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

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^{*} Paper presented at the annual meeting of the American Agricultural Economics Association, Montreal, Quebec, July 27-30, 2003.

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

Abstract

This study estimated a set of unconditional own-price and expenditure elasticities for 49 processed food categories using scanner data and the FAST multistage demand system. Overall, our estimated own-price and expenditure elasticities are generally much larger, in absolute terms, than previous estimates. The use of disaggregated product groupings and the estimation of unconditional elasticities accounts for these higher estimates. Over half of the own-price elasticities are larger, on an absolute basis, than 0.9. 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.

Keywords: demand elasticities, indirect separability, processed foods

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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; Clarke and Davies; Gisser; Peterson and Connor; Willner). Furthermore, demand elasticities are crucial in defining relevant product markets and measuring market power in antitrust enforcement activities (Cotterill; Levy and Reitzes; Starek and Stockum). 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 requires that future analyses of domestic and international agricultural commodity policies focus on the demand for processed food products rather than raw agricultural commodities (Peterson, Hertel, and Stout). 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, who estimated a complete demand system for 39 food categories and one non-food

category. He developed a time series of food quantity indices based on disappearance data and food price indices based on components of the consumer price index. Because the quantity indices are not direct estimates of actual purchases (or consumption) at the retail level, the correspondence between the price and quantity indices is not perfect since 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 provides 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 is costly to obtain, a small, but growing number of demand analyses have been conducted using scanner data (Capps; Capps and Lambregts; Cotterill and Haller; Green and Park; Maynard; Nayga and Capps; Scmit *et al.*; Wessells and Wallström; Kinoshita *et al.*). These analyses 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 has 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 achieve this objective, we will extend Moschini's flexible and separable translog (FAST) multistage demand system to include cross-sectional and time fixed-effects.

Data

The data used in this study is from Information Resources, Incorporated (IRI) InfoScan® retail data.² The IRI data includes prices and quantities sold for 140 different processed food products for 42 US metropolitan areas from the first quarter of 1988 to the fourth quarter of 1992.³ The total quantity sold 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 estimate a demand system with 140 processed food products, these food products are aggregated into 49 processed food categories shown in figure 1.

One limitation of the IRI data 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 give bar codes to these items or the codes assigned are not uniform during the sample time period. Thus, it is not possible for IRI to provide information on these food product categories. As such, they are included in the “all other goods” composite good in our empirical model.

The IRI price and quantity data is also supplemented with information on median household income from the IRI InfoScan® market profiles for each metropolitan area. Since the data on median household income is on an annual basis and the price and quantity data are on a quarterly basis, the level of median household income is re-allocated across the four quarters of each year examined in the study. This re-allocation is accomplished through the use of quarterly data series on Disposable Personal Income and Personal Outlays from the Bureau of Economic Analysis (BEA) for the years 1988 to 1992 (US Department of Commerce). Using these series, we calculate annual savings rates that are then used to adjust our annual data on median

household income in order to yield annual totals of disposable income. These annual levels of disposable income are then allocated across quarters using the quarterly percentages calculated from the BEA's series on Disposable Personal Income.

Regional CPI indices (US Department of Labor) are used to create regional price indices for the "all other goods" composite good. Regional data were 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 composite consumer price index for the Northeast, Midwest, South, and West were utilized.

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 is consistent with this hypothesis. Varian 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). Diaye, Gardes, and Starzec shows that if WARP is satisfied then one can claim that there exists a utility function that 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 nonsatiated utility function and a demand correspondence that rationalizes the data.

WARP and GARP are tested simultaneously using a variant of Warshall's algorithm (as presented by Varian) for each metropolitan area. Strict adherence to the rules of nonparametric testing would lead one to reject the hypothesis that WARP or GARP are satisfied by the data if just one violation is found. Thus, Varian proposed that one should reject an axiom if the

violation rate is greater than five percent, 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). Using this rule, the data for three of the original 42 metropolitan areas, Columbus, Kansas City, and Portland, failed the nonparametric tests and were summarily excluded from the sample.⁴

Model Specification

Following Moschini, the empirical demand model utilized in this study is based on the notion of indirect separability. Preferences are indirectly weakly separable in the partition

$\hat{I} = \{I^1, \dots, I^N\}$ if the indirect utility function $V(p/y)$ can be written as

$$(1) \quad V(p/y) = V^0[V^1(p^1/y), \dots, V^N(p^N/y)]$$

where p^r is the vector of prices in the r^{th} group, $r = 1, \dots, N$ and $V^r(p^r/y)$ are indices dependent only on p^r and total expenditure (y). It is assumed that $V^0(\cdot)$ 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 as:

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

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

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 for $V^0(\cdot)$ and $V^r(\cdot)$. Specifically:

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

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

Homogeneity is satisfied by construction and symmetry is imposed by setting $\beta_{ij} = \beta_{ji} \quad \forall i, j$ and

$\gamma_{rs} = \gamma_{sr} \quad \forall r, s$. To ensure that 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:

$$\beta_0^r = 0 \quad \text{for } r = 1, \dots, N,$$

$$\gamma_0 = 0,$$

$$\sum_{i \in I^r} \beta_i = 1 \quad \text{for } r = 1, \dots, N,$$

$$\sum_{r=1}^N \gamma_r = 1, \text{ and}$$

$$\sum_{i \in I^r} \sum_{j \in I^r} \beta_{ij} = 0 \text{ for } r = 1, \dots, N.$$

The last restriction allows for the case of asymmetric separability, where the r^{th} group has only one price.

For estimation purposes, Moschini suggests that 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, expressed as:

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

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

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

where $w^r = y^r/y$ and $B^g(p^g/y) = 1 + \sum_{j \in I^g} \sum_{i \in I^g} \beta_{ij} \log(p_i/y)$ for $g = 1, \dots, N$, are estimated. 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, if panel data is used the modeler should consider the use of fixed or random effects in the model to

account for any heterogeneity bias (Hsiao). In order to capture this heterogeneity, fixed effects across markets and time are incorporated into the conditional and group share equations.

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 that the intercept term in equation (6) is β_i .

To incorporate fixed market and time effects, redefine β_i in equation (6) to equal:

$$(8) \quad \beta_i = \lambda_i + \sum_{m \in M} \alpha_{im} D_m + \sum_{s \in S} \tau_{is} D_s \text{ for } i \in I^r, r = 1, \dots, N,$$

where λ_i is the new constant term, α_{im} is the market-specific fixed effect, D_m is a dummy variable that equals one if the observation being examined corresponds to market m , M is the set of markets, 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 time periods. One market and one time interval in M and S are dropped in the formulation of equation (8). This method of incorporating fixed effects follows the development of the error-components model as presented by Davidson and MacKinnon. 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 that $B^g(p^g/y) = 1$ for $g = 1, \dots, N$ and $\log V^r(p^r/y) = 0$ for $r = 1, \dots, N$. Thus, at the sample means, γ_r is the intercept term in equation (7). To incorporate fixed effects redefine γ_r as:

$$(9) \quad \gamma_r = \theta_r + \sum_{m=1}^{M-1} \pi_{rm} D_m + \sum_{s=1}^{S-1} \rho_{rs} D_s \text{ for } r = 1, \dots, N,$$

where θ_r , π_{rm} , and ρ_{rs} are analogous to λ_i , α_{im} , and 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 ten weakly separable partitions as shown in figure 1. Thus, the underlying indirect utility function can be expressed as:

$$V = V^0 [V^1(p^1/y), V^2(p^2/y), V^3(p^3/y), V^4(p^4/y), V^5(p^5/y), \\ V^6(p^6/y), V^7(p^7/y), V^8(p^8/y), V^9(p^9/y), V^{10}(p^{10}/y)],$$

where the indices 1 through 10 refer to the categories coffee, other beverages, condiments, milk, cheese, fruits/vegetables, milled grain, baking, deserts, and “all other goods” respectively.

Nearly all of the disaggregated goods fit neatly into each of the nine specific product groups. A few goods do not lend themselves easily to classification according to our system. These products have been placed in the group that appears to be the most reasonable from the point of view of the consumer who is constrained to allocate her expenditure budget amongst these particular product groups. For example, consider the milled grain product group. Given their hypothesized complementary relationship, we have placed pasta and pasta sauce in the same partition, i.e. milled grain. Similarly, peanut butter and jellies and jams are placed in the milled grain product group because of their hypothesized complementary relationships with bread and muffins and rolls.⁵

Results

Equations (6) and (7), modified by equations (8) and (9) to allow for fixed effects, are estimated to obtain the unconditional price and expenditure elasticities using the two-step process as presented by Moschini. In the first step, we estimate nine systems of conditional

within-group share equations. The “all other goods” group is a trivial estimation because it only contains one composite good. In the second step, a system of ten 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.⁶

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 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 one normalizes the data so that $p_i = y = 1$ ($\forall i$), the unconditional expenditure (η) and price (ε) elasticities for good i are:

$$(10) \quad \varepsilon_{ijms} = \frac{\beta_{ij}}{\beta_i(m,s)} + \frac{\gamma_{rr}\beta_j(m,s)}{\gamma_r(m,s)} - \gamma_r(m,s) \left(\sum_{q \in I^r} \beta_{jm} \right) - \delta_{ij} \text{ for } (i,j) \in I^r,$$

$$(11) \quad \varepsilon_{ikms} = \frac{\gamma_{rs}\beta_k(m,s)}{\gamma_r(m,s)} - \gamma_s(m,s) \left(\sum_{q \in I^s} \beta_{kq} \right) \text{ for } i \in I^r \text{ and } k \in I^s, \text{ and}$$

$$(12) \quad \eta_{ims} = 1 - \frac{\sum_{j \in I^r} \beta_{ij}}{\beta_i(m, s)} \text{ for } i \in I^r,$$

where δ_{ik} is the Kronecker delta ($\delta_{ij} = 1$ if $i = j$ and 0 otherwise), $m \in M$, $s \in S$, $\beta_i(m, s)$ is given by equation (8), and $\gamma_r(m, s)$ is given by equation (9). The elasticities given by equations (10) through (12) not only vary over goods, but vary over markets and time as well. To decrease the dimensionality of each of these elasticity estimates, one can take pooled means over markets and/or time. For example, the pooled mean ε_{ij} (where ε_{ijms} is averaged over markets and time) is given by:

$$\varepsilon_{ij} = \frac{1}{|M|} \cdot \frac{1}{|S|} \sum_{m=1}^M \sum_{s=1}^S \varepsilon_{ijms},$$

where $|M|$ and $|S|$ refer to the cardinality of the sets M and S . These pooled means may be more useful for research endeavors, and are what is presented in this paper.

Due to fact that the use of scanner data implies that one is aggregating over households (and/or individuals), the elasticity estimates derived from the FAST multi-stage demand model should be interpreted in aggregate terms (i.e. at a macro level) (Edgerton). This interpretation is more desirable for policymakers, given policy-oriented studies tend to be focused at the aggregate (i.e. market), not household level.

Summary of Estimation Results

Table 1 presents summary information on the parameter estimates of the empirical model. The fixed effects parameters are employed to capture seasonal and market heterogeneity in the dataset. At least two-thirds of these parameters were individually statistically significant at the ten percent level in the estimated conditional share equations. Slightly less than half of the

fixed effects parameters are individually significant in the second-stage, or group share equations. This indicates that seasonal and market heterogeneity are present in the dataset.

At least half of the estimated parameters for the second-order price variables, the β_{ij} , are individually significant in the conditional and group share equations. The only exception is the conditional share equations for the milk product group, where nine out of 20 parameters were significant at the ten percent level.

Unconditional Price and Expenditure Elasticity Estimates

The own-price and expenditure elasticity estimates for the product groupings examined are presented in Table 2.⁷ All elasticity estimates are pooled across markets and time, with the reported ranges of elasticity estimates given across markets.

Overall, the pooled mean own-price elasticity estimates tend to be fairly large. Out of the fifty estimated own-price elasticities, sixteen are less than or equal to -1 and twenty-seven are less than or equal to -0.9. Only nine of the fifty estimated own-price elasticities have a value greater than -0.6. As will be discussed later, these elasticity estimates tend to be much larger in absolute terms than those reported in previous studies.

The processed food goods that have 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, peanut butter, and ketchup, or meet some dietary need, such as coffee (and coffee creamer) for the caffeine or bottled water for consumers who may feel it is superior to tap water. The processed food products that are more price elastic 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. Also, as would

be expected, some of the more elastic processed food products are those with relatively small sales shares, such as baked beans and dry soup.

To provide some information on the variability of our results, we also present the minimum and maximum values of the elasticities estimates for each processed food product. Because of the two-step estimation procedure utilized and the nonlinear relationship between the elasticities and the model parameters, deriving the standard errors for the own-price and expenditure elasticities was not possible.⁸ For the majority of the processed food categories, the variation in the own-price elasticity estimates across markets and time is relatively small. However, there is substantial variation in the estimated own-price elasticities in ten of the processed food categories. These categories are coffee, coffee creamer, bottled water, frozen juices, refrigerated pickles and relish, ketchup, sour cream, shredded cheese, imitation cheese, and peanut butter. Such variation is evidence of the market heterogeneity across the thirty-nine regions examined in the model. In addition, due to the disaggregate nature of the product categories estimated, such variations are not surprising given the inclusion of readily available substitutes in most product groupings and the unique characteristics of certain products (Lamm).

Similar to the own-price elasticity estimates, the pooled mean expenditure elasticity estimates tend to be fairly large. Out of the fifty mean expenditure elasticity estimates, twenty three are greater than or equal to 1.0 and forty-one are greater than or equal to 0.9. Specifically, coffee creamer, tea, refrigerated juices, pourable salad dressing, sauces, ice cream/yogurt, and shredded cheese are noticeable luxury goods with expenditure elasticities greater than 1.10. Low-calorie soft drinks, regular soft drinks, frozen juices, whole milk, imitation cheese, pasta sauce, seasonings, dry soup and snack nuts are notable necessities with expenditure elasticities

less than 0.8. Again, as we will discuss in the next section, these estimates tend to be much larger than those estimated in prior studies.

The variability of the estimated expenditure elasticities is much less than for the estimated own-price elasticities. Substantial variation occurs in only six of the fifty products in the study. Interestingly, these six products, tea, frozen juices, whole milk, shredded cheese, imitation cheese, and dry soup, also have the most extreme mean expenditure elasticity estimates. The reason for this variability may be similar to the reasons given above for the own-price elasticity estimates.

Comparison with Elasticity Estimates in Literature

As mentioned earlier, on average the unconditional elasticity estimates obtained in this study are higher than elasticity estimates reported in a number of studies found in the literature. This result may reflect the three factors that differentiate this study from those previous studies. First, the product groupings examined in this study are much more disaggregated than groupings utilized in similar studies. Thus, we expect that the elasticity estimates should be of larger magnitude than those obtained using more aggregated groupings. In addition, Maynard mentions that temporal disaggregation can also lead to higher estimates. The second difference is the use of different data sets, i.e. scanner data was used in this study compared to disappearance data or household data from the Nationwide Food Consumption Survey (NCFS). Scanner data provides a more accurate picture of consumer purchases since it measures actual quantity purchases and provides 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 providing a potential explanation of the larger values of the estimates obtained here (Maynard). 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 parametric price and expenditure changes. Not surprisingly, the unconditional elasticity estimates will tend to be higher than conditional estimates.

The study by Huang is probably 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). The first two columns of table 3 provide a summary of Huang's elasticity estimates for a select set of comparable product groups. Our elasticity estimates for these same product groups are presented in the last two columns of table 3. Except for coffee, our estimated elasticities are much higher than those reported by Huang. In the case of juices, this may reflect the use of more aggregate product categories by Huang. Our elasticities 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 estimates of the own-price elasticities 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. These comparisons are in light of the above discussion.

Lamm estimated a dynamic demand model consisting of thirty-one 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 only 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 the seventh and eighth columns of table 3. Comparing

these elasticities to our own, the difference in estimates is significant for the milk/dairy products, cheese products, flour, rice, and processed vegetables. Comparing his estimates to other static studies, Lamm claims that 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. Since Lamm examines a dataset that spans three decades, one could expect that habit formation would be a significant phenomenon, but might not be as significant for shorter time periods, as in this study. In contrast, 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.

Of the other three sets of elasticity estimates given in table 3, Huang and Lin's elasticity estimates are the most similar to the range of elasticity estimates determined in this study. The exceptions being the elasticities for bread and the own-price elasticities for baking goods, ignoring the low elasticity estimate of syrups in our study. Ignoring sour cream and syrups, the elasticity estimates of Park *et al.* and Feng and Chern are also lower than our estimates.

Maynard 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, gives rise to elasticity estimates greater in absolute value when compared to elasticity estimates in studies using more aggregated groupings.

One interesting note, Huang and Lin adjusted their expenditure elasticity estimates for quality effects by incorporating variables associated with qualitative aspects of food

consumption, e.g. food consumed away from home, into their demand model. The authors concluded that estimates of expenditure elasticities would be biased upwards when these quality aspects are not taken into account. Given the similar expenditure elasticity estimates, it may be that utilizing more disaggregate data can control for quality differences more directly than indirectly doing so with more aggregate product groupings.

Summary and Conclusion

This study estimated a set of unconditional own-price and expenditure elasticities for 49 processed food categories using scanner data and Moschini's 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 regional and time fixed effects to take account of heterogeneity present in the data and to provide more reliable elasticity estimates.

Overall, our estimated own-price and expenditure elasticities are generally much larger, in absolute terms, than previous estimates. Over half of the own-price elasticities and eighty percent of the expenditure elasticities are larger, on an absolute basis, than 0.9, which tends to be greater than the estimates obtained in the other studies examined. In part, this is due to estimating elasticities for a more disaggregate set of processed food products. The implications for policy analysis of this result could be significant. First of all, having elasticity estimates available for more disaggregate products 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. Second, the estimation of unconditional demand elasticities is of greater

use to policy analysts for general market studies. Moschini states that: “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 the all prices and total expenditure (p.24).” 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 multi-stage demand system allows one to accomplish this very task.

Endnotes

1. For example, consider the case of analyzing a new HACCP regulation for a processed food product. The amount of the production cost increase that is 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.
2. The data was made available to us by an arrangement with Professor Ron Cotterill at the Food Marketing Policy Center, University of Connecticut.
3. Cotterill and Haller and Wessells and Wallström have used a subset of this data.
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. Pete, and Wichita.
5. In results not reported, these goods were found to be compliments.
6. 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).

7. Due to space limitations, it is not possible to list the complete 50x50 matrix of (pooled) unconditional price elasticities in this article. A complete set of price and expenditure elasticities is available from the authors upon request.
8. Moschini also did not report standard errors for his elasticity estimates.

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Table 1: Number of Statistically Significant Parameters

Parameters	Fixed Effects Parameters ^a				Price Parameters ^b			
Significance Level	Below 0.01	0.01– 0.05	0.05– 0.10	Above 0.10	Below 0.01	0.01– 0.05	0.05– 0.10	Above 0.10
Second Stage Product Groupings ^c								
Coffee	58	7	4	15	5	0	0	0
Other Beverages	120	17	5	68	10	1	3	6
Condiments	140	24	14	74	9	3	2	13
Milk	112	19	11	69	7	0	2	11
Cheese	70	11	6	39	7	2	0	0
Fruits/Vegetables	124	14	7	65	8	3	1	8
Milled Grain	150	26	5	71	13	3	1	10
Baking	124	19	8	59	10	0	2	8
Deserts	77	16	4	29	4	1	0	4
First Stage Group ^d								
Group Share Eqns.	129	25	18	206	18	9	4	24

^a The fixed effects parameters are those associated with equations (14) and (15).

^b The price parameters are the second-order terms in the conditional share equations and group share equations.

^c The second stage groupings examine the estimated parameters in the conditional share equations. The “All Other Goods” group is not included since there were no parameters to estimate.

^d The first stage grouping examines the parameters of the group share equations.

Table 2: Unconditional Own-Price and Expenditure Elasticity Estimates

Product Grouping	ε_i	Min^a	Max^a	η_i	Min^a	Max^a
Coffee	-0.20	-0.41	0.04	0.99	0.99	0.99
Coffee Creamer	-0.39	-0.61	0.28	1.20	1.11	1.42
Tea	-1.00	-1.05	-0.97	1.43	1.16	2.27
Bottled Water	-0.38	-0.73	0.26	0.99	0.98	1.00
Low-Calorie Soft Drinks	-0.84	-0.90	-0.78	0.86	0.80	0.91
Regular Soft Drinks	-0.94	-0.95	-0.93	0.83	0.78	0.87
Refrigerated Juices	-0.82	-0.90	-0.74	1.17	1.10	1.26
Shelf-Stable Juices	-1.22	-1.29	-1.15	1.11	1.08	1.14
Frozen Juices	-0.67	-0.83	-0.14	0.58	-0.09	0.79
Refrig. Pickles & Relish	-0.58	-0.82	-0.02	0.91	0.80	0.96
Shelf-Stable Pickles & Relish	-0.97	-1.00	-0.94	0.91	0.89	0.93
Pourable Salad Dressing	-1.11	-1.12	-1.10	1.13	1.10	1.16
Other Dressings & Toppings	-1.03	-1.03	-1.02	1.05	1.04	1.07
Mayonnaise	-0.95	-0.99	-0.90	0.90	0.87	0.92
Ketchup	-0.42	-0.62	-0.06	0.90	0.84	0.93
Sauces	-1.34	-1.43	-1.27	1.19	1.14	1.25
Sour Cream	-0.33	-0.58	0.20	1.03	1.01	1.05
Whole Milk	-0.98	-1.36	-0.78	0.74	0.36	0.86
Skim/Low-Fat Milk	-0.70	-0.92	-0.52	1.10	1.07	1.14
Powdered/ Condensed Milk	-0.75	-0.88	-0.56	0.98	0.97	0.99
Other Milk Products	-0.91	-0.93	-0.87	0.94	0.91	1.00
Ice Cream/ Yogurt	-0.78	-0.81	-0.75	1.16	1.11	1.22
Cheese (not-shredded)	-0.92	-0.98	-0.82	0.94	0.93	0.94
Shredded Cheese	-1.55	-2.23	-1.16	1.76	1.29	2.67
Imitation Cheese	-2.82	-19.15	-1.46	0.39	-5.13	0.84
Cheese Spreads	-1.01	-1.06	-0.94	1.09	1.06	1.11
Dried Fruits	-1.00	-1.00	-1.00	0.92	0.88	0.95
Shelf-Stable Fruits	-1.02	-1.03	-1.01	1.01	1.01	1.02
Baked Beans	-1.36	-1.75	-1.19	1.00	1.00	1.00
Shelf-Stable Vegetables	-0.67	-0.73	-0.62	1.06	1.05	1.07
Frozen Vegetables	-0.83	-0.88	-0.79	0.95	0.94	0.97
Frozen Potatoes/Onions	-0.85	-0.89	-0.81	0.94	0.92	0.95
Bread	-0.68	-0.77	-0.61	0.97	0.96	0.98
Muffins and Rolls	-0.95	-1.00	-0.91	1.08	1.05	1.12
Rice	-1.02	-1.08	-0.93	1.09	1.03	1.16
Pasta	-0.54	-0.68	-0.39	1.07	1.05	1.10
Pasta Sauce	-0.83	-0.87	-0.77	0.85	0.76	0.91
Peanut Butter	-0.45	-0.61	-0.10	0.92	0.86	0.95
Jams and Jellies	-0.69	-0.74	-0.63	1.08	1.06	1.10

Table 2: Continued

Product Grouping	ε_i	Min^a	Max^a	η_i	Min^a	Max^a
Mixes	-0.64	-0.72	-0.46	1.03	1.03	1.05
Seasonings	-1.01	-1.01	-1.00	0.69	0.62	0.78
Syrups	-0.22	-0.32	-0.08	0.90	0.89	0.92
Flour	-0.98	-1.00	-0.97	0.91	0.87	0.96
Canned Soup	-0.76	-0.82	-0.66	0.99	0.99	0.99
Dry Soup	-1.13	-1.22	-1.08	0.55	0.22	0.76
Gelatin/Pudding Mix	-0.95	-0.98	-0.92	0.93	0.91	0.95
Popcorn	-0.97	-0.99	-0.90	1.02	1.01	1.03
Snack Nuts	-0.90	-0.95	-0.79	0.81	0.67	0.87
Candy and Mints	-1.01	-1.04	-0.98	1.06	1.05	1.07
All Other Goods	-2.23	-2.25	-2.22	1.00	1.00	1.00

Notation: $\varepsilon_i \equiv$ uncompensated own-price demand elasticity for group i ; $\eta_i \equiv$ uncompensated income elasticity for group i

^a These estimates are the minimum and maximum of the pooled market means over time

Table 3: Elasticity Estimate Comparisons

Product Groups	Huang ^a		Feng and Chern		Huang and Lin ^b		Lamm ^c		Park et al. ^d		Our Estimates ^a	
	ε_{ii} ^e	η_i	ε_{ii}	η_i	ε_{ii}	η_i	ε_{ii}	η_i	ε_{ii}	η_i	ε_{ii}	η_i
Juices	-0.56	0.37			-1.01	1.04	-0.82	2.37			-0.67 to -1.22	0.58 to 1.17
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	-0.33 to -0.98	0.74 to 1.16
Cheese	-0.25	0.42					-0.21	0.57	-0.01 to -0.24	0.50	-0.92 to -2.82	0.39 to 1.76
Bread					-0.35	0.58			-0.17 to -0.21	0.38 to 0.52	-0.68	0.97
Flour	-0.08	0.13					-0.06	0.15			-0.98	0.91
Rice	0.07	0.15					0.00	0.00			-1.02	1.09
Processed Fruit			-0.27	0.83	-0.72	1.16	-0.93	2.68			-1.00 to -1.02	0.92 to 1.01
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			-0.67 to -1.36	0.94 to 1.06
Fruits and 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	0.69 to 1.03
Coffee	-0.18	0.82									-0.20	0.99

^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.
- e ε_{ii} is the own-price elasticity estimate and η_i is the expenditure elasticity estimate.

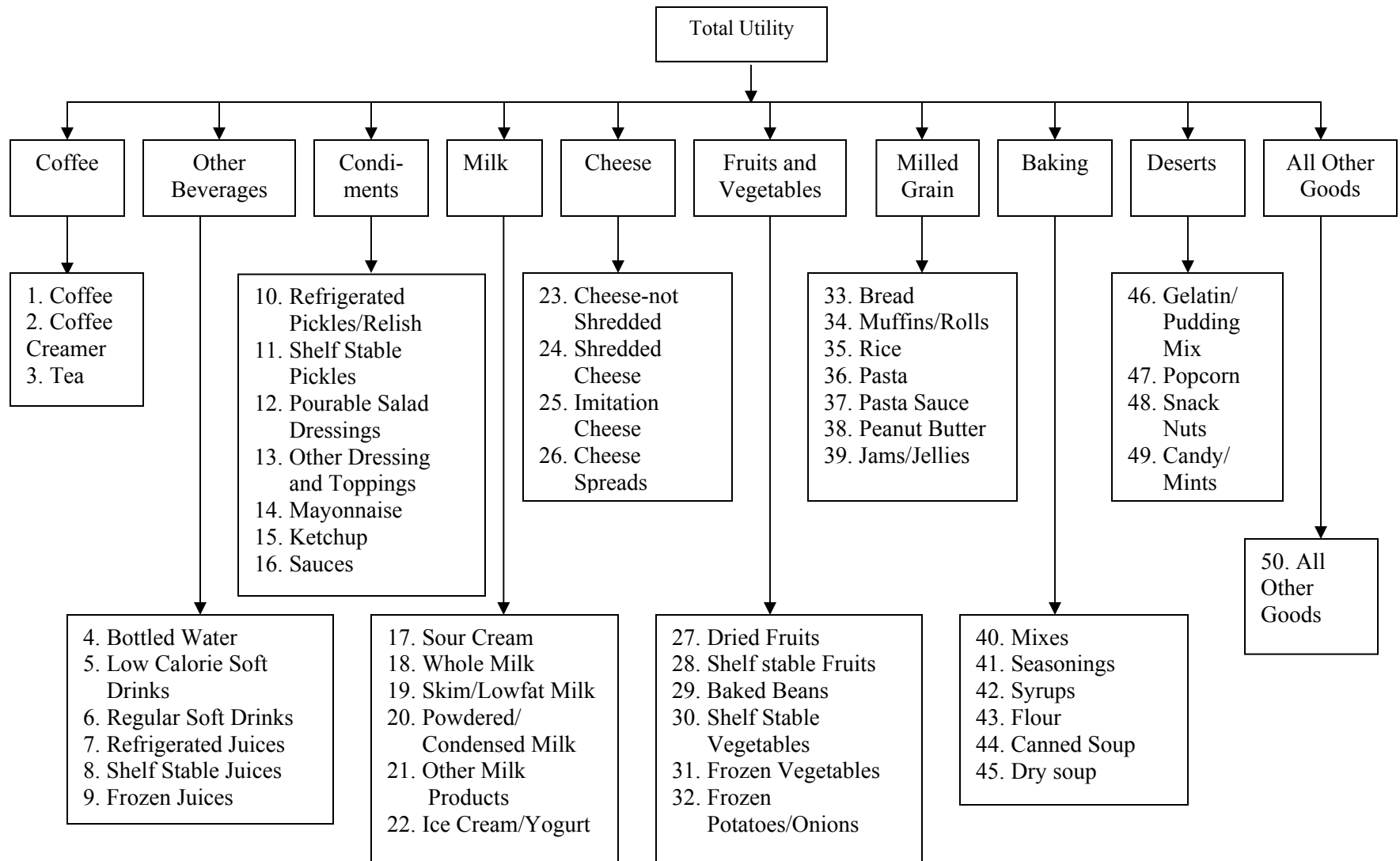


Figure 1: Separable Preference Structure of Representative Consumer