson, and Lau (1975) for $V^0(\cdot)$ and $V^r(\cdot)$. Specifically:

$$V^0(\cdot) = -\left[\gamma_0 + \sum_{r=1}^{N}\gamma_r \log V^r(\cdot) + \tfrac{1}{2}\sum_{r=1}^{N}\sum_{s=1}^{N}\gamma_{rs}\log V^r(\cdot)\log V^s(\cdot)\right], \tag{4}$$

and

$$\log V^r(p^r/y) = \beta_0^r + \sum_{i \in I^r}\beta_i \log(p_i/y) + \tfrac{1}{2}\sum_{i \in I^r}\sum_{j \in I^r}\beta_{ij}\log(p_i/y)\log(p_j/y). \tag{5}$$

Homogeneity is satisfied by construction, and symmetry is imposed by setting $\beta_{ij} = \beta_{ji}$ $\forall i,j$, and $\gamma_{rs} = \gamma_{sr} \forall r, s$. To ensure the indirect utility function based on equations (4) and (5) is a flexible functional form and satisfies the properties of indirect weak separability, Moschini shows that the following parametric restrictions are also applicable:

$$\begin{aligned}
&\beta_0^r = 0, \quad \text{for } r = 1, \ldots, N,\\
&\gamma_0 = 0,\\
&\sum_{i \in I^r} \beta_i = 1, \quad \text{for } r = 1, \ldots, N,\\
&\sum_{r=1}^{N} \gamma_r = 1, \quad \text{and}\\
&\sum_{i \in I^r} \sum_{j \in I^r} \beta_{ij} = 0, \quad \text{for } r = 1, \ldots, N.
\end{aligned}$$

The last restriction allows for the case of asymmetric separability, where the rth group has only one price.

For estimation purposes, Moschini suggests it may be convenient to estimate the conditional share equations and the group share equations using a two-step process. First, the conditional share equations are estimated, expressed as follows:

$$w_i^r = \frac{\beta_i + \sum_{j \in I^r} \beta_{ij} \log(p_j / y)}{1 + \sum_{k \in I^r} \sum_{j \in I^r} \beta_{kj} \log(p_j / y)}, \quad \forall i \in I^r, \tag{6}$$

where $w_i^r = (p_i q_i)/y_r$, and y_r is the within-group expenditure. Then, the group share equations are estimated:

$$w^r = \frac{B^r(p^r/y)\left(\gamma_r + \sum_{s=1}^{N} \gamma_{rs} \log V^s(p^s/y)\right)}{\sum_{g=1}^{N} B^g(p^g/y)\left(\gamma_g + \sum_{s=1}^{N} \gamma_{gs} \log V^s(p^s/y)\right)}, \quad \text{for } r = 1, \ldots, N, \tag{7}$$

where $w^r = y^r/y$, and

$$B^g(p^g/y) = 1 + \sum_{j \in I^g} \sum_{i \in I^g} \beta_{ij} \log(p_i/y), \quad \text{for } g = 1, \ldots, N.$$

The indices, $\log(V^r)$ and B^g, are computed using the estimated parameters of the conditional share equations in the first step.

Incorporating Fixed Effects

Given the nature of panel data and the presence of heterogeneity in pooled models, one should consider the use of fixed or random effects in the model to account for any heterogeneity bias (Hsiao, 1986). To capture this heterogeneity, fixed effects across markets and time should be incorporated into the conditional and group share equations. Due to the size of the demand system estimated here, only quarterly fixed effects are included in the empirical model, in order to leave enough degrees of freedom for estimation.

If prices and expenditure are both normalized by their respective means, then the sample mean of $\log(p_i/y) = \log(1/1) = 0$. This implies the intercept term in equation (6) is β_i. To incorporate fixed effects across time, redefine β_i in equation (6) to equal:

$$(8) \qquad \beta_i = \sum_{s \in S} \tau_{is} D_s, \quad \text{for } i \in I^r, \quad r = 1, \ldots, N,$$

where τ_{is} is the time-specific fixed effect, D_s is a dummy variable equal to one if the observation being examined occurred in time interval s, and S is the set of time periods. The set S can represent individual time periods, quarters, years, etc. For this analysis, S includes the four standard quarters of the calendar year, which makes D_s quarterly dummies. Substituting equation (8) into equation (6) gives the revised conditional share equations.

To take account of heterogeneity at the top level of the two-stage demand system, fixed effects can be incorporated into the group share equations as well. Again, the sample mean of $\log(p_i/y) = 0$ implies $B^g(p^g/y) = 1$, for $g = 1, \ldots, N$, and $\log V^r(p^r/y) = 0$ for $r = 1, \ldots, N$. Thus, at the sample means, γ_r is the intercept term in equation (7). To incorporate fixed effects, redefine γ_r as:

$$(9) \qquad \gamma_r = \sum_{s=1}^{S-1} \rho_{rs} D_s, \quad \text{for } r = 1, \ldots, N,$$

where ρ_{rs} is analogous to τ_{is} in equation (8). Substituting equation (9) into equation (7) yields the revised group share equations.

Indirectly Weakly Separable Structure

The 49 processed food categories and one composite good are partitioned into six weakly separable partitions as shown in figure 1. Thus, the underlying indirect utility function can be expressed as:

$$V^0 = \left[V^1(p^1/y), \ldots, V^5(p^5/y), p^6/y \right],$$

where the indices 1 through 5 refer to the product groupings: (1) beverages, (2) dairy products, (3) milled grain and pasta, (4) fruits and vegetables, and (5) baking, condiments, and deserts. Group 6 is an asymmetric group with only one good, the "all other goods" composite good.[5] A few goods do not lend themselves easily to classification according to our system. These products have been placed in the group which appears to be the most reasonable from the point of view of the consumer who is constrained to allocate her expenditure budget among these particular product groups. For example, consider the milled grain and pasta product group. Given their hypothesized complementary relationship, pasta and spaghetti sauce are placed in the same group (partition). Similarly, peanut butter and jellies and jams are placed in the milled grain product group because

[5] The six partitions used in this study are assumed to be weakly separable. Due to the large number of potential combinations of partitions that could be generated and the difficulty in estimating a 50-good unrestricted model, we did not test whether the data support the assumed weakly separable structure.

of their hypothesized complementary relationships with bread and muffins and rolls.[6] The fifth product group—baking, condiments, and deserts—comprises the largest number of goods (16) due to the fact that many of these goods are complements and substitutes for each other and/or were not easily placed into another group.

Results

Equations (6) and (7), modified by equations (8) and (9) to allow for fixed effects across quarters, are estimated to obtain unconditional price and expenditure elasticities across quarters using the two-step process as presented by Moschini (2001). In the first step, five systems of conditional within-group share equations are estimated. The "all other goods" group is a trivial estimation because it only contains one composite good. In the second step, a system of five group share equations is estimated. Due to the adding-up conditions, one share equation is dropped in each system during estimation to avoid singularity of the variance/covariance matrix of the residuals.[7] In total, with the fixed effects across time, there are 488 parameters to estimate for all the systems of equations at both stages.[8] With 780 observations, this gives a 1.6:1 ratio between the number of parameters and the total number of degrees of freedom.

Due to the highly nonlinear nature of the share equations, the "full information maximum likelihood" (FIML) procedure in SAS is utilized to estimate each system of equations at both stages of the estimation process. This iterative procedure was found to be superior to the iterative seemingly unrelated regression (ITSUR) estimation procedure in SAS in terms of the convergence properties of the algorithm. The specific estimation results for each system are not presented in detail, but are available from the authors upon request. The majority of the fixed effects across time were found to be statistically significant, indicating the presence of temporal heterogeneity in the data. The ultimate goal of the estimation of the demand system was to obtain unconditional expenditure and price elasticities for all of the product categories examined in the empirical model. Thus, the majority of the discussion here pertains to this goal.

Derivation of Unconditional Demand Elasticities

Moschini points out that the main payoff to using the FAST multistage demand model is the derivation of a complete matrix of unconditional Marshallian expenditure and price elasticities. If the data are normalized so that $p_i = y = 1$ ($\forall\, i$), the unconditional expenditure (η) and price (ε) elasticities for good i are expressed as:

$$(10)\qquad \varepsilon_{ijs} = \frac{\beta_{ij}}{\beta_i(s)} + \frac{\gamma_{rr}\beta_j(s)}{\gamma_r(s)} - \gamma_r(s)\left(\sum_{q\in I^r}\beta_{iq}\right) - \beta_j(s)\left(\sum_{s=1}^{N}\gamma_{rs}\right) - \delta_{ij}, \quad \text{for } (i,j)\in I^r,$$

[6] In results not reported here, these goods were found to be complements.

[7] In the system of group share equations, the "all other goods" group share equation is dropped. In addition, it should be noted that the use of maximum-likelihood estimation is invariant to the share equation being dropped (Moschini, 2001).

[8] The "beverages" group, "dairy products" group, and "milled grain and pasta" group each had 76 parameters to estimate; the "fruits and vegetables" group had 40 parameters; and the "baking, condiments, and deserts" group had 179 parameters. The second-stage system of group share equations had 41 parameters to estimate.

(11) $$\varepsilon_{ijs} = \frac{\gamma_{rs}\beta_j(s)}{\gamma_r(s)} - \gamma_s(s)\left(\sum_{q\in I^s}\beta_{qi}\right) - \beta_j(s)\left(\sum_{p=1}^{N}\gamma_{rp}\right), \quad \text{for } i \in I^r \text{ and } j \in I^s,$$

and

(12) $$\eta_{is} = 1 - \frac{\sum_{j\in I^r}\beta_{ij}}{\beta_i(s)} - \frac{\sum_{s=1}^{N}\gamma_{rs}}{\gamma_r(s)} + \sum_{r=1}^{N}\sum_{s=1}^{N}\gamma_{rs}, \quad \text{for } i \in I^r,$$

where δ_{ij} is the Kronecker delta ($\delta_{ij} = 1$ if $i = j$, and 0 otherwise), $s \in S$, $\beta_i(s)$ is given by equation (8), and $\gamma_r(s)$ is given by equation (9).[9] The elasticities given by equations (10)–(12) not only vary over goods, but vary over time as well. This last result is due to the fact that the elasticities are functions of the fixed effects across time. Given the non-linear nature of the model, no estimator of the elasticity can be derived which is not a function of the fixed effects included in the model (Heckman and MaCurdy, 1980).

To decrease the dimensionality of each of these elasticity estimates, pooled means could be taken over time, but such elasticity estimates would fail to take account of the heterogeneity present in the panel data used for estimation. Thus, elasticity estimates are reported across quarters (or temporally), to draw attention to the variation in the demand elasticities across time. Furthermore, because the use of scanner data implies that one is aggregating over households (and/or individuals), the elasticity estimates derived from the FAST multistage demand model should be interpreted in aggregate terms (i.e., at a macro level) (Edgerton, 1997). This interpretation is more desirable for policy makers, given policy-oriented studies tend to be focused at the aggregate (i.e., market), not household level.

Unconditional Price and Expenditure Elasticity Estimates

The own-price and expenditure elasticity estimates for the product groupings examined are presented in table 2.[10] All elasticity estimates are reported temporally (i.e., across quarters) with their respective standard errors given in parentheses. Standard errors were calculated using a Monte Carlo method. The estimated parameters for each system of equations are assumed to be distributed asymptotically multivariate normal, with the means being the values of the estimated parameters, and the variance-covariance matrix being the estimated variance-covariance matrix of the parameters for each system. Based on these assumed distributions, 5,000 sets of parameters for each system of equations are randomly generated. For each set of parameters generated, the corresponding price and expenditure elasticities are computed and saved. The standard errors of the elasticity estimates are then the sample standard errors of the 5,000 generated price and expenditure elasticity estimates.

---

[9] The formulas for the elasticities computed at the mean of the normalized prices and expenditure are different than those derived by Moschini because his expressions did not take into account the different restrictions imposed when using asymmetric groups. For example, the last expenditure elasticity formula given in Appendix C of Moschini's paper implies an elasticity of one for a good in an asymmetric partition because β_{ii} is equal to zero. However, there is no reason to expect that the expenditure elasticities for goods in asymmetric partitions should always be equal to one.

[10] Due to space limitations, it is not possible to list the complete 50 × 50 matrices of unconditional price elasticities for all quarters in this article. A complete set of price and expenditure elasticities is available from the authors upon request.

Table 2. Unconditional Own-Price and Expenditure Elasticity Estimates, by Product Groupings

	Uncompensated Price Elasticities				Uncompensated Expenditure Elasticities			
Product Grouping	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Bottled Water	-0.28	-0.34	-0.39	-0.29	-0.21	-0.20	-0.19	-0.21
	(0.30)	(0.27)	(0.25)	(0.29)	(0.16)	(0.15)	(0.14)	(0.16)
Low-Calorie Soft Drinks	-1.26	-1.24	-1.25	-1.28	-0.09	-0.09	-0.09	-0.09
	(0.20)	(0.19)	(0.19)	(0.21)	(0.10)	(0.09)	(0.10)	(0.10)
Regular Soft Drinks	-1.06	-1.04	-1.03	-1.05	0.03	0.02	0.02	0.03
	(0.16)	(0.15)	(0.15)	(0.16)	(0.09)	(0.09)	(0.09)	(0.09)
Coffee	-0.05	0.07	0.09	-0.07	-0.37*	-0.41*	-0.41*	-0.36*
	(0.12)	(0.15)	(0.15)	(0.13)	(0.10)	(0.10)	(0.10)	(0.10)
Coffee Creamer and Flavorings	-0.34	-0.24	-0.22	-0.34	-0.24*	-0.27*	-0.27*	-0.24*
	(0.15)	(0.18)	(0.19)	(0.16)	(0.12)	(0.13)	(0.13)	(0.12)
Tea	-1.07	-1.08	-1.08	-1.07	-0.14	-0.15	-0.15	-0.15
	(0.09)	(0.10)	(0.09)	(0.09)	(0.12)	(0.12)	(0.13)	(0.12)
Refrigerated Juices	-0.53	-0.52	-0.53	-0.53	-0.09	-0.10	-0.09	-0.09
	(0.22)	(0.23)	(0.22)	(0.22)	(0.11)	(0.11)	(0.11)	(0.11)
Shelf-Stable Juices	-0.78	-0.78	-0.78	-0.78	-0.06	-0.06	-0.06	-0.06
	(0.12)	(0.12)	(0.12)	(0.12)	(0.09)	(0.09)	(0.09)	(0.09)
Frozen Juices	-0.70	-0.71	-0.70	-0.70	-0.14	-0.14	-0.14	-0.14
	(0.07)	(0.07)	(0.07)	(0.07)	(0.08)	(0.08)	(0.08)	(0.08)
Cheese (not shredded)	-0.70	-0.70	-0.70	-0.70	-0.17*	-0.17	-0.17	-0.18*
	(0.13)	(0.13)	(0.14)	(0.13)	(0.09)	(0.09)	(0.09)	(0.08)
Shredded Cheese	-0.95	-0.95	-0.95	-0.95	0.47*	0.53*	0.53*	0.48*
	(0.40)	(0.44)	(0.44)	(0.41)	(0.13)	(0.14)	(0.14)	(0.13)
Imitation Cheese	-1.84	-1.89	-1.96	-1.90	-0.39*	-0.41*	-0.44*	-0.42*
	(0.16)	(0.17)	(0.18)	(0.17)	(0.18)	(0.19)	(0.20)	(0.19)
Sour Cream	-0.58	-0.59	-0.60	-0.62	0.02	0.02	0.04	-0.01
	(0.32)	(0.31)	(0.31)	(0.29)	(0.14)	(0.14)	(0.14)	(0.13)
Whole Milk	-0.91	-0.91	-0.91	-0.92	-0.28*	-0.28*	-0.28*	-0.30*
	(0.47)	(0.48)	(0.48)	(0.50)	(0.12)	(0.12)	(0.12)	(0.11)
Skim/Low-Fat Milk	-0.69	-0.69	-0.69	-0.71	0.01	0.01	0.01	0.01
	(0.28)	(0.29)	(0.29)	(0.29)	(0.10)	(0.10)	(0.10)	(0.09)
Powdered/Condensed Milk	-0.80	-0.79	-0.79	-0.86	-0.16	-0.16	-0.16	-0.13
	(0.17)	(0.18)	(0.18)	(0.11)	(0.11)	(0.11)	(0.11)	(0.09)
Cocoa Mix and Flavored Milks	-0.86	-0.81	-0.82	-0.88	-0.11	-0.14	-0.14	-0.10
	(0.19)	(0.29)	(0.27)	(0.13)	(0.10)	(0.12)	(0.11)	(0.08)
Ice Cream/Yogurt	-0.89	-0.85	-0.85	-0.91	0.04	0.03	0.03	0.05
	(0.09)	(0.08)	(0.07)	(0.10)	(0.09)	(0.09)	(0.09)	(0.08)
Cheese Spreads	-1.88	-1.87	-1.87	-1.90	1.40*	1.41*	1.41*	1.40*
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Peanut Butter	-0.61	-0.63	-0.62	-0.61	-0.52*	-0.50*	-0.50*	-0.52*
	(0.37)	(0.34)	(0.35)	(0.37)	(0.13)	(0.14)	(0.14)	(0.13)
Jams and Jellies	-0.96	-0.95	-0.95	-0.96	0.18	0.18	0.19	0.20
	(0.30)	(0.29)	(0.30)	(0.31)	(0.11)	(0.12)	(0.13)	(0.11)
Refrigerated Pickles and Relish	-0.82	-0.84	-0.84	-0.79	-0.12	-0.11	-0.10	-0.18
	(0.40)	(0.36)	(0.37)	(0.47)	(0.20)	(0.19)	(0.19)	(0.23)
Shelf-Stable Pickles and Relish	-1.02	-1.02	-1.02	-1.02	0.02	0.02	0.04	-0.01
	(0.15)	(0.13)	(0.14)	(0.14)	(0.09)	(0.09)	(0.10)	(0.07)

(continued . . .)

Table 2. Continued

	Uncompensated Price Elasticities				Uncompensated Expenditure Elasticities			
Product Grouping	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Pourable Salad Dressing	-0.59	-0.66	-0.63	-0.44	0.06	0.06	0.07	0.05
	(0.15)	(0.12)	(0.13)	(0.20)	(0.10)	(0.09)	(0.10)	(0.10)
Dry Dressings and Toppings	-1.01	-1.00	-1.01	-1.01	0.08	0.07	0.09	0.05
	(0.02)	(0.02)	(0.02)	(0.02)	(0.10)	(0.09)	(0.10)	(0.08)
Mayonnaise	-1.14	-1.12	-1.12	-1.15	0.05	0.05	0.06	0.03
	(0.09)	(0.08)	(0.07)	(0.10)	(0.10)	(0.09)	(0.10)	(0.09)
Ketchup	-0.67	-0.67	-0.64	-0.57	-0.01	-0.01	0.00	-0.04
	(0.13)	(0.13)	(0.14)	(0.17)	(0.10)	(0.10)	(0.11)	(0.10)
Sauces and Marinades	-1.94	-1.75	-1.86	-2.15	0.05	0.04	0.06	0.03
	(0.31)	(0.26)	(0.30)	(0.38)	(0.12)	(0.11)	(0.12)	(0.13)
Bread	-0.82	-0.78	-0.77	-0.82	-0.21*	-0.21*	-0.21*	-0.21*
	(0.05)	(0.06)	(0.06)	(0.05)	(0.08)	(0.10)	(0.10)	(0.08)
Muffins and Rolls	-1.05	-1.00	-1.01	-1.04	-0.60*	-0.50*	-0.52*	-0.58*
	(0.83)	(0.62)	(0.67)	(0.78)	(0.17)	(0.15)	(0.15)	(0.16)
Rice	-0.83	-0.83	-0.83	-0.83	0.10	0.11	0.11	0.12
	(1.23)	(1.25)	(1.23)	(1.30)	(0.25)	(0.26)	(0.26)	(0.27)
Pasta	-0.91	-0.90	-0.90	-0.91	-0.23*	-0.23*	-0.23*	-0.23*
	(0.04)	(0.04)	(0.04)	(0.04)	(0.08)	(0.10)	(0.10)	(0.08)
Spaghetti Sauce	-0.90	-0.89	-0.90	-0.90	-0.24*	-0.24*	-0.23*	-0.24*
	(0.10)	(0.10)	(0.10)	(0.11)	(0.08)	(0.10)	(0.10)	(0.08)
Gelatin/Pudding Mix	-1.15	-1.16	-1.18	-1.17	0.01	0.01	0.02	-0.02
	(0.14)	(0.15)	(0.17)	(0.17)	(0.10)	(0.10)	(0.12)	(0.10)
Popcorn	-1.13	-1.15	-1.15	-1.16	0.02	0.02	0.03	-0.01
	(0.11)	(0.14)	(0.14)	(0.14)	(0.10)	(0.11)	(0.11)	(0.10)
Snack Nuts	-1.21	-1.20	-1.19	-1.16	-0.23	-0.22	-0.19	-0.20*
	(0.26)	(0.26)	(0.25)	(0.21)	(0.13)	(0.12)	(0.13)	(0.10)
Candy and Mints	-0.76	-0.73	-0.74	-0.79	0.05	0.06	0.07	0.02
	(0.18)	(0.20)	(0.19)	(0.16)	(0.10)	(0.11)	(0.11)	(0.08)
Dried Fruits	-1.03	-1.03	-1.03	-1.03	-0.30*	-0.30*	-0.31*	-0.29*
	(0.20)	(0.21)	(0.22)	(0.18)	(0.09)	(0.11)	(0.13)	(0.09)
Shelf-Stable Fruits	-1.04	-1.04	-1.04	-1.04	-0.30*	-0.31*	-0.31*	-0.30*
	(0.15)	(0.15)	(0.16)	(0.14)	(0.08)	(0.10)	(0.13)	(0.08)
Baked Beans	-1.16	-1.10	-1.11	-1.17	-0.39*	-0.33*	-0.34*	-0.39*
	(0.29)	(0.17)	(0.18)	(0.31)	(0.13)	(0.11)	(0.14)	(0.13)
Shelf-Stable Vegetables	-1.78	-1.85	-1.80	-1.79	-0.12	-0.11	-0.12	-0.12
	(0.16)	(0.17)	(0.17)	(0.16)	(0.08)	(0.10)	(0.12)	(0.08)
Frozen Vegetables	-1.00	-1.00	-1.00	-1.00	-0.36*	-0.36*	-0.37*	-0.36*
	(0.18)	(0.19)	(0.19)	(0.19)	(0.09)	(0.11)	(0.13)	(0.09)
Frozen Fries and Onion Rings	-1.07	-1.09	-1.10	-1.07	-0.27*	-0.27*	-0.27*	-0.27*
	(0.14)	(0.16)	(0.18)	(0.14)	(0.07)	(0.10)	(0.12)	(0.08)
Mixes	-0.72	-0.69	-0.69	-0.71	0.12	0.14	0.15	0.10
	(0.13)	(0.15)	(0.15)	(0.14)	(0.20)	(0.22)	(0.23)	(0.20)
Seasonings/Preservatives	-1.01	-1.01	-1.01	-1.01	0.09	0.09	0.10	0.05
	(0.14)	(0.15)	(0.13)	(0.12)	(0.18)	(0.19)	(0.18)	(0.15)
Syrups	-0.31	-0.22	-0.26	-0.26	-0.67*	-0.76*	-0.71*	-0.75*
	(0.09)	(0.10)	(0.10)	(0.10)	(0.15)	(0.17)	(0.17)	(0.16)

(continued . . .)

Table 2. Continued

	Uncompensated Price Elasticities				Uncompensated Expenditure Elasticities			
Product Grouping	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Flour	-1.02	-1.02	-1.02	-1.01	-0.01	-0.01	0.00	-0.04
	(0.06)	(0.06)	(0.06)	(0.06)	(0.08)	(0.08)	(0.09)	(0.07)
Canned Soup	-0.94	-0.97	-0.97	-0.93	-0.11	-0.07	-0.07	-0.11
	(0.09)	(0.12)	(0.12)	(0.09)	(0.09)	(0.11)	(0.11)	(0.09)
Dry Soup	-2.08	-2.04	-2.04	-2.08	1.26*	1.26*	1.26*	1.26*
	(0.11)	(0.12)	(0.12)	(0.11)	(0.08)	(0.10)	(0.10)	(0.08)
All Other Goods	-1.00	-1.00	-1.00	-1.00	0.99*	0.99*	0.99*	0.99*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)

Notes: An asterisk (*) denotes that the specified expenditure elasticity estimate is statistically different from zero at the 0.05 level of significance. Values in parentheses are standard errors. Standard errors were calculated using a Monte Carlo method. The estimated parameters for each system of equations are assumed to be distributed asymptotically multivariate normal, with the means being the values of the estimated parameters and the variance-covariance matrix being the estimated variance-covariance matrix of the parameters for each system. Based on these assumed distributions, 5,000 sets of parameters for each system of equations are randomly generated. For each set of parameters generated, the corresponding price and expenditure elasticities are computed and saved. The standard errors of the elasticity estimates are then the sample standard errors of the 5,000 generated price and expenditure elasticity estimates.

Overall, the pooled mean own-price elasticity estimates tend to be fairly large. Of the 50 estimated own-price elasticities, 23 are less than or equal to -1.00, and 30 are less than or equal to -0.85 across all four quarters. Only six of the 50 estimated own-price elasticities have a value greater than -0.6 across all four quarters. As will be discussed later, the price elasticity estimates tend to be much larger in absolute terms than those reported in previous studies.

The processed food goods having the most inelastic own-price elasticities tend to be products that are likely used as condiments or ingredients in a prepared meal, such as sour cream, syrup, and ketchup, or meet some perceived need, such as coffee (and coffee creamer and flavorings) for the caffeine, or bottled water for consumers who may feel it is superior to tap water. The more price-elastic processed food products tend to have good substitutes available. For example, examining cross-price elasticities within product groups indicates that consumers could easily substitute regular cheese for shredded cheese, shredded cheese for imitation cheese, refrigerated juice for shelf-stable or frozen juices, and canned soup for dry soup. The imitation cheese, cheese spreads, sauces and marinades, and dry soup food categories have the largest own-price elasticities in absolute value (less than -1.78) across all four quarters. These high elasticity estimates could be reflective of the nature of these products—i.e., consumers primarily purchase these products in bulk when prices are significantly reduced due to price discounts.

Many of the own-price elasticities in table 2 exhibit temporal fluctuations across quarters. For the majority of the processed food categories, the variation in the own-price elasticity estimates across time is relatively small, changing by an amount less than or equal to 0.1. There is substantial variation (0.12 to 0.40) in the estimated own-price elasticities across time for the coffee creamer and flavorings, pourable salad dressings, and sauces and marinades processed food categories. These differences likely reflect temporal consumption behavior of consumers. For instance, sales and the own-price elasticities for coffee creamer and flavorings are much larger during the colder months (first and fourth quarters). In contrast, consumption of ice cream and yogurt increases during the warmer months (second and third quarters), resulting in lower own-price elasticities. These different temporal patterns are consistent with the different characteristics of the product categories being examined. In addition, the temporal variations in the own-price elasticities could be attributed to the availability of complements and substitutes. For example, the lower own-price elasticities in the first and fourth quarters for shelf-stable vegetables could be due in part to the decreased availability of substitutes, such as fresh vegetables and fruits during the winter season (Feng and Chern, 2000).

The expenditure elasticity estimates vary from -0.75 to 1.41 across products and quarters. Twenty-one of the processed food categories have statistically significant expenditure elasticities, with 17 of them having estimates less than or equal to zero. The remaining expenditure elasticities are not significantly different from zero. The relatively large number of nonsignificant expenditure elasticities may be due to consumers not changing their consumption of these processed food products as income increases, and/or the introduction of measurement error in the allocation of median household income across quarters. Of the product categories with expenditure elasticities less than or equal to zero, certain product categories, such as imitation cheese, powdered/condensed milk, whole milk, peanut butter, bread, muffins and rolls, pasta, spaghetti sauce, shelf-stable fruit, frozen and shelf-stable vegetables, baked beans, and syrups, could be considered basic food categories. For example, as income increases, households substitute fresh vegetables for frozen or shelf-stable vegetables. For product categories such as coffee and coffee creamer and flavorings, the negative expenditure elasticities likely arise due to the perceived need for caffeine on a daily basis.

The variability of the estimated expenditure elasticities is much less than for the estimated own-price elasticities. Variation across quarters by more than 0.06 occurs in only five of the 50 product categories in the study: shredded cheese, refrigerated pickles and relish, muffins and rolls, baked beans, and syrups. Again, these variations are likely due to changes in temporal consumption, but could have arisen due to the potential introduction of measurement error.

Comparison with Elasticity Estimates in the Literature

As noted earlier, on average, the unconditional own-price elasticity estimates obtained in this study are higher than elasticity estimates reported in a number of studies found in the literature, whereas the expenditure elasticities tend to be lower. This result may reflect the three factors that differentiate this study from previous studies (e.g., Feng and Chern, 2000; Huang, 1993; Huang and Lin, 2000; and Lamm, 1982).

- First, the product groupings examined in this study are much more disaggregated than groupings utilized in similar studies. Thus, we expect the own-price elasticity estimates should be of larger magnitude than those obtained using more aggregated groupings. In addition, Maynard (2000) argues that temporal disaggregation can also lead to higher estimates.

- The second difference between this and earlier studies is the use of different data sets; i.e., scanner data were used in this study compared to disappearance data or household data from the Nationwide Food Consumption Survey (NFCS). Scanner data give a more accurate picture of consumer purchases because they measure actual quantity purchases and provide an exact correspondence between quantity and price levels. This higher level of accuracy will result in elasticity estimates being more reflective of actual purchasing behavior, thereby offering a potential explanation for the differing estimates obtained here (Maynard, 2000).

- The third difference has to do with the use of unconditional rather than conditional demand functions as the basis for deriving the own-price and expenditure elasticities. The unconditional elasticity estimates are based on total rather than on group expenditure. Thus, they allow for more interaction between separable groups as the consumer reallocates consumption in response to price and expenditure changes. Not surprisingly, the unconditional own-price elasticity estimates will tend to be higher, by taking account of the effect of price changes on the allocation of expenditures between groups. In contrast, because expenditure elasticities have to satisfy Engel aggregation, conditional (or within-group) expenditure elasticities will be larger than unconditional expenditure elasticities since they apply to a smaller set of products (i.e., on group expenditure).

The study by Huang (1993) probably offers the most comprehensive disaggregate estimated demand system, in terms of number of goods, available in the literature. But the majority of goods included in the model were meats, fresh fruits, and vegetables (20 of the 39 food product categories). Table 3 provides a comparison of elasticity estimates reported in the literature for a select set of 11 comparable product groups. The estimates from our study are shown in the last pair of columns [6] in the table. The first pair of columns in table 3 give a summary of Huang's (1993) elasticity estimates. Except for juices and coffee, our estimated own-price elasticities are greater in absolute value than those reported by Huang. For a number of the product categories, these differences may reflect the use of more aggregate product categories by Huang. Our own-price elasticity estimates for frozen juices are fairly close to those reported in Huang's aggregate juice category. However, for the remaining product categories, the differences are substantial. For example, Huang's estimate of the own-price elasticity for fluid milk is -0.04, which is more than an order of magnitude smaller than our estimate. The same is true for the flour and rice categories. Furthermore, except for fruits and vegetables, our estimated expenditure elasticities are lower than those reported by Huang. These comparisons are in light of the above discussion.

Lamm (1982) estimated a dynamic demand model consisting of 31 disaggregated groups, in some cases more disaggregated than Huang. As a result, Lamm's study tends to not fully characterize some food groups. For example, Lamm examines fluid whole milk, but not fluid low-fat or skim milk. His estimated own-price and expenditure elasticities for the relevant processed food categories are provided in column pair [4] of table 3. Comparing these elasticities to our own, the difference in estimates is significant for all the products listed in table 3, except rice. Comparing his estimates to other static studies, Lamm claims his estimates are more price inelastic due to the inclusion of habit formation in his empirical model, resulting in a negative specification bias if lagged consumption is omitted. In view of the fact that Lamm examines a data set spanning three decades, habit formation might be expected to be a significant phenomenon, but might not be as significant for shorter time periods, as in the current study. However, this phenomenon could partially explain the lower expenditure elasticities

Table 3. Comparison of Elasticity Estimates Reported in the Literature with Estimates Obtained in Current Study

	[1] Huang (1993)[a]		[2] Feng & Chern (2000)		[3] Huang & Lin (2000)[b]		[4] Lamm (1982)[c]		[5] Park et al. (1996)[d]		[6] Our Estimates[a]	
Product Category	ε_{ij}	η_i	ε_{ij}	η_i	ε_{ij}	η_i	ε_{ij}	η_i	ε_{ij}	η_i	ε_{ij}	η_i
Juices	-0.56	0.37			-1.01	1.04	-0.82	2.37			-0.52 to -0.78	-0.06 to -0.14
Milk/Dairy	-0.04 to -0.28	0.12 to 0.51			-0.79	0.67	-0.17 to 0.08	-0.19 to 0.47	-0.47 to -0.53	0.60	-0.69 to -0.91	-0.28 to 0.01
Cheese	-0.25	0.42					-0.21	0.57	-0.01 to -0.24	0.50	-0.70 to -1.96	-0.44 to 1.41
Bread					-0.35	0.58			-0.17 to -0.21	0.38 to 0.52	-0.77 to -0.82	-0.21
Flour	-0.08	0.13					-0.06	0.15			-1.01 to -1.02	-0.04 to 0.0
Rice	0.07	0.15					0.00	0.00			-0.83	0.10 to 0.12
Processed Fruit			-0.27	0.83	-0.72	1.16	-0.93	2.68			-1.03 to -1.04	-0.29 to -0.31
Processed Vegetables	-0.17 to -0.53	0.68 to 0.87	-0.56	0.62	-0.72	0.98	-0.12 to -0.09	0.27 to 0.33			-1.07 to -1.85	-0.11 to -0.39
Fruits & Vegetables	-0.09 to -1.18	-0.49 to 1.29							-0.32 to -0.52	0.56 to 0.69		
Baking Goods			-0.48	0.64	-0.40	0.82					-0.22 to -1.01	-0.76 to 0.10
Coffee	-0.18	0.82									-0.05 to 0.09	-0.36 to -0.41

Note: ε_{ij} is the own-price elasticity estimate, and η_i is the expenditure elasticity estimate.

[a] The elasticity ranges are across products within the product group.

[b] The expenditure elasticity estimates are those that have been adjusted for quality.

[c] All elasticities are from a dynamic linear expenditure system.

[d] The elasticity ranges are across income groups.

obtained here. In contrast to our results, Lamm's expenditure elasticity estimates for juices and processed fruits are significantly greater than ours. In both of these categories, only one specific commodity was examined: frozen orange juice concentrate and canned fruit cocktail, respectively. Further, it is interesting to note that Lamm obtained a negative expenditure elasticity for fluid whole milk (−0.19) close to ours (−0.28).

As observed from table 3, the other three sets of elasticity estimates also differ from the estimates obtained in this study. Again, our own-price elasticities tend to be substantially higher than those obtained by Feng and Chern (2000), Huang and Lin (2000), and Park et al. (1996), while our expenditure elasticities tend to be substantially lower.

Maynard (2000) estimates a double-log model of seven demand equations for chunk, sliced, grated, shredded, snack food, cubed, and other cheese products using weekly scanner data. The own-price and expenditure demand elasticities estimated are equal to or greater than the range of estimates found in this study. These higher estimates provide evidence that disaggregated scanner data, both temporally and by product, give rise to elasticity estimates greater in absolute value when compared to elasticity estimates in studies using more aggregated groupings. Maynard's own-price and expenditure elasticities for cheese products ranged from −0.154 to −3.965, and from −0.747 to −0.782, respectively. Comparing the ranges of these estimates to those found in table 3 reveals some evidence in support of the above discussion.

Other studies have found negative expenditure elasticities for product categories similar to those examined in this study, lending support for the estimates obtained here. Edgerton (1997) obtained a negative expenditure elasticity for potatoes equal to −0.05, providing justification for our negative expenditure elasticity for the frozen potatoes and onions product group. You, Epperson, and Huang (1996) found negative expenditure elasticities for a number of fresh fruits, suggesting the negative expenditure elasticities obtained here for dry and shelf-stable fruits are plausible. Brown, Lee, and Seale (1994) obtained similar expenditure elasticity estimates (between −0.10 and 0.10) using the CBS model developed by the Netherlands Central Bureau of Statistics for the juice categories.[11]

Summary and Conclusions

This study has estimated a set of unconditional own-price and expenditure elasticities for 49 processed food categories using scanner data and Moschini's (2001) FAST multistage demand system. Because of the richness of the scanner data and the availability of a consistent specification of the unconditional demand functions and conditional demand functions of a weakly separable preference structure, this study overcomes previous barriers to estimating large, disaggregate demand systems. In addition, the FAST model formulation was expanded to incorporate fixed effects across time to take account of temporal heterogeneity present in the data and to provide more reliable elasticity estimates.

Overall, our estimated own-price elasticities are generally much larger, in absolute terms, than previous estimates, while our expenditure elasticities tend to be significantly lower than previous estimates. Over 40% of the own-price elasticities were larger,

[11] Although these other studies provide support for the findings of this analysis, the estimates obtained here are not invariant to the use of other functional forms such as the AIDS or Rotterdam.

on an absolute basis, than 1.0, which tended to be greater than the estimates obtained in the other studies examined. In contrast, 60% of the expenditure elasticities were less than or equal to zero across all four quarters examined, substantially lower than the expenditure elasticities in many of the studies examined. In part, this is due to estimating unconditional elasticities for a more disaggregate set of processed food products using scanner data.

The implications of this result for policy analysis could be significant. First, having elasticity estimates available for more disaggregate products across time may help analysts select more appropriate elasticity values. This would aid in estimating more accurately the changes in consumer surplus from any proposed policy change, and would allow policy analysts to take into account temporal fluctuations in the elasticity estimates when examining products that are subject to temporal consumption and pricing fluctuations. Second, the estimation of unconditional demand elasticities is of greater use to policy analysts for general market studies. Moschini (2001, p. 24) states: "It is clear that such conditional demand functions cannot provide the parameters (i.e., elasticities) that are typically of interest for policy questions. This is because the optimal allocation of expenditure to the goods in any one partition depends on all prices and total expenditure." In essence, if one wants to say something meaningful about a consumer's response to a change in the price of a particular good, then one needs to determine what the unconditional elasticities are (Moschini). The FAST multistage demand system allows the accomplishment of this very task.

[*Received October 2002; final revision received May 2004.*]

References

Brown, M. G., J. Lee, and J. L. Seale, Jr. "Demand Relationships Among Juice Beverages: A Differential Demand System Approach." *J. Agr. and Appl. Econ.* 26(December 1994):417–429.

Bhuyan, S., and R. A. Lopez. "Oligopoly Power and Allocative Efficiency in U.S. Food and Tobacco Industries." *J. Agr. Econ.* 4,3(September 1998):434–442.

Capps, O., Jr. "Utilizing Scanner Data to Estimate Retail Demand Functions for Meat Products." *Amer. J. Agr. Econ.* 71(1989):750–760.

Capps, O., Jr., and J. A. D. Lambregts. "Assessing Effects of Prices and Advertising on Purchases of Finfish and Shellfish in a Local Market in Texas." *S. J. Agr. Econ.* 23(1991):191–194.

Christensen, L. R., D. W. Jorgenson, and L. J. Lau. "Transcendental Logarithmic Utility Functions." *Amer. Econ. Rev.* 65(1975):367–383.

Clarke, R., and S. W. Davies. "Market Structure and Price-Cost Margins." *Economica* 49(August 1982):277–287.

Cotterill, R. W. "Scanner Data: New Opportunities for Demand and Competitive Analysis." *Agr. and Resour. Econ. Rev.* 23(October 1994):125–139.

Cotterill, R. W., and L. E. Haller. "Market Strategies in Branded Dairy Product Markets." In *Competitive Strategy Analysis for Agricultural Marketing Cooperatives*, ed., R. W. Cotterill, pp. 99–144. Boulder, CO: Westview Press, 1994.

Diaye, M., F. Gardes, and C. Starzec. "The World According to GARP: Non-parametric Tests of Demand Theory and Rational Behavior." Work. pap., Institut National De La Statistique Et Des Etudes Economiques, September 2001. Online. Available at http://www.crest.fr/doctravail/documents.html. [Accessed March 2002.]

Edgerton, D. L. "Weak Separability and the Estimation of Elasticities in Multistage Demand Systems." *Amer. J. Agr. Econ.* 79(February 1997):62–79.

Feng, X., and W. S. Chern. "Demand for Healthy Foods in the United States." Selected paper presented at annual meetings of the American Agricultural Economics Association, Tampa, FL, July 30–August 2, 2000.

Gisser, M. "Price Leadership and Welfare Losses in U.S. Manufacturing." *Amer. Econ. Rev.* 76(September 1986):756–767.

Green, G. M., and J. L. Park. "Retail Demand for Whole vs. Low-Fat Milk: New Perspectives on Loss Leader Pricing." Selected paper presented at annual meetings of the American Agricultural Economics Association, Salt Lake City, UT, August 2–5, 1998.

Heckman, J., and T. E. MaCurdy. " A Life Cycle Model of Female Labour Supply." *Rev. Econ. Stud.* 47(1980):47–74.

Hsiao, C. *Analysis of Panel Data.* Cambridge, UK: Cambridge University Press, 1986.

Huang, K. S. "A Complete System of U.S. Demand for Food." Tech. Bull. No. 1821, USDA/Economic Research Service, Washington, DC, September 1993.

Huang, K. S., and B. Lin. "Estimation of Food Demand and Nutrient Elasticities from Household Survey Data." Tech. Bull. No. 1887, USDA/Economic Research Service, Washington, DC, August 2000.

Kinoshita, J., N. Suzuki, T. Kawamura, Y. Watanabe, and H. M. Kaiser. "Estimating Own and Cross Brand Price Elasticities and Price-Cost Margin Ratios Using Store-Level Daily Scanner Data." *Agribus.: An Internat. J.* 17,4(Autumn 2001):515–525.

Lamm, R. M., Jr. "A System of Dynamic Demand Functions for Food." *Appl. Econ.* 14(1982):375–389.

Levy, D., and J. Reitzes. "Anticompetitive Effects of Mergers in Markets with Localized Competition." *J. Law, Econ., and Organization* 8(1992):427–437.

Maynard, L. J. "Sources of Irreversible Consumer Demand in U.S. Dairy Products." Selected paper presented at annual meetings of the American Agricultural Economics Association, Tampa, FL, July 30–August 2, 2000.

Moschini, G. "A Flexible Multistage Demand System Based on Indirect Separability." *S. Econ. J.* 68,1(2001):22–41.

Nayga, R., Jr., and O. Capps, Jr. "Tests of Weak Separability in Disaggregated Meat Products." *Amer. J. Agr. Econ.* 76(November 1994):800–808.

Park, J. L., R. B. Holcomb, K. C. Raper, and O. Capps, Jr. "A Demand System Analysis of Food Commodities by U.S. Households Segmented by Income." *Amer. J. Agr. Econ.* 78,2(1996):290–300.

Peterson, E. B., and J. M. Connor. "A Comparison of Oligopoly Welfare Loss Estimates for U.S. Food Manufacturing." *Amer. J. Agr. Econ.* 77(May 1995):300–308.

Peterson, E. B., T. W. Hertel, and J. V. Stout. "A Critical Assessment of Supply-Demand Models of Agricultural Trade." *Amer. J. Agr. Econ.* 76(November 1994):709–721.

Schmit, T. M., C. Chung, D. Dong, H. M. Kaiser, and B. Gould. "The Effects of Generic Dairy Advertising on the Household Demand for Milk and Cheese." Selected paper presented at annual meetings of the American Agricultural Economics Association, Tampa, FL, July 30–August 2, 2000.

Starek, R., and S. Stockum. "What Makes Mergers Anticompetitive? 'Unilateral Effects' Analysis Under the 1992 Merger Guidelines." *Antitrust Law J.* 63(1995):801–821.

U.S. Department of Commerce, Bureau of Economic Analysis. "NIPA Table 2.2. Personal Consumption Expenditures by Major Type of Product." USDC/BEA, Washington, DC, 1988–1992. Online. Available at http://www.bea.doc.gov/bea/dn/nipaweb/TableViewFixed.asp#Mid. [Accessed April 2002.]

U.S. Department of Labor, Bureau of Labor Statistics. "Consumer Price Index: All Urban Consumers." USDL/BLS, Washington, DC, 1988–1992. Online. Available at http://data.bls.gov/cgi-bin/dsrv. [Accessed June 2002.]

Varian, H. R. "The Nonparametric Approach to Demand Analysis." *Econometrica* 50,4(July 1982): 945–974.

Wessells, C. R., and P. Wallström. "Modeling Demand Structure Using Scanner Data: Implications for Salmon Enhancement Policies." *Agribus.: An Internat. J.* 15,4(Autumn 1999):449–461.

Willner, J. "Price Leadership and Welfare Losses in U.S. Food Manufacturing: Comment." *Amer. Econ. Rev.* 79(June 1989):604–609.

You, Z., J. E. Epperson, and C. L. Huang. "A Composite System Demand Analysis for Fresh Fruits and Vegetables in the United States." *J. Food Distribution Res.* 27(October 1996):11–22.