Robert Mondavi Institute
Center for Wine Economics

Demand for Food in the United States.

A Review of Literature, Evaluation of Previous Estimates, and Presentation of New Estimates of Demand

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Dedication

The work here was inspired in part by Giannini Monograph 25, *Consumer Demand for Food in the United States with Projections for 1980*, by P.S. George and G.A. King, published in 1971. Forty years later, we dedicate this work to the memory of Gordon A. (Gordy) King (1924–2008).

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EXECUTIVE SUMMARY

Many findings and policy recommendations in the academic literature are influenced by published estimates of elasticities of demand for food. However, the quality of these estimates is diverse and depends on modeling choices and assumptions, including the functional form for demands, types of data used, separability structure, food definitions, and statistical techniques used to estimate the models. In this monograph, we make three contributions to the empirical literature on demand for food in the United States. First, we evaluate the elasticities of demand for food from previous studies using the mean absolute error in elasticity-based predictions of quantity responses to actual past changes in prices and total expenditure. Second, we estimate elasticities of demand for aggregate food products using annual and monthly data under various alternative assumptions about functional form. We evaluate how well these new estimates of elasticities of demand predict quantity responses to actual price and expenditure changes, both absolutely and compared with previous estimates from the literature. Third, we estimate two sets of elasticities of demand for disaggregated fruit and vegetables: one that is conditional on the total expenditure on fruit and vegetables and a second that is conditional on expenditure on goods. To facilitate and provide context for these empirical contributions, we begin the monograph with a succinct statement of the relevant theory that underpins demand models, some specific discussion of separability and aggregation assumptions and their implications for the interpretation of demand elasticities, and a review of issues more generally that arise in empirical demand analysis.

1. INTRODUCTION

An empirical understanding of demand response to prices, total expenditures, and other economic factors is critical for developing sound policy, especially when the policy is specifically related to food consumption. In many cases, the relevant aspects of demand response are summarized in terms of elasticities, and the quality of policy analysis is contingent on the quality of the available elasticity estimates. The global obesity problem is an important contemporary example. Policymakers have proposed a variety of tools to address the problem, including taxes and subsidies on food (Adamy 2009; Chan 2008). Several studies that address obesity-related policies use estimates of elasticities of demand with respect to price and expenditure from the literature to quantify the effects of actual or hypothetical changes in food prices or expenditure (or income) (e.g., Cash, Sunding and Zilberman 2005; Guthrie et al. 2007; Schroeter, Lusk and Tyner 2008).

More generally, food policy analysis implicitly or explicitly makes use of food demand elasticities from the literature one way or another. Policy simulation models may be calibrated entirely using either published elasticities or elasticities estimated specifically for the purpose, or they may use a combination of estimated and calibrated parameter values. For example, several studies have estimated demand systems for food to determine whether the impacts of price and expenditure on food consumption vary among income groups or between food stamp program participants and others (Raper, Wanzala and Nayga 2002; Park et al. 1996; Yen, Lin and Smallwood 2003). Other studies use elasticities of demand for food in equilibrium displacement models of the food sector to determine how farm policy may affect food markets (e.g., Wohlgenant 1989) and how such price changes may affect economic welfare (e.g., Okrent 2010). Even when studies estimate the elasticities they use directly, they make indirect use of the estimates from the literature as an informal check and guide on the quality of the estimated elasticities. Thus, many findings and policy recommendations in the academic literature and beyond are influenced by published estimates of elasticities of demand for food.

The quality of these estimates is diverse and depends on modeling choices and assumptions, including the functional form for demands, types of data used, separability structure, food definitions, and statistical techniques used to estimate food demand models. In this monograph, we both assess the literature on demand for food in the United States and contribute to it. We begin with a presentation of relevant elements of demand theory that includes a review of the primal and dual approaches to estimating demand, the properties of demand, and assumptions about the structure of preferences in terms of separability, two-stage budgeting, and aggregation over consumers. We then review the methods used to estimate models of demand, including consideration of issues related to rank of a demand system, structural change, and separability assumptions, and the statistical implications of the type of data used in estimation. Our review of the literature concludes with an evaluation of elasticities of demand for food from a selection of previous studies using the mean absolute error in elasticity-based predictions of quantity responses to actual price and expenditure changes.

From our review of the literature, we find that published estimates of elasticities of demand suffer from two shortcomings. First, food purchased at grocery stores for at-home use (FAH) is typically lumped together with food purchased at restaurants for use away from home (FAFH) or FAFH is completely ignored. This problem stems primarily from the fact that the majority of estimates of elasticities of demand are based on time-series data that lump FAFH with FAH (i.e., per capita disappearance data published by the U.S. Department of Agriculture's (USDA's) Economic Research Service). Only a handful of studies present estimates of elasticities of demand for both disaggregated FAH products and a composite FAFH product. Second, studies of food demand typically model either fairly aggregated food products or disaggregated foods within a particular weakly separable group representing a subset of food products. Estimates of elasticities of demand for aggregated food products may be too broad for investigating the potential impacts of price-changing policies. On the other hand, estimates of elasticities of demand based on expenditure on a subset of food products do not reflect any inter-group substitution effects that occur through changes in total expenditure on foods. Elasticities of demand for disaggregated food products conditional on total expenditure on all goods and services, rather than expenditures on a weakly separable subgroup of food products, would be more appropriate generally to use in policy analysis.

With these shortcomings in mind, we estimate elasticities of demand using annual and monthly data under various alternative assumptions about functional form. Unlike those from many previous studies, the new elasticity estimates we present are conditional on expenditure on all goods rather than just food expenditure and are based on models that explicitly distinguish between FAFH and FAH. We also approximate elasticities of demand for disaggregated fruit and vegetable products conditional on total expenditure on goods and services. Our estimates are consistent with demand theory and, compared with other estimates from the literature, can accurately predict quantity changes given changes in prices.

2. DEMAND THEORY

Standard demand theory analyzes the choice behavior of an individual who gains utility or satisfaction from consuming goods and services given a limited budget set that is determined by exogenous prices and expenditure.[1,2] It assumes that consumers have complete information about the choices available and that they use this information to catalog and evaluate their choices prior to selecting goods or services to consume. The consumer chooses a utility-maximizing bundle of goods that can be observed in the market. This traditional model of consumer behavior provides a foundation for developing statistical models of demand. Thus, a review of the elements of traditional demand theory is an appropriate starting place before surveying the literature about the demand for food in the United States. In this section, we first review the primal and dual approaches to demand analysis, which provide the foundations for approaches to estimating demand econometrically. Second, we discuss the theoretical properties of demand that typically are tested or imposed a priori in estimation. Last, we discuss assumptions commonly made about the structure of preferences to reduce the number of parameters that must be estimated in a demand system.

2.1. Marshallian Demand Functions: Primal and Dual Approaches

The primal and dual approaches are two ways to derive Marshallian demand functions. Under the primal approach, we assume that the consumer seeks to maximize utility by choosing quantities of N goods, $q_1,\ldots,q_N$, subject to a linear budget constraint defined by fixed market prices (p) and total expenditure (M):

$$\max_{\{q_1,\ldots,q_N\}} \mathrm{u}(q_1,\ldots,q_N) \ \text{ s.t. } \sum_{n=1}^{N} p_n q_n \le M. \tag{1}$$

Given that $\mathrm{u}(\cdot)$ is strictly quasiconcave and the optimal bundle of commodities, $q_1^*,\ldots,q_N^*$, represented by the vector $\mathbf{q}^*$ is an interior optimum for (1), a Lagrange multiplier $\varphi \ge 0$ exists such that for all $n = 1,\ldots,N$:

$$\frac{\partial\, \mathrm{u}(\mathbf{q}^*)}{\partial q_n} = \varphi p_n. \tag{2}$$

The Lagrange multiplier, or the marginal utility of income, is the increment to utility for an additional dollar of expenditure. Condition (2) tells us that, at an interior optimum, the change in utility from a change in consumption of good n must be proportional to the price of good n. Letting $\mathbf{p}$ denote the vector of fixed prices, the solution to (1) is the system of Marshallian demand functions of the form:

$$q_n^* = \mathrm{q}_n(\mathbf{p}, M) \text{ for } n = 1,\ldots,N. \tag{3}$$

1 This section is derived largely from Mas-Colell, Whinston, and Green (1995, pp. 29–71) and Deaton and Muellbauer (1980b, pp. 25–53).

2 Expenditure is the exogenous budget outlay for a given period on some or all goods or services available to the consumer.

The set of Marshallian demand equations represents the observable choices of a consumer who maximizes utility given exogenous prices and expenditure.

The value function resulting from evaluating u(•) at $\mathbf{q}^*$ is called the indirect utility function and is denoted as:

$$\mathrm{v}(\mathbf{p}, M) = \mathrm{u}(\mathbf{q}^*(\mathbf{p}, M)).$$

The indirect utility function is the maximum value of utility attained for a given set of prices and expenditure. The Marshallian demand functions can be recovered from the indirect utility function using Roy's identity. If u(•) is a continuous utility function representing locally nonsatiated and strictly convex preferences and the indirect utility function is differentiable at the particular set of prices and expenditure, then

$$\mathrm{q}_n(\mathbf{p}, M) = -\frac{\partial\, \mathrm{v}(\mathbf{p}, M) / \partial p_n}{\partial\, \mathrm{v}(\mathbf{p}, M) / \partial M}. \tag{4}$$

Roy's identity is useful for empirical applications, as discussed later.

In the dual problem it is assumed that the consumer chooses the bundle of goods and services that will minimize the expenditure required to reach a certain utility level (i.e., u($\mathbf{q}^*$)):

$$\min_{\{q_1,\ldots,q_N\}} \sum_{n=1}^{N} p_n q_n \ \text{ s.t. } \ \mathrm{u}(\mathbf{q}) \geq \mathrm{u}(\mathbf{q}^*). \tag{5}$$

The optimal solution of the dual problem is the system of Hicksian demand functions and takes the following form:

$$h_n = \mathrm{h}_n(\mathbf{p}, u) \text{ for } n = 1, \ldots, N.$$

The Hicksian demands reflect only the substitution effect of changes in prices, unlike Marshallian demands, which reflect both substitution and income effects. The system of Hicksian demand functions minimizes the cost of achieving a given level of utility. The set of Hicksian demands is convenient for mathematical manipulation and welfare analysis because the functions are conditioned by utility rather than expenditure, but Hicksian demands are unobservable in the marketplace.

The solution to the cost minimization problem in (5) is called the expenditure function and is denoted by e($\mathbf{p}$,u). The expenditure function is the minimum expense required for a given utility. Analogous to Roy's identity, Shephard's lemma can be used to recover Hicksian demand functions. If a continuous utility function represents locally nonsatiated and strictly convex preferences, then the Hicksian demand function for good n is given by the derivative of the expenditure function with respect to the price of good n:

$$h_n = \frac{\partial\, \mathrm{e}(\mathbf{p}, u)}{\partial p_n}, \forall n = 1, \ldots, N. \tag{6}$$

Shephard's lemma is useful for empirical applications, as discussed later.

The relationship between the expenditure function and the indirect utility function is based on the fact that, if $\mathbf{q}^*$ is the optimal solution to the utility maximization problem of (1), then $\mathbf{q}^*$ is the optimal solution to the cost minimization problem of (5) when the required utility level is u($\mathbf{q}^*$) (see Figure 1). Moreover, the minimum cost of achieving this utility, defined by the expenditure function e($\mathbf{p}$,u), is equivalent to the total expenditure, M, in the primal problem that generated the maximum utility, u($\mathbf{q}$*), in the primal problem. Hence, the expenditure function and the indirect utility function are connected by the following relationships:

$$\mathrm{e}\big(\mathbf{p}, \mathrm{v}(\mathbf{p}, M)\big) = M, \tag{7a}$$

$$\mathrm{v}\big(\mathbf{p}, \mathrm{e}(\mathbf{p}, u)\big) = u. \tag{7b}$$

In addition, the Hicksian and Marshallian demand functions are related as follows:

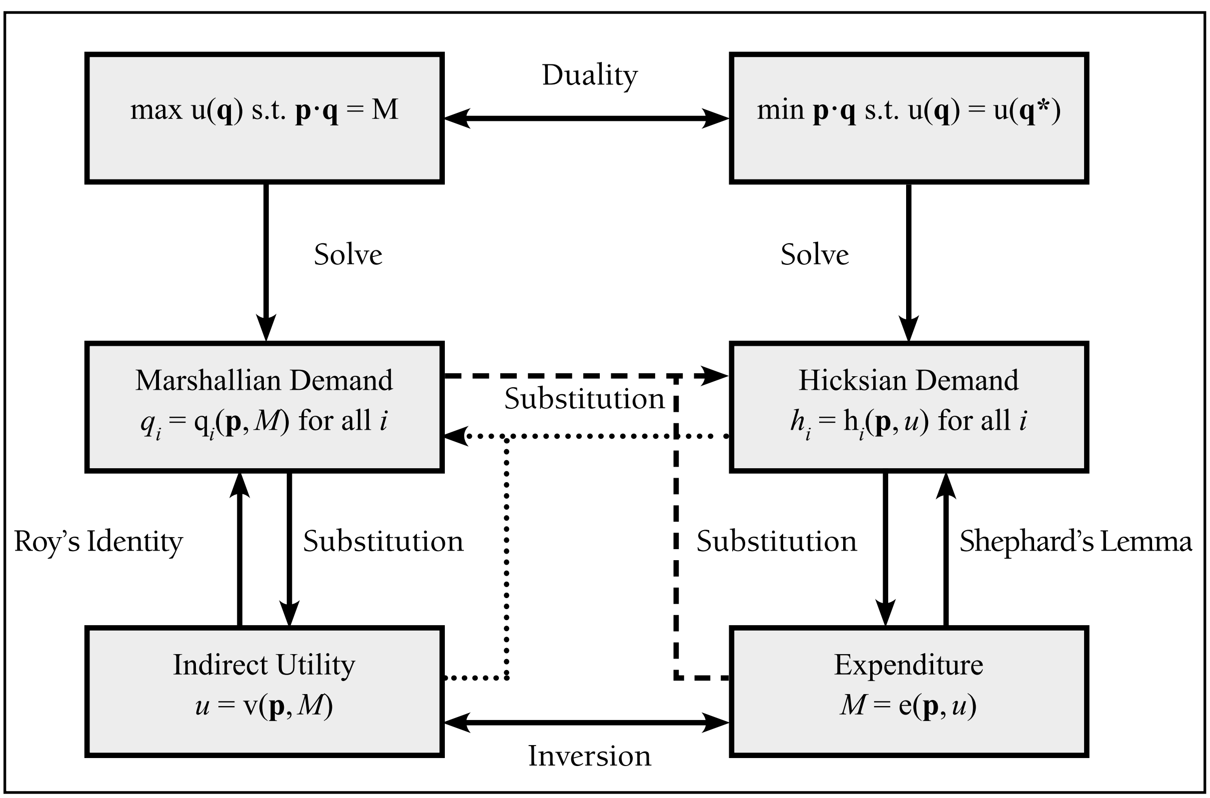
$$\mathrm{h}_n(\mathbf{p}, u) = \mathrm{q}_n\big(\mathbf{p}, \mathrm{e}(\mathbf{p}, u)\big), \forall n = 1, \ldots, N, \tag{8a}$$

$$\mathrm{q}_n(\mathbf{p}, M) = \mathrm{h}_n\big(\mathbf{p}, \mathrm{v}(\mathbf{p}, M)\big), \forall n = 1, \ldots, N. \tag{8b}$$

From (8a), the Slutsky equation can be derived by taking the partial derivative of the Hicksian demand for good n with respect to the price of good j at e($\mathbf{p}$,u):

$$\frac{\partial \mathrm{h}_n(\mathbf{p}, u)}{\partial p_j} = \frac{\partial \mathrm{q}_n\big(\mathbf{p}, \mathrm{e}(\mathbf{p}, u)\big)}{\partial p_j} + \frac{\partial \mathrm{q}_n\big(\mathbf{p}, \mathrm{e}(\mathbf{p}, u)\big)}{\partial M} \frac{\partial \mathrm{e}(\mathbf{p}, u)}{\partial p_j}. \tag{9}$$

Figure 1. **Approaches to Modeling Marshallian Demand Functions**



Substituting (6), (7a), and (8a) into (9) results in the Slutsky equation, which shows that the unobservable Hicksian demand response to prices (a pure substitution effect) can be represented as a combination of observable Marshallian price and income effects:

$$s_{nj} = \frac{\partial \mathrm{h}_n(\mathbf{p},u)}{\partial p_j} = \frac{\partial \mathrm{q}_n(\mathbf{p},M)}{\partial p_j} + \frac{\partial \mathrm{q}_n(\mathbf{p},M)}{\partial M}\mathrm{q}_j(\mathbf{p},M). \tag{10}$$

Equation (11) represents the elasticity form of (10), which is used in empirical applications, as discussed later:

$$\eta^*_{nj} = \eta_{nj} + \eta_{nM} w_j, \tag{11}$$

where η_{nj} and η_{nM} are Marshallian elasticities of demand for good *n* with respect to the price of good *j* and total expenditure, η^*_{nj} is the Hicksian price elasticity, and w_j is the expenditure share for good *j*.

2.2. Properties of Demand

The assumptions that a consumer faces a linear budget constraint and has preferences that are rational, nonsatiated, continuous, and strictly convex lead to certain desirable and testable properties of the Marshallian demand functions of (3). Assuming that the budget constraint is linear and satisfied with equality implies that the Marshallian demand functions are homogenous of degree zero in prices and expenditure, and satisfy the adding-up conditions.

The homogeneity property is sometimes referred to as the absence of money illusion. If all prices and expenditure increase by any positive proportion, κ, then demand for good *n* will remain unchanged, i.e.,

$$\mathrm{q}_n(\kappa\mathbf{p}, \kappa M) = \mathrm{q}_n(\mathbf{p}, M).$$

Applying Euler's theorem to the Marshallian demand functions, which are homogenous of degree zero, implies that

$$\sum_{j=1}^{N} p_j \frac{\partial \mathrm{q}_n(\mathbf{p},M)}{\partial p_j} + M\frac{\partial \mathrm{q}_n(\mathbf{p},M)}{\partial M} = 0, \forall n = 1,\ldots,N,$$

which can be expressed in elasticity form as[3]

$$\sum_{j=1}^{N} \eta_{nj} + \eta_{nM} = 0.$$

This equation states that the sum of all own- and cross-price elasticities (η_{nj}) for good *n* is equal to the negative of its expenditure elasticity (η_{nM}).

[3] According to Euler's theorem, if the function f(x) is homogenous of degree zero, then

$$\sum_{n=1}^{N} \left(\partial f(\mathbf{x}) / \partial x_n\right) x_n = 0.$$

The linear budget constraint also implies the adding-up, or Cournot and Engel aggregation conditions. The partial derivatives of the budget constraint with respect to p_k and M are

$$\sum_{n=1}^{N} \frac{\partial \mathrm{q}_n(\mathbf{p}, M)}{\partial p_j} p_n + \mathrm{q}_j(\mathbf{p}, M) = 0, \forall j = 1,\ldots,N,$$

$$\sum_{n=1}^{N} \frac{\partial \mathrm{q}_n(\mathbf{p}, M)}{\partial M} p_n = 1.$$

Converting to elasticities, the Cournot and Engel aggregation conditions are

$$\sum_{n=1}^{N} \eta_{nj} w_n + w_j = 0, \quad (12)$$

$$\sum_{n=1}^{N} w_n \eta_{nM} = 1. \quad (13)$$

Cournot and Engel aggregations imply that changes in total expenditure and prices cause rearrangements in purchases that do not violate Walras' law.

Other properties of demand are derived from properties of the expenditure function, including symmetry and negativity. Specifically, since the expenditure function is concave, the matrix of own- and cross-price effects in Hicksian demands is negative semidefinite, and Young's theorem implies that the matrix is symmetric. In other words,

$$\frac{\partial \mathrm{h}_n(\mathbf{p}, u)}{\partial p_n} < 0, \forall n = 1,\ldots,N, \quad (14)$$

$$\frac{\partial \mathrm{h}_n(\mathbf{p}, u)}{\partial p_j} = \frac{\partial \mathrm{h}_j(\mathbf{p}, u)}{\partial p_n}, \forall n, j = 1,\ldots,N. \quad (15)$$

Equation (14) means that the compensated own-price effects are negative and equation (15) means that the Slutsky substitution terms, s_{nj} and s_{jn}, are equal (equation (10)). Adding-up (Engel and Cournot aggregation), homogeneity, and Slutsky symmetry are usually invoked a priori or tested in empirical demand system models.

2.3. Commodity Groups, Separability, and Incomplete Demand Systems

Given the large number of goods available to the consumer, estimating consumer demand is made difficult by limited data and a relatively large number of parameters to estimate. Therefore, assumptions are made about how goods can be aggregated and separated into groups to make estimation possible and as a means of conserving degrees of freedom. Both aggregation and separability assumptions imply restrictions on preferences or prices. An alternative is to use an incomplete demand system approach. We briefly discuss the theory behind the composite commodity theorem and incomplete demand systems. We explicate in much greater detail the theory behind separability and two-stage budgeting because we apply them in this study to estimate elasticities of demand for disaggregated products (see section 6.5).

2.3.1. Composite Commodity Theorem

One way to reduce the number of parameters to estimate in a demand system is by combining N goods into a set of $S < N$ commodity aggregates. The existence of consistent commodity aggregates for demand can be justified by making use of the Hicks-Leontief composite commodity theorem. The composite commodity theorem asserts that, if all prices in a group move proportionately, then the corresponding group of commodities can be treated as a single good. Formally, let $\varphi_i = \log(p_i / P_I)$ where p_i is the price of good i, P_I is the composite price index for group I, and i is an element of I. Denoting $\boldsymbol{\varphi}$ as a vector of φ_i, the Hicks-Leontief composite goods theorem states that $\mathbf{q}^*$ maximizes a utility function given $\mathbf{P}$ if $\boldsymbol{\varphi}$ is constant (Deaton 1986).

While prices of related goods do tend to be strongly correlated over time, the Hicks-Leontief theorem requires that prices of goods within the same group are perfectly correlated, which typically does not hold. Lewbel (1996) relaxed the assumption of perfect collinearity of prices, by allowing $\boldsymbol{\varphi}$ to move over time and instead assumed that the distribution of $\boldsymbol{\varphi}$ is independent of $\mathbf{P}$.

2.3.2. Incomplete Demand Systems

Applied demand analysis often deals with an incomplete rather than complete demand system. This may be done because the practitioner is not concerned with demand for a group of goods that forms a subset of a household's budget or because data are not available for these goods. For example, suppose $\mathbf{q}$ is an n_q-vector of quantities of interest at corresponding prices $\mathbf{p}$, $\mathbf{z}$ is an n_z-vector of quantities of all other goods at prices $\mathbf{r}$, and y is total expenditure on all goods in both groups, $\mathbf{q}$ and $\mathbf{z}$. The observed demand functions are given by

$$\mathbf{q} = \mathbf{q}(\mathbf{p}, \mathbf{r}, y) \qquad (16)$$

while the other demand functions, $\mathbf{z} = \mathbf{z}(\mathbf{p}, \mathbf{r}, y)$, are not observed. When $n_z = 1$, the demand function z_1 can be derived from (16) by exploiting the adding-up condition:

$$z_1 = \mathbf{z}_1(\mathbf{p}, r_1, y) = (y - \mathbf{p}'\mathbf{q}) / r_1. \qquad (17)$$

If $n_z > 1$, then (16) is an incomplete demand system and, because the demands for the elements of $\mathbf{z}$ are unknown, it is not possible to recover the complete preference relation.

However, Epstein (1982) and LaFrance and Hanemann (1989) showed that, by artificially augmenting an incomplete demand system with a composite numeraire representing total expenditure on all other goods and deflating $\mathbf{p}$ by an aggregate price index for products that are not of interest (i.e., $\pi(\mathbf{r})$), the augmented system can be treated as if it were complete. Epstein (1982) showed that, if the demand functions in (16) satisfy regularity conditions that are analogous to classical integrability conditions for a complete demand system, then an expenditure function exists that is twice differentiable and increasing in $\mathbf{p}$, homogenous of degree one, and concave in $\mathbf{p}$ and $\mathbf{q}$ and satisfies Shephard's lemma for all $\mathbf{p}$, $\mathbf{q}$, and y. These regularity conditions are:

1. $\mathbf{z}$ is twice differentiable,
2. $\mathbf{z}$ is homogenous of degree zero,

3. **z** is greater than or equal to zero,
4. **p'q** < y,
5. the Slutsky matrix is symmetric and negative semidefinite,
6. a price index exists that is a function of **r**, i.e., π(**r**), and that function is twice differentiable and continuous, increasing in **r**, homogenous of degree one, and concave in **r** and satisfies **q**(**p**, **r**, *y*) ≡ **q**'[**p** / π(**r**), *y* / π(**r**)].

LaFrance and Hanemann (1989) argued that condition 6 is too restrictive and that conditions 1–6 do not necessarily imply that **q** is a solution to a utility maximization problem. Extending upon Epstein, they proved that conditions 1–5,

6a. $\partial s_{ij} / \partial y = \partial s_{ji} / \partial y$, where s_{ij} is the Slutsky substitution term, and

6b. $\partial s_{ij} / \partial p_k = \partial s_{ji} / \partial p_k$

hold if and only if the system is weakly integrable. They defined an incomplete demand system as weakly integrable if (16) and (17) are solutions to the utility maximization problem. Based on weak integrability, they derived a quasi-expenditure function, a quasi-indirect utility function, and quasi-utility in terms of an incomplete demand system. Hence, weak integrability allows the practitioner to treat an incomplete demand system in virtually the same manner as a complete system.

2.3.3. Separability

An alternative to applying the composite goods theorem is to assume that a group of closely related commodities is separable from other goods.[4] Separability assumptions imply restrictions on the nature of substitutability between goods in different groups, which, in turn, limits the number of parameters needed to estimate demand functions. For example, preferences are typically assumed to be separable between consumption in one time period and another time period and between leisure and goods. Such restrictions can be thought of in terms of two-stage budgeting—the idea that a consumer can allocate total expenditure in two stages. In the first stage, expenditure is allocated to broad groups of goods (e.g., food, housing, and entertainment) while in the second stage, expenditures within a group are allocated among elementary goods (e.g., meats, eggs, cereals, and so on). Substitution between goods in different groups is limited in different ways by various separability assumptions. Several types of separability have been defined that differ in the implied restrictions on the substitution effects of price changes between goods in different groups. For the purpose of this study, only weak and strong separability are described because they are most commonly invoked.

Suppose a vector of goods, **q**, can be partitioned into *S* subvectors, $q^1, \ldots, q^S$, where q^I contains N^I goods and the preference ordering of goods in each subvector can be represented

[4] This section is based on Deaton and Muellbauer (1980b) and Pollak and Wales (1992, pp. 35–53).

by a utility function, $u^I(\mathbf{q}^I)$, for all $I = 1,\ldots, S$. The utility function is said to be weakly separable with respect to this partition if and only if $u(\mathbf{q})$ is of the form

$$\mathrm{u}(\mathbf{q}) = \mathrm{f}\left(\mathrm{u}^1(\mathbf{q}^1),\ldots,\mathrm{u}^S(\mathbf{q}^S)\right), \tag{18}$$

where f(•) is a monotonically increasing function. A utility function of this form implies subgroup (conditional) demand functions of the following form:

$$q_i = \mathrm{q}_i\left(\mathrm{M}^I(\mathbf{p}^1,\ldots,\mathbf{p}^S, M), \mathbf{p}^I\right) \forall I = 1,\ldots,S, i = 1,\ldots,N^I, \tag{19}$$

where $M^I(\bullet)$ is expenditure on group I and q_i is a function of prices for group I, $\mathbf{p}^I$, and group expenditure M^I (the subscript denotes the elementary good and the superscript denotes the group). By differentiating (19) with respect to p_j while holding utility constant, the Slutsky substitution term of equation (10) can be written as

$$s_{ij} = \delta^{IJ} \left.\frac{\partial q_i}{\partial p_j}\right|_{u=\bar{u}} + \left.\frac{\partial q_i}{\partial M^I}\frac{\partial M^I}{\partial p_j}\right|_{u=\bar{u}}, i \in I, j \in J, \delta^{IJ} = \begin{cases} 1, & \text{if } I = J \\ 0, & \text{if } I \neq J \end{cases}. \tag{20}$$

By symmetry of the Slutsky matrix, we know that

$$\delta^{IJ} \left.\frac{\partial q_i}{\partial p_j}\right|_{u=\bar{u}} + \left.\frac{\partial q_i}{\partial M^I}\frac{\partial M^I}{\partial p_j}\right|_{u=\bar{u}} = s_{ij} = s_{ji} = \delta^{JI} \left.\frac{\partial q_j}{\partial p_i}\right|_{u=\bar{u}} + \left.\frac{\partial q_j}{\partial M^J}\frac{\partial M^J}{\partial p_i}\right|_{u=\bar{u}}.$$

Solving for the partial derivative of M^I with respect to p_j,

$$\frac{\partial M^I}{\partial p_j} = \delta^{IJ}\left[\frac{\partial q_j / \partial p_i}{\partial q_i / \partial M^I} - \frac{\partial q_i / \partial p_j}{\partial q_i / \partial M^I}\right] + \left(\frac{\partial M^J / \partial p_i}{\partial q_i / \partial M^I}\right)\frac{\partial q_j}{\partial M^J}.$$

Notice that the term on the right-hand side in round brackets is independent of j so we can rewrite this term as a proportionality factor that is specific to groups I and J,

$$\lambda_{JI} = \frac{\partial M^J / \partial p_i}{\partial q_i / \partial M^I},$$

and

$$\frac{\partial M^I}{\partial p_j} = \delta^{IJ}\left[\frac{\partial q_j / \partial p_i}{\partial q_i / \partial M^I} - \frac{\partial q_i / \partial p_j}{\partial q_i / \partial M^I}\right] + \lambda^{JI}\frac{\partial q_j}{\partial M^J}. \tag{21}$$

Substituting (21) into (20), we can rewrite the Slutsky substitution term as

$$s_{ij} = \delta^{IJ}\frac{\partial q_i}{\partial p_j} + \lambda^{JI}\frac{\partial q_i}{\partial M^I}\frac{\partial q_j}{\partial M^J}, \forall i \in I, j \in J, \delta^{IJ} = \begin{cases} 1, & \text{if } I = J \\ 0, & \text{if } I \neq J \end{cases}. \tag{22}$$

If good i is in the same group as good j, then s_{ij} is composed of both price and expenditure effects. However, if good i belongs to a different group than good j, then substitution between goods in different groups is composed only of group expenditure effects.[5]

Alternatively, strong separability places more severe restrictions on group preference ordering and hence on inter-group substitution. The utility function is said to be strongly separable with respect to the partition $\{N^1,\ldots, N^S\}$ if and only if $\mathrm{u}(\mathbf{q})$ is of the form

$$\mathrm{u}(\mathbf{q}) = \mathrm{f}\left(\mathrm{u}^1(\mathbf{q}^1) + \ldots + \mathrm{u}^S(\mathbf{q}^S)\right), \quad (23)$$

where f(•) is a monotonically increasing function. Since a strongly separable utility function is certainly weakly separable, (22) holds. However, additivity of the subutility functions implies that any new group can be formed from a combination of any two or more groups, which prevents any particular relationships between pairs of groups (i.e., λ is the same for all groups).[6] Hence, the assumption of additive preferences holds if and only if the Slutsky substitution terms defined in (10) are

$$s_{ij} = \lambda \frac{\partial q_i}{\partial M^I} \frac{\partial q_j}{\partial M^J}, \forall i \in I, j \in J, I \neq J, \quad (24)$$

where λ is the same for all expenditure groups.

Strong separability has several empirical consequences. First, for the law of compensated demand to be satisfied (equation (14)),

$$s_{ii} = -\frac{\lambda}{p_i} \frac{\partial q_i}{\partial M}\left(1 - p_i \frac{\partial q_i}{\partial M}\right) < 0,$$

---

5 The own-price Slutsky substitution term can be recovered using homogeneity. Since Hicksian demand functions are homogenous of degree zero,

$$\sum_{j=1}^{N} p_j s_{jn} = 0, \forall n = 1,\ldots, N.$$

Hence, the own-price Slutsky substitution term is

$$s_{ii} = -\frac{1}{p_i}\left[\sum_{\substack{j=1 \\ n \neq i}}^{N} p_j s_{ji}\right], i \in I, I = 1,\ldots, S,$$

where

$$s_{ji} = \delta^{JI} \frac{\partial q_j}{\partial p_i} + \lambda^{JI} \frac{\partial q_j}{\partial M^J} \frac{\partial q_i}{\partial M^I}, \forall i \in I, j \in J, \delta^{JI} = \begin{cases} 1 \text{ if } I{=}J \\ 0 \text{ otherwise} \end{cases}.$$

6 To see this, denote three goods, i, j, and k, each belonging to a different group: I, J, and K. By combining groups J and K into a new group, L, by (22), the Slutsky substitution terms for i and j and for i and k are:

$$s_{ij} = \lambda_{IJ} \frac{\partial q_i}{\partial M_I} \frac{\partial q_j}{\partial M_J} = \lambda_{IL} \frac{\partial q_i}{\partial M_I} \frac{\partial q_j}{\partial M_J},$$
$$s_{ik} = \lambda_{IK} \frac{\partial q_i}{\partial M_I} \frac{\partial q_k}{\partial M_K} = \lambda_{IL} \frac{\partial q_i}{\partial M_I} \frac{\partial q_k}{\partial M_K}.$$

Dividing s_{ij} by s_{ik} yields $\lambda_{IJ} = \lambda_{JI}$, which means λ_{IJ} is dependent only on J. Symmetry implies that λ_{IJ} is independent of I and J, or that $\lambda_{IJ} = \lambda$ (Deaton and Muellbauer, 1980b, pp. 141–142).

at which point $\lambda > 0$ and all elasticities with respect to aggregate expenditure must be positive.[7] Under these assumptions, goods can only be normal ($\partial q_i / \partial M > 0$) and substitutes ($s_{ij} > 0$). Second, if the number of goods is large, then

$$\eta_{ii} \approx -(\lambda / M)\eta_{iM}, \tag{25}$$

which is referred to as Pigou's Law (Deaton 1974).

Strong separability is sometimes called block additivity and the subsets are referred to as blocks, whereas the weakly separable utility function is represented by a "utility tree" in which the subsets are called "branches." This terminology arises from the nature of substitution between groups under the two assumptions. For example, if the utility function is a tree with S branches, we cannot, in general, combine two branches into a single branch and treat the new utility function as a tree with $S-1$ branches. However, with block additivity, it is always permissible to combine blocks into a single block because λ is independent of groups.

Separability restrictions limit the number of parameters to be estimated by restricting inter-group substitution. More precisely, under weak and strong separability (equations (22) and (24), respectively), the unconditional Slutsky substitution term between goods i and j in groups I and J (where $J \neq I$) is proportional to their expenditure effects. The restrictions placed on the Slutsky substitution term allow for estimation of demand functions based solely on group expenditure and prices (conditional demand). Indeed, weak separability is both necessary and sufficient for the second stage of two-stage budgeting. The estimation of unconditional demand functions using two-stage budgeting is complicated by the requirement to use price and quantity indexes to allocate total expenditure among groups at the first stage.

2.3.4. Two-Stage Budgeting

Strotz (1957, 1959) and Gorman (1959) pioneered the concept of two-stage budgeting. They assumed that in the first stage a consumer allocates total expenditure among broad groups of goods I, $I = 1,\ldots, S$ containing $N^1,\ldots, N^S$ goods, and then, given group expenditure in the second stage, the consumer chooses among elementary goods within each group. Formally, the budget allocation problem of the consumer at the first stage can be defined as

$$\max_{u^1,\ldots,u^S} \mathrm{F}\left(\mathrm{u}^1(\mathbf{q}^1),\ldots,\mathrm{u}^S(\mathbf{q}^S)\right) \text{s.t. } M = \sum_{I=1}^{S} M^I = \sum_{I=1}^{S} \mathrm{c}^I(\mathbf{p}^I, u^I), \tag{26}$$

where $\mathrm{c}^I(\mathbf{p}^I, u^I)$ is the cost of consuming the given quantities in group I at the price vector $\mathbf{p}^I$ and is equivalent to the expenditure on group I, designated M^I, while $\mathrm{F}(\cdot)$ is an aggregator utility function that consists of subutility functions, $\mathrm{u}^I(\cdot)$, $I = 1,\ldots, S$, and is associated with the quantity vector for group I, designated $\mathbf{q}^I$. To solve the first-stage allocation problem, knowledge of all prices and quantities of elementary goods is required, which provides no useful restrictions for estimation.

For separability to provide meaningful restrictions for estimation of demand equations, it must be possible to summarize the price vector for each subgroup by a single price index.

[7] Equation (24) defines the off-diagonal terms of the Slutsky matrix. The diagonal terms can be filled in using the relationship

$$\sum_{n=1}^{N} s_{ni} p_i = 0.$$

However, an exact solution to the two-stage budgeting problem holds only under stringent restrictions on the utility and subutility functions. To show this, let $c^I(\bar{\mathbf{p}}^I, u^I)$ denote the cost of consuming subutility u^I at base-period group prices, $\bar{\mathbf{p}}^I$. The cost of consuming group I at price vector $\mathbf{p}^I$ can be rewritten as

$$c^I(\mathbf{p}^I, u^I) = c^I(\bar{\mathbf{p}}^I, u^I)\frac{c^I(\mathbf{p}^I, u^I)}{c(\bar{\mathbf{p}}^I, u^I)} = c^I(\bar{\mathbf{p}}^I, u^I)\, P^I(\mathbf{p}^I, \bar{\mathbf{p}}^I, u^I), \forall I = 1, \ldots, S, \qquad (27)$$

where $P^I(\mathbf{p}^I, \bar{\mathbf{p}}^I, u^I)$ is the true cost-of-living price index and $c^I(\bar{\mathbf{p}}^I, u^I)$ can be thought of as a quantity index (Carpentier and Guyomard 2001).

The problem with the true cost-of-living price index is that it is dependent on utility. Gorman (1959) derived conditions under which a single price index and a single quantity index can be used in the first-stage allocation.[8] One possibility is that the aggregator utility function is additive among groups (equation (23)) and the indirect utility function of each group is of the Gorman generalized polar form.[9] As previously discussed, strong separability is unrealistic for use in estimating demand. Alternatively, Gorman proposed that price indexes are independent of utility if the subutility functions of the second stage are homothetic.[10] However, this assumption implies that all of the conditional expenditure elasticities in the second stage are one, which is also unrealistic.

In practice, it is usually assumed that the true cost-of-living price index can be approximated by a conventional price index (e.g., a Paasche or Laspeyres price index) that might not hold utility constant:

$$P^I\left(\mathbf{p}^I, \bar{\mathbf{p}}^I, u^I\right) \cong P^I\left(\mathbf{p}^I, \bar{\mathbf{p}}^I\right). \qquad (28)$$

---

[8] Bieri and de Janvry (1971) noted that, if the aggregator utility function is weakly separable, then local price indexes exist that are specific to each expenditure equation. This implies knowledge of S^2 price indexes, which is not useful for estimation.

[9] Suppose the indirect utility function for group I, $\Psi^I(\bullet)$, is of the Gorman generalized polar form,

$$\Psi^I(M^I, \mathbf{p}^I) = F^I\left[M^I / b^I(\mathbf{p}^I)\right] + a^I(\mathbf{p}^I),$$

for some increasing function $F^I(\bullet)$ while the first-stage (aggregator) utility function is additive:

$$u = \Psi^1(M^1, \mathbf{p}^1) + \ldots + \Psi^S(M^S, \mathbf{p}^S).$$

When $b^I(\mathbf{p}^I)$ is interpreted as a price index and $v^I = M^I / b^I(\mathbf{p}^I)$ as a quantity index, the consumer maximization problem becomes

$$\max u = \sum_{I=1}^{S} F^I(\mathbf{v}^I) + \sum_{I=1}^{S} a^I(\mathbf{p}^I) \text{ s.t. } M = \sum_{I=1}^{S} M^I = \sum_{I=1}^{S} b^I(\mathbf{p}^I) v^I,$$

where the price index is independent of u (Deaton and Muellbauer, 1980b, pp.130–131).

[10] Deaton and Muellbauer (1980b) showed that the cost function is proportional to utility if the subutility functions are homothetic:

$$c\left(\mathbf{p}^I, u^I\right) = u^I\, b^I(\mathbf{p}^I).$$

Hence, the true cost-of-living index is independent of utility:

$$P^I\left(\mathbf{p}^I, \bar{\mathbf{p}}^I, u^I\right) = \frac{c^I\left(\mathbf{p}^I, u^I\right)}{c\left(\bar{\mathbf{p}}^I, u^I\right)} = \frac{u^I\, b^I(\mathbf{p}^I)}{u^I\, b^I(\bar{\mathbf{p}}^I)} = \frac{b^I(\mathbf{p}^I)}{b^I(\bar{\mathbf{p}}^I)}.$$

Under assumption (28), the utility maximization problem of (26) can be approximated as

$$\max_{c^1,\ldots,c^S} \Phi\left(\mathrm{c}^1(\bar{\mathbf{p}}^1,u^1),\ldots,\mathrm{c}^S(\bar{\mathbf{p}}^S,u^S),\bar{\mathbf{p}}^1,\ldots,\bar{\mathbf{p}}^S\right)$$
$$\text{s. t. } M=\sum_{i=1}^{S}\mathrm{c}^I\left(\bar{\mathbf{p}}^I,u^I\right)\mathrm{P}^I\left(\mathbf{p}^I,\bar{\mathbf{p}}^I\right),$$

where $\mathrm{c}^I(\bar{\mathbf{p}}^I, u^I)$ can be approximated by a quantity index and $\mathrm{P}^I(\mathbf{p}^I, \bar{\mathbf{p}}^I)$ by an implicit price deflator.

Carpentier and Guyomard (2001) approximated unconditional elasticities of demand using an approximation to the Slutsky substitution term that assumed weak separability (equation (22)).[11] Denoting the superscript as representing the composite group and the subscript as representing the elementary good, they approximated the unconditional Marshallian expenditure (η_{iM}) and price (η_{ij}) elasticities of demand and the Hicksian (η_{ij}^*) elasticities of demand as

$$\eta_{iM}=\eta_{iM}^I\eta^{IM}, \tag{29}$$

$$\eta_{ij}=\delta_{IJ}\eta_{ij}^I+w_j^J\eta_{iM}^I\eta_{iM}^J\left(\delta_{IJ}/\eta_{jM}^J+\eta^{IJ}\right)+w_j^J w^J\eta^{IM}\eta_{iM}^I(\eta_{jM}^J-1),\text{ and} \tag{30}$$

$$\eta_{ij}^*=\delta_{IJ}\eta_{ij}^{I*}+w_j^J\eta^{IJ*}\eta_{iM}^I\eta_{jM}^J, \tag{31}$$

---

[11] Suppose that j is an element of group J, i is an element of group I, $I\neq J$, and the Marshallian and Hicksian demands for composite good I are $\mathrm{Q}^I(P^1,\ldots, P^S, M)$ and $H^I(P^1,\ldots, P^S, u)$, respectively. At an optimum, we know that

$$\left.\frac{\partial M^I}{\partial p_j}\right|_{u=\bar{u}}=\left.\frac{\partial\left(\mathrm{P}^I(\mathbf{p}^I,\bar{\mathbf{p}}^I,u^I)\mathrm{H}^I(\cdot)\right)}{\partial p_j}\right|_{u=\bar{u}}\cong P^I\left.\frac{\partial\mathrm{H}^I(\cdot)}{\partial P^J}\frac{\partial P^J}{\partial p_j}\right|_{u=\bar{u}},$$

where the approximation results from the assumption that each price index, $\mathrm{P}^I(\mathbf{p}^I, \bar{\mathbf{p}}^I, u^I)$, can be approximated by (28). Using the definition of $\mathrm{P}^I(\mathbf{p}^I, \bar{\mathbf{p}}^I, u^I)$ in (27) and Shephard's lemma, we know that

$$\left.\frac{\partial P^J}{\partial p_j}\right|_{u=\bar{u}}=\left.\frac{\partial\,\mathrm{c}^J(\mathbf{p}^J,u^J)}{\partial p_j}\frac{1}{\mathrm{c}^I(\bar{\mathbf{p}}^J,u^J)}\right|_{u=\bar{u}}=\frac{\mathrm{h}_j(\mathbf{p}^J,u^J)}{\mathrm{c}^J(\bar{\mathbf{p}}^J,u^J)},$$

where $\mathrm{h}_j(\bullet)$ is Hicksian demand for good j in group J. By multiplying (21) by p_j and summing over all j in J, we get

$$\sum_{j\in J}^{N}p_j\left.\frac{\partial M^J}{\partial p_j}\right|_{u=\bar{u}}=\lambda_{IJ}\sum_{j\in J}^{N}p_j\frac{\partial q_j}{\partial M^J}=\lambda_{IJ},$$

which, after substitution, is

$$\lambda_{IJ}=\sum_{j\in J}^{N}p_j\left.\frac{\partial M^J}{\partial p_j}\right|_{u=\bar{u}}=P^IP^J\frac{\partial\mathrm{H}^I(\cdot)}{\partial P^I}.$$

Based on (22) and the preceding, the Slutsky substitution term can be written as

$$s_{ij}=P^IP^J\frac{\partial\mathrm{H}^I(P^1,\ldots,P^S,u)}{\partial P^I}\frac{\partial\,\mathrm{q}_i(\mathbf{p}^I,M^I)}{\partial M^I}\frac{\partial\,\mathrm{q}_j(\mathbf{p}^J,M^J)}{\partial M^J},\ j\in J,i\in I,J\neq I,$$

which, in elasticity form, is the unconditional Hicksian elasticity of demand in (31). Using the Slutsky equation, the unconditional Marshallian elasticity demand in (30) can be derived (Carpentier and Guyomard 2001).

where

η_{iM}^{I} = the expenditure elasticity for good $i \in I$ conditional on expenditure for group I,

η^{IM} = the expenditure elasticity for composite group I with respect to total expenditure, M,

η_{ij}^{I} = the Marshallian elasticity of demand for good $i \in I$ with respect to price $j \in J$ conditional on $J = I$,

η^{IJ} = the Marshallian elasticity of demand for composite group I with respect to composite price J,

w_{j}^{J} = the budget share for good $j \in J$ conditional on J,

w^{J} = the budget share for composite group J,

η_{ij}^{I*} = the Hicksian elasticity of demand for good $i \in I$ with respect to price $j \in J$ conditional on $J = I$,

η^{IJ*} = the Hicksian elasticity of demand for composite group I with respect to composite price J,

δ_{IJ} = $\begin{cases} 1, \text{if } I = J \\ 0, \text{otherwise} \end{cases}$.

Under the assumption that the subutility functions are homothetic, the price index is a true cost-of-living index and (29) and (31) reduce to

$$\eta_{ij} = \delta_{IJ}\eta_{ij}^{I} + w_{j}^{J}\left(\delta_{IJ} + \eta^{IJ}\right),$$

$$\eta_{ij}^{*} = \delta_{IJ}\eta_{ij}^{I*} + w_{j}^{J}\eta^{IJ*},$$

$$\eta_{iM} = \eta^{IM}$$

because $\eta_{iM}^{I} = \eta_{jM}^{J} = 1$.

It can be seen from (29)–(31) that the unconditional Marshallian price elasticities of demand for goods within the same group ($I = J$) consist of two parts: (a) the effect of price j on quantity i that arises from estimation of conditional demand (η_{ij}^{I}), and (b) the effect of the first- stage budget allocation process (the second and third terms on the right-hand side). The conditional Marshallian price elasticity of demand is equal to its unconditional counterpart if any of the following conditions holds:

$$w_{j}^{J} = 0,$$

$$\eta_{iM}^{I} = 0,$$

$$w^{J} = \left(1 + \eta^{IJ}\eta_{jM}^{J}\right) / \left(1 - \eta_{jM}^{J}\right).$$

The unconditional expenditure elasticity is proportional to the product of the conditional expenditure elasticity and the first-stage expenditure elasticity. Hence, conditional elasticities of demand can be substantially different from unconditional elasticities.

2.4. Market Demand: Aggregation over Consumers

The theory of demand discussed thus far has been concerned with decisions of the individual. Clearly, when modeling micro or panel data representing individual consumers, aggregation over individuals is generally not an issue, but much of demand analysis is carried out using data on aggregate consumption either in total or per capita. Certain assumptions about the structure of preferences for individuals allow for aggregate demand functions to exist. Gorman (1953, 1961) showed that individuals could be linearly aggregated into a representative consumer if the cost function for individual i, for all $i = 1,\ldots, I$, is of the form

$$\mathrm{c}^i\left(u^i, \mathbf{p}\right) = \mathrm{a}^i(\mathbf{p}) + u^i\,\mathrm{b}(\mathbf{p}). \tag{32}$$

The cost function of the representative consumer is simply (32) without the i superscript. The preference structure implied by equation (32) (otherwise known as the Gorman polar form) is quasihomothetic and implies that the Engel curves for all I are linear and parallel. To see this, note that (32) implies that an indirect utility function of the Gorman polar form is

$$\mathrm{v}(\mathbf{p}, M) = \frac{M - \mathrm{a}(\mathbf{p})}{\mathrm{b}(\mathbf{p})}.$$

By Roy's identity, demand is of the form

$$q_n = \frac{\partial\,\mathrm{a}(\mathbf{p})}{\partial p_n} + \frac{\partial\,\mathrm{b}(\mathbf{p})}{\partial p_n}\left(\frac{M - \mathrm{a}(\mathbf{p})}{\mathrm{b}(\mathbf{p})}\right).$$

If $\mathrm{a}(\mathbf{p}) = 0$, the Engel curves are linear and must go through the origin (homotheticity), which is a necessary and sufficient condition for unitary expenditure elasticities (Deaton and Muellbauer 1980b, p. 144). The assumption of linear Engel curves is somewhat stringent and may not hold empirically (Deaton and Muellbauer 1980b, pp. 149–153; Banks, Blundell and Lewbel 1997).

Muellbauer (1975, 1976) showed that the requirements for exact nonlinear aggregation imply that the cost function of the representative consumer is of the form

$$c(u, \mathbf{p}) = \theta[u, \mathrm{a}(\mathbf{p}), \mathrm{b}(\mathbf{p})], \tag{33}$$

where $\mathrm{a}(\mathbf{p})$ and $\mathrm{b}(\mathbf{p})$ are linearly homogenous functions of prices and the function $\theta[\bullet]$ is linearly homogenous in $\mathrm{a}(\bullet)$ and $\mathrm{b}(\bullet)$. When the representative expenditure function is independent of prices and depends only on the distribution of expenditures, then the representative cost function is of the price-independent generalized linear (PIGL) form:

$$\mathrm{c}(u, \mathbf{p}) = [\mathrm{a}(\mathbf{p})^{\alpha} + u\,\mathrm{b}(\mathbf{p})^{\alpha}]^{1/\alpha}.$$

The limit of this representative cost function as α approaches zero yields the price-independent generalized logarithmic (PIGLOG) cost function:

$$\ln \mathrm{c}(u, \mathbf{p}) = \ln \mathrm{a}(\mathbf{p}) + u \ln \mathrm{b}(\mathbf{p}).$$

The PIGLOG cost function forms the basis for many of the demand models discussed in section 3. Inverting the PIGLOG cost function yields an indirect utility function of the form

$$\mathrm{v}(\mathbf{p}, M) = \frac{\ln M - \ln \mathrm{a}(\mathbf{p})}{\ln \mathrm{b}(\mathbf{p})}.$$

The demand function for good n can be recovered using Roy's identity and is

$$\mathrm{q}_n(\mathbf{p}, M) = M\left[\frac{\partial\, \mathrm{a}(\mathbf{p}) / \partial p_n}{\mathrm{a}(\mathbf{p})} - \frac{\partial\, \mathrm{b}(\mathbf{p}) / \partial p_n}{\mathrm{b}(\mathbf{p}) \ln \mathrm{b}(\mathbf{p})}\left(\ln M - \ln \mathrm{a}(\mathbf{p})\right)\right],$$

and the equations for expenditure shares ($w_n = p_n q_n / M$) are

$$w_n = p_n\left[\frac{\partial\, \mathrm{a}(\mathbf{p}) / \partial p_n}{\mathrm{a}(\mathbf{p})} - \frac{\partial\, \mathrm{b}(\mathbf{p}) / \partial p_n}{\mathrm{b}(\mathbf{p}) \ln \mathrm{b}(\mathbf{p})}\left(\ln M - \ln \mathrm{a}(\mathbf{p})\right)\right].$$

The PIGLOG cost function yields Engel curves that are consistent with the Working-Leser model:

$$w_n = \alpha_n + \beta_n \ln M,$$

where α_n and β_n are functions of prices.

Gorman (1981) considered a more general form of Engel curves for an exactly aggregable class of demands that are linear in functions of nominal expenditure:

$$q_n = \sum\nolimits_{s=0}^{S} \mathrm{a}_{ns}(\mathbf{p})\, \mathrm{g}_s(M), \forall n = 1, \ldots, N, \tag{34}$$

where q_n is quantity demanded of good n, $\mathbf{p}$ is an $N \times 1$ vector of prices of goods, M is total expenditure, and S is a finite set. If we let $\mathbf{q}$ be an $N \times 1$ vector of quantities demanded, $\mathbf{a}$ be the $N \times S$ matrix of functions $\mathrm{a}_{ns}(\cdot)$, and $\mathbf{g}$ be an S-vector of functions $\mathrm{g}_s(\cdot)$, then (34) can be written in matrix notation as

$$\mathbf{q} = \mathbf{ag}. \tag{35}$$

Gorman (1981) proved that the rank of the matrix $\mathbf{a}$ is at most three for an integrable demand system, and the constituent Engel curve $\mathrm{g}_s(\cdot)$ must take one of the following generic forms:

$$\mathrm{g}_s(M) = M(\ln M)^s,$$

$$\mathrm{g}_s(M) = M^{\kappa+1}, \kappa \neq 0,$$

$$\mathrm{g}_s(M) = M \sin(\tau \ln M) \text{ and } \mathrm{g}_s(M) = M \cos(\tau \ln M), \tau > 0.$$

This implies that, for demand systems of rank three, (34) must be

$$q_n = \mathrm{a}_{0n}(\mathbf{p})M + \sum\nolimits_{j=1}^{J} \mathrm{a}_{jn}(\mathbf{p})M(\ln M)^j,$$

$$q_n = \mathrm{a}_{0n}(\mathbf{p})M + \sum\nolimits_{\kappa\in K-} \mathrm{a}_{\kappa n}(\mathbf{p})M^{1-\kappa} + \sum\nolimits_{\kappa\in K+} \mathrm{a}_{\kappa n}(\mathbf{p})M^{1+\kappa},$$

$$q_n = \mathrm{a}_{0n}(\mathbf{p})M + \sum\nolimits_{\tau\in T} \mathrm{a}_{\tau n}(\mathbf{p})M\sin(\tau\ln M) + \sum\nolimits_{\tau\in T} \mathrm{a}_{\tau n}(\mathbf{p})M\cos(\tau\ln M),$$

where K is a finite set of elements of κ such that K– contains the negative elements, K+ contains the positive elements, and T is a set of positive constants (LaFrance, Beatty and Pope 2006).

Demand systems that are not full rank have some columns in **a** that are linear combinations of other columns. Lewbel (1990) argued that full rank systems are parsimonious because they maximize the degree of income flexibility of demands with the fewest number of parameters. He characterized all possible full rank Gorman Engel curve demand systems (i.e., equation (34)):

1. Homothetic ($S = 1$): $q_n = \mathrm{a}_{0n}(\mathbf{p})M$,
2. PIGL ($S = 2$): $q_n = \mathrm{a}_{0n}(\mathbf{p})M + \mathrm{a}_{1n}(\mathbf{p})M^{1-\kappa}, \kappa \neq 0$,
3. PIGLOG ($S = 2$): $q_n = \mathrm{a}_{0n}(\mathbf{p})M + \mathrm{a}_{1n}(\mathbf{p})M\ln M$,
4. Generalized Quadratic ($S = 3$): $q_n = \mathrm{a}_{0n}(\mathbf{p})M + \mathrm{a}_{1n}(\mathbf{p})M^{1-\kappa} + \mathrm{a}_{2n}(\mathbf{p})M^{1+\kappa}$,
5. Quadratic Logarithmic ($S = 3$):$q_n = \mathrm{a}_{0n}(\mathbf{p})M + \mathrm{a}_{1n}(\mathbf{p})M\ln M + \mathrm{a}_{2n}(\mathbf{p})M\left(\ln M\right)^2$,
6. Trigonometric ($S = 3$): $q_n = M\left\{\mathrm{a}_{0n}(\mathbf{p}) + \mathrm{a}_{1n}(\mathbf{p})\sin\left[\tau\ln M\right] + \mathrm{a}_{2n}(\mathbf{p})\cos\left[\tau\ln M\right]\right\}$.

The full, rank three demand systems allow for quadratic and trigonometric Engel curves. Banks, Blundell, and Lewbel (1997) and Beatty and LaFrance (2005) argued that empirical evidence indicates that observed demands are rank three.

3. MODELS OF FOOD DEMAND

The choice of functional form for demand is limitless but several models have become staples in the literature on estimation of food demand. Linear and logarithmic (or double-log) single-equation models of demand have been popular since the inception of empirical estimation of demand because they are comparatively easy to estimate and interpret. However, some properties of demand, as discussed in section 2.2, cannot be satisfied using such models. In section 3.1 we describe popular single-equation models and discuss their strengths and weaknesses.

Alternatively, demand can be specified as a system of demand equations derived from one of the following approaches (see Figure 1): (a) specifying a utility function and solving the maximization problem, (b) specifying an indirect utility function and applying Roy's identity (equation (4)), (c) specifying an expenditure function and applying Shephard's lemma (equation (6)), and (d) taking a differential approximation to the demand system. The parameters estimated using models derived using any of these approaches can be restricted to make the system satisfy the properties of demand implied by the theory (i.e., homogeneity, Slutsky symmetry, and Cournot and Engel aggregation conditions). In section 3.2 we discuss several popular demand systems derived using each of the four approaches and the corresponding sets of restrictions that can be imposed on the parameters. We also discuss the tradeoffs between parsimony and flexibility among the alternative demand system models, including the implication of each model for the price relationships between goods and the shape of Engel curves.

3.1. Single-Equation Models of Demand

The earliest studies of food consumption estimated ad hoc single-equation models of demand for particular individual foods. The most popular functional forms used in the single-equation approach include linear, semi-log, double-log, and Box-Cox models (Chern, Huang and Lee 1993). The Box-Cox functional form, which nests the linear ($\sigma_q = \sigma_M = \sigma_p = 1$), double-log ($\sigma_q = \sigma_M = \sigma_p = 0$), and semi-log ($\sigma_q = 1$, $\sigma_M = \sigma_p = 0$) models, takes the form of

$$q_n^{(\sigma_q)} = c_{0n} + c_{nM} M^{(\sigma_M)} + \sum_{j=1}^{N} c_{nj} p_j^{(\sigma_p)}, \forall n = 1,\dots,N,$$

where

$$q_n^{(\sigma_q)} = \begin{cases} \left(q_n^{\sigma_q} - 1\right)/\sigma_q \ \text{ if } \sigma_q \neq 0 \\ \ln \sigma_q \ \text{ if } \sigma_q = 0 \end{cases},$$

$$M^{(\sigma_M)} = \begin{cases} \left(M^{\sigma_M} - 1\right)/\sigma_M \ \text{ if } \sigma_M \neq 0 \\ \ln \sigma_M \ \text{ if } \sigma_M = 0 \end{cases},$$

$$p_n^{(\sigma_p)} = \begin{cases} \left(p_n^{\sigma_p} - 1\right)/\sigma_p \ \text{ if } \sigma_p \neq 0 \\ \ln \sigma_p \ \text{ if } \sigma_p = 0 \end{cases},$$

where q_n is the quantity of food n, M is total expenditure, and p_j is the price of food j. This model and its nested counterparts are still used today because the parameters are easy to estimate and interpret. For example, the parameters resulting from the double-log model (c_{nM} and c_{nj}) are the elasticities of demand with respect to expenditure and prices.

However, such models are inconsistent with standard utility maximization. For the double-log model to satisfy the adding-up restrictions (Engel aggregation in particular), all of the expenditure elasticities must be unit elastic (Deaton and Muellbauer 1980b, p. 17; Johnson, Hassan and Green 1984, p. 75). Thus, the expenditure shares will add to one only if the elasticities of demand with respect to expenditure are restricted to implausible values.[12] Estimates from such models may have limited use in food demand analysis because they violate the adding-up condition.

3.2. Four Approaches to Estimating Models Consistent with Demand Theory

Four approaches that are consistent with demand theory have also been used to estimate demand relationships. In the first approach the utility function is specified and Marshallian demand functions are derived by maximizing the utility function subject to a budget constraint. In the second approach, Roy's identity is used to recover Marshallian demand functions from a specified indirect utility function. Similarly, in the third approach Shephard's lemma is used to recover the Hicksian demand functions from a specified expenditure function and the Hicksian demand functions are then transformed to obtain Marshallian demands. In the fourth approach, a differential approximation is applied directly to the demand function. These approaches include functional forms that range in restrictiveness. All four approaches include models known as flexible functional forms.[13]

A theme throughout the literature on demand estimation is the tradeoff between flexibility of the demand system and parsimony with respect to the number of parameters required to estimate the demand system. A related issue is the degree to which a demand system imposes theoretical restrictions from demand theory a priori or can be used to test such restrictions. In this section, we discuss the four approaches to derivation of the demand systems that are consistent with utility maximization and give examples of models based on these approaches that are frequently used in empirical investigations of demand. We highlight the tradeoffs of each approach in terms of parsimony and flexibility.

[12] Pollak and Wales (1992) noted that a demand system is said to exhibit expenditure proportionality if the demand for each good is proportional to expenditure, $q_i(P, M) = b_i(P)M$, or, equivalently, if all expenditure elasticities are equal to one (p. 24).

[13] Pollak and Wales (1992) defined a flexible functional form as being "capable of providing a second-order approximation to the behavior of any theoretically plausible demand system at a point in the price-expenditure space. More precisely, a flexible functional form can mimic not only the quantities demanded, the income derivatives and the own-price derivatives, but also the cross-price derivatives at a particular point" (p. 60).

3.2.1. Maximization of the Utility Function

One way to derive Marshallian demand functions that are consistent with utility maximization is to specify a utility function and solve for the demand equations that maximize the utility function subject to the budget constraint, as in the primal approach. For example, the linear expenditure system (LES) is based on the utility function suggested by Klein and Rubin (1947):

$$\mathrm{u}(\mathbf{q}) = \sum_{n=1}^{N} \beta_n \ln(q_n - \gamma_n), \tag{36}$$

where q_n is quantity of good n, β_n is the marginal budget share for good n, and γ_n is the minimum quantity of good n consumed. Maximizing (36) subject to the budget constraint,

$$\sum_{n=1}^{N} p_n q_n = M,$$

yields Marshallian demand functions of the form

$$q_n = \gamma_n + \frac{\beta_n (M - \sum_{j=1}^{N} p_j \gamma_j)}{p_n}, \forall n = 1,\ldots,N.$$

The resulting expenditure function for good n is

$$p_n q_n = p_n \gamma_n + \beta_n (M - \sum_{j=1}^{N} p_j \gamma_j), \forall n = 1,\ldots,N. \tag{37}$$

Because preferences are additive, the demand system reflects the consumer's budget allocation process under strong separability. First, the consumer allocates expenditures to achieve the minimum quantity of each good ($p_n \gamma_n$). Second, the consumer distributes the remainder of the available expenditure ($M - \sum_{n=1}^{N} p_n \gamma_n$) over all goods in fixed proportions, β_n for good n. The price and expenditure elasticities are shown in Table 1 (on page 34), along with those for the other functional forms derived from maximization of a specified utility function. The adding-up, homogeneity, and symmetry conditions hold when

$$\sum_{n=1}^{N} \beta_n = 1. \tag{38}$$

The number of structural parameters required for estimation of the LES is small (Deaton 1986, p. 1788; Johnson, Hassan and Green 1984, p. 64). To estimate the LES, one needs to estimate only $2N$ parameters, which is considerably less than the potential number of independent shares and elasticities in a theoretically plausible demand system, $N(N-1)/2 + 2N - 2$ (Pollak and Wales 1992, p. 60).[14]

[14] At a point, a demand system has N expenditure shares, N expenditure elasticities, N own-price elasticities, and $N(N-1)$ cross-price elasticities. However, not all of these $N^2 + 2N$ values are independent. By Walras' law, the expenditure shares must add up to one, so only $N-1$ shares are independent. This implies that $N-1$ expenditure elasticities will be independent. By symmetry, only $N(N-1)/2$ of the cross-price elasticities are independent. Given the expenditure shares, expenditure, elasticities of demand, and cross-price elasticities of demand, the own-price elasticities of demand can be inferred from these values using Cournot aggregation. Hence, adding up these values, a theoretically plausible demand system entails at most $N(N-1)/2 + 2N - 2$ independent shares and elasticities.

However, the LES utility function is typically too restrictive for demand analysis in that it provides a poor approximation of the actual process that generated the data. Note that the indirect utility function associated with (37) is

$$\mathrm{v}(\mathbf{p}, M) = \left(M - \sum_{n=1}^{N} p_n \gamma_n\right) / \prod_{n=1}^{N} p_n^{\beta_n}.$$

By inversion, the cost function is

$$\mathrm{c}(\mathbf{p}, u) = \sum_{n=1}^{N} p_n \gamma_n + u \prod_{n=1}^{N} p_n^{\beta_n}.$$

For the cost function to be concave and the compensated law of demand to hold, β_n must be greater than zero, which implies that all goods must be normal and must be substitutes for each other. In addition, the cost function is of the Gorman polar form, which further restricts behavior by allowing only for linear Engel curves. This is contrary to household budget studies for food that find a nonlinear relationship between expenditure and food budget shares. However, cost functions that are of the Gorman polar form do allow for exact linear aggregation across consumers such that aggregate demand can be treated as coming from a "representative" consumer (Deaton 1974). Another restrictive property of the LES is that it represents an additive utility function, so the own-price elasticity of demand for good n is approximately proportional to the elasticity of demand for good n with respect to total expenditure (i.e., Pigou's Law, equation (25)) (Deaton and Muellbauer 1980b, p. 66).

Alternative popular functional forms derived from the utility function approach include the S-Branch system (Brown and Heien 1972) and the constant elasticity of substitution (CES) model. The generalized CES utility function nests a translation of the Cobb-Douglas ($\sigma = 1$), the Leontief ($\sigma = 0$), and the linear ($\sigma = \infty$) forms of the utility function:

$$\mathrm{u}(\mathbf{q}) = \sum_{n=1}^{N} \gamma_n (q_n - \alpha_n)^{(\sigma-1)/\sigma}.$$

This form of utility yields demand functions that are just as restrictive as those from the LES in that the Engel curves are linear and substitution between goods is constant across all pairs. The S-Branch system assumes a strongly separable utility function in which the block subutility functions for S groups, $\mathrm{u}(\mathbf{q}^I)$,…, $\mathrm{u}(\mathbf{q}^S)$, are of the generalized CES form and the aggregator utility function, u[•], is a CES (superscript denotes group and subscript denotes individual good):

$$\mathrm{u}\left[\mathrm{u}^1(\mathbf{q}^1),\ldots,\mathrm{u}^S(\mathbf{q}^S)\right] = \left(\sum_{I=1}^{S} \alpha^I (\mathrm{u}^I(\mathbf{q}^I))^{(\sigma-1)/\sigma}\right)^{\sigma/(\sigma-1)}$$

$$\text{where } \mathrm{u}^I(\mathbf{q}^Y) = \left(\sum_{i\in I}^{N^I} \gamma_i (q_i - \alpha_i)^{(\sigma^I-1)/\sigma^I}\right)^{\sigma^I/(\sigma^I-1)}.$$

The S-Branch nests the LES utility function and is less restrictive than the LES in that it allows goods to be complements, but it does not allow inferior goods and the Engel curves are still linear. Deaton noted that applications of utility-derived demand systems with such strict restrictions on parameters should "be seen for what they are, i.e., untested theory with 'sensible' parameters, and not as fully-tested data-consistent models" (Deaton 1986, p. 1788).

3.2.2. Application of Roy's Identity to the Indirect Utility Function

A second way to derive Marshallian demand functions that are consistent with demand theory is by specifying an indirect utility function and applying Roy's identity. One of the earliest applications of this approach was by Houthakker (1960), who derived the indirect addilog demand system. The indirect utility function for the indirect addilog demand system is

$$\mathrm{v}(\mathbf{p}, M) = \sum_{n=1}^{N} a_n (M / p_n)^{b_n}. \tag{39}$$

Application of Roy's identity to (39) yields a system of demand functions, as shown in Table 1, that are homogenous of degree zero and satisfy Engel aggregation and Slutsky symmetry a priori (Johnson, Hassan and Green 1984, p. 66). The complete set of demand parameters in the indirect addilog system can be estimated with $2N-1$ independent coefficients (i.e., $N \times b_n$ and $(N-1) \times a_n$). The addilog demand system enforces a priori restrictions on the elasticities of demand and is not a flexible functional form. In fact, the indirect utility function is indirectly additive, which generates several of the implications of direct additivity discussed in section 2.3.3, including the own-price elasticity of demand for good n being approximately proportional to the expenditure elasticity of demand for good n (Deaton 1974).

Alternatively, Christensen, Jorgenson, and Lau (1975) specified a quadratic approximation to the indirect utility function,v($\mathbf{p}$, M), where

$$\mathrm{v}(\mathbf{p}, M) = -\sum_{n=1}^{N} \alpha_n \ln(p_n / M) - \tfrac{1}{2}\sum_{n=1}^{N}\sum_{j=1}^{N} \gamma_{nj} \ln(p_n / M)\ln(p_j / M). \tag{40}$$

When Roy's identity is applied to (40), the demand for good n is

$$\mathrm{q}_n(\mathbf{p}, M) = \frac{M}{p_n}\left[\frac{\alpha_n + \tfrac{1}{2}\sum_{j=1}^{N} \gamma_{nj} \ln(p_j / M)}{\sum_{j=1}^{N}\alpha_j + \tfrac{1}{2}\sum_{k=1}^{N}\sum_{j=1}^{N} \gamma_{kj} \ln(p_j / M)\ln(p_k / M)}\right].$$

Hence, the expenditure share equations with the conventional normalization that $\sum_{n=1}^{N} \alpha_n = -1$ are

$$\mathrm{w}_n(\mathbf{p}, M) = \frac{\alpha_n + \tfrac{1}{2}\sum_{j=1}^{N} \gamma_{nj} \ln(p_j / M)}{-1 + \tfrac{1}{2}\sum_{k=1}^{N}\sum_{j=1}^{n} \gamma_{kj} \ln(p_j / M)\ln(p_k / M)}, \forall n = 1,..,N.^{15} \tag{41}$$

This system is known as the indirect translog (ITL) demand system, for which adding-up and symmetry conditions are listed in Table 1. The ITL indirect utility function is a generalization of the Cobb-Douglas form and reduces to the Cobb-Douglas form when all of the γs are equal to zero. An extension of the ITL is the generalized translog (GTL) demand system with an indirect utility function of the form

$$\ln \mathrm{v}(\mathbf{p}, M) = -\sum_{n=1}^{N} \alpha_n \ln\left(\frac{p_n}{M^*}\right) - \tfrac{1}{2}\sum_{n=1}^{N}\sum_{j=1}^{N} \gamma_{nj} \ln\left(\frac{p_n}{M^*}\right)\ln\left(\frac{p_j}{M^*}\right), \tag{42}$$

[15] Since the share equations are homogenous of degree zero in the parameters, α_n cannot be identified and a normalization is needed.

where

$$M^* = M - \sum_{n=1}^{N} p_n b_n$$

(Pollak and Wales 1980) . Similar to the LES, a portion of total expenditure M in the GTL is allocated to pre-committed quantities; i.e., $M - \sum_{n=1}^{N} p_n b_n$, implying a commitment of "subsistence" expenditure and leaving a remainder for discretionary expenditure. Hence, the GTL nests the ITL system when $b_1 = \ldots = b_n = 0$ and the LES system when $\sum_{n=1}^{N} \sum_{k=1}^{N} \gamma_{nk}$.[16] The GTL and its nested counterparts belong to the PIGLOG class of demand systems (see section 2).

3.2.3. Application of Shephard's Lemma to the Expenditure Function

A third approach to estimating demand systems is to specify an expenditure function and recover the Hicksian demand functions using Shephard's lemma. One popular demand system that uses this approach is the almost ideal demand system (AIDS). Deaton and Muellbauer (1980a) suggested approximating a cost function consistent with PIGLOG preferences,

$$\ln \mathrm{c}(\mathbf{p}, u) = \mathrm{a}(\mathbf{p}) + u\mathrm{b}(\mathbf{p}), \tag{43}$$

with a($\mathbf{p}$) and b($\mathbf{p}$) as

$$\mathrm{a}(\mathbf{p}) = \alpha_0 + \sum_{n=1}^{N} \alpha_n \ln p_n + \tfrac{1}{2} \sum_{n=1}^{N} \sum_{l=1}^{n} \gamma_{nl}^{*} \ln p_n \ln p_l, \tag{44}$$

$$\mathrm{b}(\mathbf{p}) = \beta_0 \prod_{n=1}^{N} p_n^{\beta_n}, \tag{45}$$

$$\gamma_{nl}^{*} = \tfrac{1}{2}(\gamma_{nl} + \gamma_{ln}).$$

By applying Shephard's lemma and noting that $w_n = \partial \ln \mathrm{c}(\mathbf{p}, u) / \partial \ln p_n$, the expenditure share for good n is[17]

$$w_n = \frac{\partial \ln \mathrm{c}(\mathbf{p}, u)}{\partial \ln p_n} = u \beta_n \beta_0 \prod_{k=1}^{N} p_k^{\beta_k} + \alpha_n + \sum_{k=1}^{N} \gamma_{nk} \ln p_k. \tag{46}$$

Inverting the cost function yields the equation for u,

$$u = \frac{\ln M - \mathrm{a}(\mathbf{p})}{\mathrm{b}(\mathbf{p})}, \tag{47}$$

[16] Pollak and Wales (1992) provided a detailed description of other members of the translog family, including the linear translog ($\sum_{n=1}^{N} \gamma_{ni} = 0$), the homothetic translog ($b_1 = \ldots = b_n = 0$, $\sum_{n=1}^{N} \gamma_{in} = 0$), and the log translog.

[17] By Shephard's lemma, $\partial \mathrm{c}(\mathbf{p}, u) / \partial p_n = q_n$. Multiplying both sides by $p_n / \mathrm{c}(u, \mathbf{p})$,

$$\frac{\partial \ln \mathrm{c}(u, \mathbf{p})}{\partial \ln p_n} = \frac{p_n q_n}{\mathrm{c}(u, \mathbf{p})} = w_n .$$

and u can be substituted back into (46) to yield expenditure share equations as functions of only the observable prices and expenditure:

$$w_n = \alpha_n + \sum_{j=1}^{N} \gamma_{nj} \ln p_j + \beta_n \ln\left(\frac{M}{\mathrm{P}}\right), \tag{48}$$

where

$$\ln \mathrm{P} = \alpha_0 + \sum_{k=1}^{N} \alpha_k \ln p_k + \tfrac{1}{2} \sum_{k=1}^{N} \sum_{l=1}^{N} \gamma_{kl} \ln p_k \ln p_l .$$

The adding-up conditions imply the following parametric restrictions:

$$\sum_{n=1}^{N} \gamma_{nj} = 0, \; \sum_{n=1}^{N} \beta_n = 0, \sum_{n=1}^{N} \alpha_n = 1.$$

Symmetry requires that $\gamma_{ij} = \gamma_{ji}$, and c(**p**, u) must be homogenous of degree 1 and increasing in **p**, which implies that

$$\sum_{n=1}^{N} \gamma_{jn} = 0.$$

Since the cost function is PIGLOG, the Engel curves are log-linear, allowing exact nonlinear aggregation of consumers into a representative consumer.

One drawback to estimating the AIDS is that it is nonlinear in the parameters because the price index used to deflate total expenditure, P, is a function of parameters to be estimated. To circumvent the associated problems, Deaton and Muellbauer (1980a) suggested approximating P with Stone's price index:

$$\ln P = \sum_{n=1}^{N} w_n \ln p_n . \tag{49}$$

This system is referred to as the linearized AIDS (LAIDS). While very convenient and therefore popular, this approximation has some drawbacks that have been discussed in the food demand literature. First, while the LAIDS is an approximation to a well-behaved demand system, the model does not satisfy the requirements for integrability. Second, Stone's price index (which does not satisfy the requirements for a price index discussed by Moschini (1995)) contains the dependent variables as elements in the share equation system with potential implications for estimation bias.

Banks, Blundell, and Lewbel (1997) argued that consumption data yield Engel curves that are more nonlinear (rank > 2) than what is permitted by the AIDS and ITL models. They extended the AIDS to allow for quadratic Engel curves and called it quadratic AIDS (QUAIDS). They derived the QUAIDS from an indirect utility function of the form

$$\ln \mathrm{v}(\mathbf{p}, M) = \left(\left[\frac{\ln M - \ln \mathrm{a}(\mathbf{p})}{\mathrm{b}(\mathbf{p})} \right]^{-1} + \lambda(\mathbf{p}) \right)^{-1}, \tag{50}$$

where a(**p**) and b(**p**) are as defined in (44) and (45) and

$$\lambda(\mathbf{p}) = \sum_{n=1}^{N} \lambda_n \ln p_n .$$

By Roy's identity, the expenditure shares of the QUAIDS model are

$$w_n = \alpha_n + \sum_{j=1}^{N} \gamma_{nj} \ln p_n + \beta_n \ln\left(\frac{M}{\mathrm{a}(\mathbf{p})}\right) + \frac{\lambda_n}{\mathrm{b}(\mathbf{p})}\left[\ln\left(\frac{M}{\mathrm{b}(\mathbf{p})}\right)\right]^2 . \tag{51}$$

The QUAIDS is rank three and has quadratic logarithmic expenditure shares.

The AIDS cost function and ITL indirect utility functions are only locally concave and convex, respectively (Deaton 1986). Gallant (1984) proposed using a Fourier-series rather than a Taylor-series expansion to approximate indirect utility, making the indirect utility function approximation globally convex. Gallant (1984) argued that the Fourier flexible form (FFF) is a semi-nonparametric model that avoids model misspecification errors induced by parametric models like the AIDS and ITL, which may generate biased and inconsistent estimators. Indeed, Gallant (1984) argued that desirable statistical properties of elasticities also may not hold at any particular data point (e.g., the mean of the data) chosen arbitrarily as a point at which to evaluate elasticities when a locally flexible model is estimated. The FFF has been combined with the AIDS and ITL models to create globally flexible versions of these models (Chalfant 1987; Piggott 2003). Several studies have also generalized the AIDS and ITL functional forms to create other demand systems (e.g., Bollino 1987; Lewbel 1989; Moschini 2001; Pollak and Wales 1980). Table 1 contains an extensive, but by no means exhaustive, list of the flexible functional forms that have been applied to studies of food in the United States, along with their associated parametric restrictions and elasticity formulas.

3.2.4. Differential Approximation to the Demand Function

A final approach is based on a direct approximation of the Marshallian demands. Transforming the differentials of the Marshallian demands yields a set of equations that are local first-order approximations to the underlying relationship between quantities, prices, and income. The most common differential demand system is the Rotterdam model (Theil 1965; Barten 1966). More-recent alternatives include the first-differenced linear AIDS (FDLAIDS) (Deaton and Muellbauer 1980a), the National Bureau of Research (NBR) demand system (Neves 1987), and the Central Bureau of Statistics (CBS) demand system (Keller and Van Driel 1985). Barten (1993) showed that these four differential demand systems can be nested into a model referred to as Barten's synthetic model.

Consider the Rotterdam model of Theil (1965) and Barten (1966). Theil derived the Rotterdam model, beginning with the logarithmic differential of the Marshallian demand for good n, $q_n(p_1,\ldots,p_N, M)$, such that

$$d\ln q_n = \sum_{j=1}^{N} \eta_{nj} d\ln p_j + \eta_{nM} d\ln M, \tag{52}$$

where q_n is quantity of good n, p is price, M is total expenditure, and η_{nj} and η_{nM} are Marshallian price and expenditure elasticities.[18] Using the Slutsky equation in (11), (52) becomes

$$d\ln q_n = \sum_{j=1}^{N} \eta_{nj}^{*} d\ln p_j + \eta_{nM}\left(d\ln M - \sum_{j=1}^{N} w_j d\ln p_j\right).$$

[18] In practice, the assumption is made that the model derived in continuous time can be approximated using data measured in discrete time, i.e., $d\ln p_n \approx \Delta \ln p_n = \ln p_{n,t} - \ln p_{n,t-1}$, where t is the time period (Theil 1965). This approximation is discussed in greater detail in the application of the differential type models in section 6.

Multiplying both sides of this equation by the expenditure share for good n, w_n, results in the Rotterdam demand system:

$$w_n d \ln q_n = \sum_{j=1}^{N} \pi_{nj} d \ln p_j + \theta_n d \ln Q, \tag{53}$$

where $d \ln Q$ is a Divisia volume index; that is

$$d \ln Q = d \ln M - \sum_{n=1}^{N} w_n d \ln p_n \tag{54}$$

or

$$d \ln Q = \sum_{n=1}^{N} w_n d \ln q_n ,$$

the parameters of the system are defined as

$$\pi_{nj} = \frac{p_n p_j}{M} s_{nj}, \tag{55}$$

$$\theta_n = \frac{\partial q_n}{\partial M} p_n, \tag{56}$$

and s_{nj} is the Slutsky substitution term from equation (10).

It can be shown that the FDLAIDS is a transformation of the Rotterdam model. The AIDS (or the LAIDS) can be expressed in differential form following Deaton and Muellbauer (1980a). Specifically, if the logarithmic price terms in the LAIDS are replaced by their logarithmic differentials and Stone's price index is replaced with the Divisia price index, the FDLAIDS is[19]

$$dw_n = \sum_{j=1}^{N} \gamma_{nj} d \ln p_j + \beta_n d \ln Q, \tag{57}$$

$$d \ln P = \sum_{n=1}^{N} w_n d \ln p_n .$$

The right-hand side terms of the Rotterdam and FDLAIDS are similar. The left-hand side terms differ but the Rotterdam model can be transformed to have the same dependent variable as the FDLAIDS. To show this, note that the differential of a budget share, w_n, can be written as

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[19] Denote the true cost-of-living price index as equation (28), i.e.,

$$\mathrm{P}(\mathbf{p}, \bar{\mathbf{p}}, u) = \mathrm{c}(\mathbf{p}, u) / \mathrm{c}(\bar{\mathbf{p}}, u),$$

where $\bar{\mathbf{p}}$ is a vector of base-period prices and u is utility. The proportional rate of change in the price index is then

$$d \ln \mathrm{P}(\mathbf{p}, \bar{\mathbf{p}}, u) = d \ln \mathrm{c}(\mathbf{p}, u).$$

Footnote 17 implies that

$$d \ln \mathrm{c}(\mathbf{p}, u) = \sum_{n=1}^{N} \mathrm{w}_n (\mathbf{p}, u) d \ln p_n .$$

Hence, for any fixed utility level u, the price index can be written as

$$\ln \mathrm{P}(\mathbf{p}, \bar{\mathbf{p}}, u) = \int_{p}^{\bar{p}} \sum_{n=1}^{N} \mathrm{w}_n (\mathbf{p}, u) d \ln p_n .$$

This suggests that $w_n(\mathbf{p}, u)$ should be replaced with the observed budget shares, w_n. However, as discussed in section 2.3.4, unless preferences are homothetic, the utility-constant budget shares are not equal to the actual budget shares. In addition, as discussed in footnote 18, prices are not observed continuously, so the preceding equation would have to be approximated by some formula containing finite changes (Deaton and Muellbauer 1980b, pp. 174–175).

$$dw_n = w_n d\ln q_n + w_n d\ln p_n - w_n d\ln M. \tag{58}$$

Also, the logarithmic differential of the budget equation is

$$d\ln M \quad = \quad \sum_{n=1}^{N} w_n d\ln p_n + \sum_{n=1}^{N} w_n d\ln q_n \tag{59}$$

$$= \quad d\ln P + d\ln Q. \tag{60}$$

Substituting (60) into (58),

$$dw_n = w_n d\ln q_n + w_n d\ln p_n - w_n(d\ln P + d\ln Q).$$

Solving for $w_n d\ \ln q_n$,

$$w_n d\ln q_n = dw_n - w_n d\ln p_n + w_n(d\ln P + d\ln Q),$$

and substituting this term into (53) yields

$$dw_n - w_n d\ln p_n + w_n(d\ln P + d\ln Q) = \sum_{j=1}^{N} \pi_{nj} d\ln p_j + \theta_n d\ln Q.$$

Rearranging this equation yields

$$dw_n = \left(\theta_n - w_n\right) d\ln Q + \sum_{j=1}^{N} \left(\pi_{nj} - w_n w_j + w_n \delta_{nj}\right) d\ln p_j, \tag{61}$$

where

$$\delta_{nj} = \begin{cases} 1 \text{ if } n = j \\ 0 \text{ otherwise} \end{cases}.$$

Hence, if $\beta_n = \theta_n - w_n$ and $\gamma_{nj} = \pi_{nj} - w_n w_j + w_n \delta_{nj}$, the two models are approximately equivalent (Brown, Lee and Seale 1994).

The CBS and NBR specifications are hybrids of the Rotterdam model and FDLAIDS. The CBS model incorporates Working and Leser's Engel model into the Rotterdam specification (Brown, Lee and Seale 1994). In particular, Working and Leser proposed modeling the expenditure share for good *i* as

$$w_n = \alpha_n + \beta_n \ln M. \tag{62}$$

Multiplying this by M and then differentiating with respect to M yields

$$\frac{\partial q_n}{\partial M} p_n = \alpha_n + \beta_n(\ln M + 1). \tag{63}$$

Solving for α_n in (63) and substituting the resulting expression and (56) into (62) yields

$$\theta_n = w_n + \beta_n. \tag{64}$$

Replacing θ_n in (53) with (64) yields the CBS model, which has Rotterdam price coefficients and an FDLAIDS income term:

$$w_n d\ln q_n = \left(\beta_n + w_n\right) d\ln Q + \sum_{j=1}^{N} \pi_{nj} d\ln p_j.$$

Similarly, the NBR model can be derived from the FDLAIDS model by letting $\beta_i = \theta_i - w_i$ in (57), such that

$$dw_n = \theta_n d\ln Q + \sum_{j=1}^{N} \gamma_{nj} d\ln p_j,$$

where the price coefficients are the same as the FDLAIDS price coefficients and the expenditure term is the same as in the Rotterdam model.

By parameterizing the four models to have the same right-hand-side terms, we can consider the differences in the marginal budget shares between models. Rewriting the Rotterdam (R), CBS (C), FDLAIDS (F), and NBR (N) models so that they all have the same right-hand-side terms yields

$$y_R = w_n d\ln q_n = \theta_n d\ln Q + \sum_{j=1}^{N} \pi_{nj} d\ln p_j, \quad (65)$$

$$y_F = dw_n = \beta_n d\ln Q + \sum_{j=1}^{N} \gamma_{nj} d\ln p_j, \quad (66)$$

$$y_C = w_n \left(d\ln q_n - d\ln Q\right) = \beta_n d\ln Q + \sum_{j=1}^{N} \pi_{nj} d\ln p_j, \quad (67)$$

$$y_N = dw_n + w_n d\ln Q = \theta_n d\ln Q + \sum_{j=1}^{N} \gamma_{nj} d\ln p_j. \quad (68)$$

The coefficient on the income term in the Rotterdam and NBR models (i.e., θ_n) is the marginal budget share and is constant, whereas the marginal budget shares for the FDLAIDS and CBS models (i.e., $\beta_n = \theta_n - w_n$) vary with the expenditure shares. Conversely, the Slutsky terms are considered to be constants in the Rotterdam and CBS models (i.e., π_{nj}) but vary with expenditure shares in the NBR and FDLAIDS models.

Barten (1993) nested the four differential demand system models into the following general model by exploiting the similarities between the models:

$$\alpha_R \mathbf{y}_R + \alpha_C \mathbf{y}_C + \alpha_F \mathbf{y}_F + \alpha_N \mathbf{y}_N = \mathbf{X\Omega}, \quad (69)$$

where y_i, $i = R, C, N, F$ is a $t \times 1$ vector of transformed basic endogenous variables; $\mathbf{X}$ is a $t \times k$ matrix of exogenous price and expenditure variables; and $\mathbf{\Omega} = \alpha_R \boldsymbol{\omega}_R + \alpha_C \boldsymbol{\omega}_C + \alpha_F \boldsymbol{\omega}_F + \alpha_N \boldsymbol{\omega}_N$ and $\boldsymbol{\omega}_i$, $i = R, C, N, F$ comprise a $k \times 1$ vector of coefficients. Without loss of generality, the sum of the αs is set to zero and α_R is

$$\alpha_R = 1 - \alpha_F - \alpha_C - \alpha_N. \quad (70)$$

Substituting α_R into (69) and solving for $\mathbf{y}_R$ yields

$$\mathbf{y}_R = \alpha_C(\mathbf{y}_R - \mathbf{y}_C) + \alpha_F(\mathbf{y}_R - \mathbf{y}_F) + \alpha_N(\mathbf{y}_R - \mathbf{y}_N) + \mathbf{X\Omega}. \quad (71)$$

Unconstrained estimation of the αs is not possible since α_R is a linear combination of α_F, α_C, and α_N. However, (71) can be rewritten using the fact that

$$\mathbf{y}_R - \mathbf{y}_C + \mathbf{y}_F - \mathbf{y}_N = 0, \quad (72)$$

or

$$(\mathbf{y}_R - \mathbf{y}_C) - (\mathbf{y}_R - \mathbf{y}_F) + (\mathbf{y}_R - \mathbf{y}_N) = 0. \quad (73)$$

Solving (73) for $\mathbf{y}_R - \mathbf{y}_F$ yields

$$(\mathbf{y}_R - \mathbf{y}_C) + (\mathbf{y}_R - \mathbf{y}_N) = (\mathbf{y}_R - \mathbf{y}_F),$$

and substituting this into (71) gives

$$\begin{aligned}\mathbf{y}_R &= \mathbf{X\Omega} + \alpha_C(\mathbf{y}_R - \mathbf{y}_C) + \alpha_F(\mathbf{y}_R - \mathbf{y}_F) + \alpha_N(\mathbf{y}_R - \mathbf{y}_N),\\ &= \mathbf{X\Omega} + (\alpha_C + \alpha_F)(\mathbf{y}_R - \mathbf{y}_C) + (\alpha_N + \alpha_F)(\mathbf{y}_R - \mathbf{y}_N),\\ &= \mathbf{X\Omega} + \delta_1(\mathbf{y}_R - \mathbf{y}_C) + \delta_2(\mathbf{y}_R - \mathbf{y}_N). \qquad (74)\end{aligned}$$

The nesting coefficient $\delta_1 = \alpha_C + \alpha_F$ measures the difference between the marginal budget shares of the Rotterdam model and the marginal budget shares of the CBS and FDLAIDS models. The nesting coefficient $\delta_2 = \alpha_N + \alpha_F$ measures the difference between the price coefficients of the Rotterdam model and price coefficients of the FDLAIDS and NBR models. Substituting (65)–(68) into (74) yields

$$\mathbf{w}_n d\ln\mathbf{q}_n = \mathbf{X\Omega} + \delta_1 d\ln\mathbf{Q} + \delta_2\left(\mathbf{w}_n d\ln\mathbf{q}_n - d\mathbf{w}_n - \mathbf{w}_n d\ln\mathbf{Q}\right), \forall n = 1,\ldots,N. \qquad (75)$$

Using (58) and (59), the bracketed term multiplied by δ_2 is equivalent to

$$\mathbf{w}_n d\ln\mathbf{q}_n - d\mathbf{w}_n - \mathbf{w}_n d\ln\mathbf{Q} = \mathbf{w}_n\sum_{j=1}^{N}\mathbf{w}_j d\ln\mathbf{p}_j - \mathbf{w}_n d\ln\mathbf{p}_n, \forall n = 1,\ldots,N,$$

and substituting this into (75) yields

$$\mathbf{w}_n d\ln\mathbf{q}_n = \mathbf{X\Omega} + \delta_1 d\ln\mathbf{Q} + \delta_2\left(\mathbf{w}_n\sum_{j=1}^{N}\mathbf{w}_j d\ln\mathbf{p}_j - \mathbf{w}_n d\ln\mathbf{p}_n\right). \qquad (76)$$

Since the FDLAIDS (Rotterdam) model has the same coefficient on the expenditure variable as in the CBS (NBR) model and the FDLAIDS (Rotterdam) model has the same coefficients on the price variables as in the NBR (CBS) model, we can rewrite $\mathbf{X\Omega}$ as

$$\mathbf{X\Omega} = \left[\delta_1\beta_n + (1-\delta_1)\theta_n\right]d\ln\mathbf{Q} + \sum_{j=1}^{N}\left[\delta_2\gamma_{nj} + (1-\delta_2)\pi_{nj}\right]d\ln\mathbf{p}_j. \qquad (77)$$

Hence, by substituting (77) into (76) and rearranging, Barten's synthetic model takes the form

$$\mathbf{w}_n d\ln\mathbf{q}_n = (a_i + \delta_1\mathbf{w}_n)d\ln\mathbf{Q} + \sum_{j=1}^{N}\left[b_{nj} - \delta_2\mathbf{w}_n(\delta_{nj} - \mathbf{w}_j)\right]d\ln\mathbf{p}_j, \qquad (78)$$

where δ_1 and δ_2 are nesting parameters, $a_n = \delta_1\beta_n + (1-\delta_1)\theta_n$ and $b_{nj} = \delta_2\gamma_{nj} + (1-\delta_2)\pi_{nj}$ are expenditure and price coefficients to be estimated, δ_{ij} is the Kronecker delta, $\mathbf{w}_n$ is a $t \times 1$ vector

Table 2. **Nesting Parameter Values for Differential Demand Systems**

	Barten's Synthetic Model		Generalized Ordinary Differential Demand System	
	δ_1	δ_2	φ_1	φ_2
Rotterdam	0	0	−1	1
FDLAIDS	1	1	0	0
CBS	1	0	0	1
NBR	0	1	−1	0

Source: Brown, Lee, and Seale (1994) and Eales, Durham, and Wessells (1997).

of expenditure shares for good n, p_j is a $t \times 1$ vector of prices of good j, and $\mathbf{Q}$ is a $t \times 1$ vector of Divisia volume indexes (equation (54)). Table 2 lists the values for δ_1 and δ_2 that allow Barten's synthetic model to collapse into the various nested models. The formulas for the elasticities of demand with respect to expenditure and prices and the adding-up, homogeneity, and symmetry conditions are listed in Table 1.

Matsuda (2005) showed that, at an individual level, Barten's synthetic model has the same marginal budget shares as generated by specific forms of Engel curves formulated by a Box-Cox transformation. If $\delta_1 = 0$, then the Engel curves are linear. On the other hand, if $\delta_1 = 1$, then the Engel curves are linear logarithmic.

Eales, Durham, and Wessells (1997) specified an alternative parameterization of Barten's synthetic model with an FDLAIDS dependent variable for the generalized ordinary differential demand system (GODDS). Instead of solving for α_R in (70), they solved for α_F and substituted α_F into (69) to yield

$$\mathbf{y}_F = \alpha_C(\mathbf{y}_F - \mathbf{y}_C) + \alpha_R(\mathbf{y}_F - \mathbf{y}_R) + \alpha_N(\mathbf{y}_F - \mathbf{y}_N) + \mathbf{X\Omega}. \tag{79}$$

Their alternative specification takes the form

$$d\mathbf{w}_n = (c_n + \varphi_1 \mathbf{w}_n) d\ln \mathbf{Q} + \sum_{k=1}^{N} \left[d_{nk} + \varphi_2 \mathbf{w}_n (\delta_{nk} - \mathbf{w}_k) \right] d\ln \mathbf{p}_k, \tag{80}$$

where $c_n = \varphi_1\beta_n + (1 - \varphi_1)\theta_n$ and $d_{nj} = \varphi_2\gamma_{nj} + (1 - \varphi_2)\pi_n$ are expenditure and price coefficients to be estimated. Table 2 lists the values for φ_1 and φ_2 that allow the GODDS to collapse into the various nested models. Adding-up, homogeneity, and symmetry restrictions and formulas for expenditure and price elasticities of demand for (80) are summarized in Table 1.

3.3. Summary of Approaches to Modeling Demand

The choice of model for a demand system is difficult. Ad hoc single-equation models might be found to fit the data better than other functional forms, but such models do not generally conform to demand theory. On the other hand, demand systems derived directly from a utility function are consistent with demand theory but require the use of restrictively simple functional forms that may not well represent the true data-generating process. Flexible functional forms may be flexible enough to approximate the data-generating process while allowing the imposition of restrictions from demand theory like Cournot and Engel aggregation, homogeneity, and symmetry. However, a difficulty with flexible functional forms is that the number of structural parameters required to maintain generality is large (Johnson, Hassan and Green 1984, p. 76). In addition, flexible functional forms may be too flexible in the sense that they allow elasticities of demand to take values that are implausible or inconsistent with priors. As discussed by Alston and Chalfant (1991a, 1991b), the choice of functional form is "whimsical" in that theory offers little or no guidance to the choice and the results from a particular choice may be "fragile"—sensitive to the choice even when a flexible functional form is employed. For instance, choosing an incorrect functional form could induce autocorrelation or other patterns that could be mistaken for structural change in data generated by a known, stable data-generating process with no autocorrelation in the sampling errors (Alston and Chalfant 1991a, 1991b).

Table 1a. Popular Functional Forms Used in Estimating the Demand for Food: Equations

Demand System	Estimating Form	Homogeneity	Adding-up	Symmetry
Demand Derived from Specified Utility Functions				
LES	$w_i = \frac{p_i \gamma_i}{M} + \beta_i \left(1 - \sum_{j=1}^{n} \frac{p_j \gamma_j}{M} \right)$	$\sum_{i=1}^{N} \beta_i = 1$	$\sum_{i=1}^{N} \beta_i = 1$	$\sum_{i=1}^{N} \beta_i = 1$
CES	$q_i = \frac{M(p_i / \gamma_i)^{-\sigma}}{\sum_{k=1}^{n} p_k (p_k / \gamma_k)^{-\sigma}}$ $\sigma = 1 \rightarrow$ Cobb-Douglas $\sigma = \inf \rightarrow$ Leontief $\sigma = 0 \rightarrow$ Linear	Holds	Holds	Holds
S-Branch	$p_i q_i = p_{Si}\gamma_{Si} + \left(\frac{\alpha_s^{\sigma} \beta_{Si}^{\sigma_S} p_{Si}^{1-\sigma_S} X_s^{(\sigma_S - \sigma)/(1-\sigma_S)}}{\sum_{r=1}^{S} \alpha_r^{\sigma} X_R^{(1-\sigma)/(1-\sigma_R)}} \right) \times \left(M - \sum_{r=1}^{S} \sum_{j \in r}^{n_R} p_{rj}\gamma_{rj} \right)$ where $X_S = \sum_{j \in S}^{n_S} \beta_{Sj}^{\sigma_S} p_{Sj}^{1-\sigma_S}$ $X_R = \sum_{j \in R}^{n_R} \beta_{Rj}^{\sigma_S} p_{Rj}^{1-\sigma_S}$	Holds	Holds	Holds

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Table 1b. Popular Functional Forms Used in Estimating the Demand for Food: Elasticities

Demand System	Price Elasticity	Expenditure Elasticity
Demand Derived from Specified Utility Functions		
LES	$\eta_{ik} = -\frac{\beta_i}{p_i q_i}\left(\delta_{ik}(M - \sum_{j=1}^{n} p_j \gamma_j) + p_k \gamma_k\right)$	$\eta_{iM} = \frac{\beta_i}{w_i}$
CES	$\eta_{ij} = -\sigma\delta_{ij} + \frac{(1-\sigma)\left(\frac{p_i^{(\sigma-1)/\sigma}}{\gamma_i}\right)^{-\sigma}}{\sum_{k=1}^{n} p_k \left(\frac{p_k}{\gamma_k}\right)^{-\sigma}}$	$\eta_{iM} = \left(\frac{1}{w_i}\right)\frac{\left(\frac{p_i^{(\sigma-1)/\sigma}}{\gamma_i}\right)^{-\sigma}}{\sum_{k=1}^{n} p_k \left(\frac{p_k}{\gamma_k}\right)^{-\sigma}}$
S-Branch	$\eta_{ii} = -\left(\frac{q_{Si} - \gamma_{Si}}{q_{Si}}\right) w_{Si} + \sigma(W_{Si} - w_{si})$ $+\sigma_S W_{Si}$ $w_{si} = \frac{p_{si}(q_{si} - \gamma_{si})}{m - \sum_{r=1}^{S} \sum_{j \in R}^{n_R} p_{rj}\gamma_{rj}}$ $W_{Si} = \frac{p_{Si}(q_{Si} - \gamma_{Si})}{m_s - \sum_{j \in S}^{n_S} p_{Sj}\gamma_{Sj}}$	$\eta_{iM} = \frac{p_{Si}(q_{Si} - \gamma_{Si})}{m - \sum_{r=1}^{S} \sum_{j \in R}^{n_R} p_{rj}\gamma_{rj}}$

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Table 1a. Popular Functional Forms Used in Estimating the Demand for Food: Equations (cont.)

Demand System	Estimating Form	Homogeneity	Adding-up	Symmetry
Demand Derived from Specified Indirect Utility or Expenditure Functions				
Indirect Addilog	$q_i = \frac{a_i b_i (M / p_i)^{b_i + 1}}{\sum_{i=1}^{n} a_i b_i (M / p_i)^{b_i + 1}}$	Holds	Holds	Holds
ITL	$w_i = \frac{\alpha_i + \sum_{j=1}^{n} \gamma_{ij} \log(p_j / M)}{1 + \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \gamma_{ij} \ln(p_j / M) \ln(p_i / M)}$	Holds	$\sum_{i=1}^{n} \gamma_{ij} = 0$ $\sum_{i=1}^{n} \alpha_i = 1$	$\gamma_{ij} = \gamma_{ji}$
AIDS	$w_i = \alpha_0 + \sum_{j=1}^{n} \gamma_{ij} \log p_j + \beta_i \log \frac{M}{P}$ where $\log P = \alpha_0 + \sum_{j=1}^{n} \alpha_j \log p_j + \frac{1}{2} \sum_{k=1}^{n} \sum_{l=1}^{n} \gamma_{kl} \log p_k \log p_l$ (or approximately for LAIDS, $\log P \approx \sum_{j=1}^{n} w_j \log p_j$)	$\sum_{j=1}^{n} \gamma_{ij} = 0$	$\sum_{i=1}^{n} \beta_i = 0$ $\sum_{i=1}^{n} \gamma_{ij} = 0$ $\sum_{i=1}^{n} \alpha_i = 1$	$\gamma_{ij} = \gamma_{ji}$
AITL	$w_i = \frac{\alpha_i + \sum_{j=1}^{n} \gamma_{ij} \log\left(\frac{p_i}{M}\right) \beta_i \left[a(p) \log M - \log P\right]}{\Delta}$ where $a(p) = \sum_{j=1}^{n} \alpha_j + \sum_{i=1}^{n} \sum_{j=1}^{n} \gamma_{ij} \log p_i - \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \gamma_{ij} \log M$ $\log P = \alpha_0 + \sum_{j=1}^{n} \alpha_j \log p_j + \frac{1}{2} \sum_{k=1}^{n} \sum_{l=1}^{n} \gamma_{kl} \log p_k \log p_l$ $\Delta = \sum_{i=1}^{n} \alpha_i + \sum_{i=1}^{n} \sum_{j=1}^{n} (\gamma_{ij} \log p_i / M)$	$\sum_{i=1}^{n} \sum_{j=1}^{n} \gamma_{ij} = 0$	$\sum_{i=1}^{n} \beta_i = 0$ $\sum_{i=1}^{n} \gamma_{ij} = 0$ $\sum_{i=1}^{n} \alpha_i = 1$	$\gamma_{ij} = \gamma_{ji}$

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Table 1b. Popular Functional Forms Used in Estimating the Demand for Food: Elasticities (cont.)

Demand System	Price Elasticity	Expenditure Elasticity
Demand Derived from Specified Indirect Utility or Expenditure Functions		
Indirect Addilog	$\eta_{ii} = -(1+b_i)+b_i w_i$	$\eta_{iM} = (1+b_i)+\sum_{i=1}^{n} b_i w_i$
ITL	$\eta_{ij} = \dfrac{\frac{\gamma_{ij}}{w_i} - \sum_{k=1}^{n}\gamma_{ki} - \delta_{ij}}{1+\sum_{k=1}^{n}\sum_{l=1}^{n}\gamma_{kl}\log\left(\frac{p_l}{M}\right)}$	$\eta_{iM} = 1+\dfrac{-\sum_{j=1}^{n}\frac{\gamma_{ij}}{w_i}+\sum_{i=1}^{n}\sum_{j=1}^{n}\gamma_{ij}}{1+\sum_{i=1}^{n}\sum_{j=1}^{n}\gamma_{ij}\log\left(\frac{p_j}{M}\right)}$
AIDS	$\eta_{ij} = \dfrac{\gamma_{ij}-\beta_i\left(\alpha_j-\sum_{k=1}^{n}\gamma_{ij}\log p_k\right)}{w_i} - \delta_{ij}$ $\left(\text{for LAIDS, } \eta_{ij} = \dfrac{\gamma_{ij}-\beta_i w_j}{w_i} - \delta_{ij}\right)$	$\eta_{iM} = 1+\dfrac{\beta_i}{w_i}$
AITL	$\eta_{ij} = \dfrac{\gamma_{ij}-\beta_i\left(\alpha_i+\sum_{j=1}^{n}\gamma_{ij}\log p_j\right)+\Omega_i}{w_i\Delta} - \delta_{ij}$ where $\Omega_i = \sum_{j=1}^{n}\gamma_{ij}(\beta_i\log M - w_i)$	$\eta_{iM} =$ $\dfrac{1+\sum_{i=1}^{n}\sum_{j=1}^{n}\gamma_{ij}w_i - \sum_{j=1}^{n}\gamma_{ij}+\beta_i(\Xi)}{w_i\Delta}$ where $\Xi = a(p)+\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}\gamma_{ij}\log M$

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Table 1a. Popular Functional Forms Used in Estimating the Demand for Food: Equations (cont.)

Demand System	Estimating Form	Homogeneity	Adding-up	Symmetry
Demand Derived from Differential Approximation to Marshallian Demand				
GODDS	$dw_i = (c_i + \varphi_1 w_i) d\log Q + \sum_{k=1}^{n} (d_{ik} + \varphi_2 w_i(\delta_{ik} - w_k)) d\log p_k$	$\sum_{j=1}^{n} d_{ij} = 0$	$\sum_{i=1}^{n} d_{ij} = 0$ $\sum_{i=1}^{n} c_i = -\varphi_1$	$d_{ik} = d_{ki}$
Barten's synthetic	$w_i d\ln q_i = (a_i + \delta_1 w_i) d\log Q + \sum_{k=1}^{n} (b_{ik} - \delta_2 w_i(\delta_{ik} - w_k)) d\log p_k$	$\sum_{j=1}^{n} b_{ij} = 0$	$\sum_{i=1}^{n} b_{ij} = 0$ $\sum_{i=1}^{n} a_i = 1 - \delta_1$	$b_{ik} = b_{ki}$
Rotterdam	$w_i d\log q_i = \beta_i d\log Q + \sum_{j=1}^{n} \gamma_{ij} d\log p_j$	$\sum_{j=1}^{n} \gamma_{ij} = 0$	$\sum_{i=n}^{n} \beta_i = 1$ $\sum_{i=1}^{n} \gamma_{ij} = 0$	$\gamma_{ij} = \gamma_{ji}$
FDLAIDS	$dw_i = \beta_i d\log Q + \sum_{k=1}^{n} \gamma_{ik} d\log p_k$	$\sum_{j=1}^{n} \gamma_{ij} = 0$	$\sum_{i=1}^{n} \beta_i = 0$ $\sum_{i=1}^{n} \gamma_{ij} = 0$	$\gamma_{ij} = \gamma_{ji}$
NBR	$dw_i = (\beta_i - w_i) d\log Q + \sum_{k=1}^{n} \gamma_{ik} d\log p_k$	$\sum_{j=1}^{n} \gamma_{ij} = 0$	$\sum_{i=1}^{n} \beta_i = 0$ $\sum_{i=1}^{n} \gamma_{ij} = 0$	$\gamma_{ij} = \gamma_{ji}$
CBS	$w_i d\log q_i = (\beta_i + w_i) d\log Q + \sum_{j=1}^{n} \gamma_{ij} d\log p_j$	$\sum_{j=1}^{n} \gamma_{ij} = 0$	$\sum_{i=n}^{n} \beta_i = 1$ $\sum_{i=1}^{n} \gamma_{ij} = 0$	$\gamma_{ij} = \gamma_{ji}$

Notes: w_i is the expenditure share of good i, p_i is the price, and q_i is the quantity.

Source: Authors' compilation.

Table 1b. Popular Functional Forms Used in Estimating the Demand for Food: Elasticities (cont.)

Demand System	Price Elasticity	Expenditure Elasticity
Demand Derived from Differential Approximation to Marshallian Demand		
GODDS	$\eta_{ik} = \frac{d_{ik} - c_i w_k}{w_i} + (\varphi_2 - 1)\delta_{ik} - (\varphi_1 + \varphi_2) w_k$	$\eta_{iM} = \frac{c_i + \varphi_1 w_i + w_i}{w_i}$
Barten's synthetic	$\eta_{ik} = -\left(\frac{a_i + \delta_1 w_i}{w_i}\right) w_k + \frac{b_{ik} - \delta_2 w_i (\delta_{ik} - w_k)}{w_i}$	$\eta_{iM} = \frac{a_i + \delta_1 w_i}{w_i}$
Rotterdam	$\eta_{ij} = \frac{\gamma_{ij} - \beta_i w_j}{w_i}$	$\eta_{iM} = \frac{\beta_i}{w_i}$
FDLAIDS	$\eta_{ij} = \frac{\gamma_{ij} - \beta_i w_j}{w_i} - \delta_{ij}$	$\eta_{iM} = 1 + \frac{\beta_i}{w_i}$
NBR	$\eta_{ij} = \frac{\gamma_{ij} - \beta_i w_j}{w_i} + w_j - \delta_{ij}$	$\eta_{iM} = \frac{\beta_i}{w_i}$
CBS	$\eta_{ij} = \frac{\gamma_{ij} - w_j(\beta_i + w_i)}{w_i}$	$\eta_{iM} = 1 + \frac{\beta_i}{w_i}$

Notes: w_i is the expenditure share of good i, p_i is the price, and q_i is the quantity.

Source: Authors' compilation.

4. OTHER ISSUES PERTAINING TO ESTIMATING DEMAND FOR FOOD

A range of other modeling issues must be addressed in any applied demand analysis. These include (a) considerations of whether and how to incorporate variables to represent structural change in the model, and (b) whether to seek to estimate elasticities of demand conditional on expenditure on a subgroup of goods or on all goods and what that implies about the appropriate assumptions to make regarding separability and aggregation. These and some other aspects of the analysis are dictated at least to some extent by the types of data that are available, with major distinctions between models based on aggregative time-series data versus individual cross-sectional data.

4.1. Structural Change

In the demand analysis literature, structural change refers to changes in parameters of a model. In some cases, individual utility functions of a stable population of consumers may change in response to changes in health concerns or other information. In other cases, changes in the demographic composition of a heterogeneous collection of consumers could result in different preferences for a representative consumer. Alternatively, preferences may be affected by strategies of firms such as advertising and product innovation.

In previous studies, parametric and nonparametric methods have been used to detect structural change. Nonparametric methods include testing whether data are consistent with axioms of revealed preference such as the generalized axiom of revealed preference (GARP), the strong axiom of revealed preference (SARP), and the weak axiom of revealed preference (WARP).[20] Consistency of the data with these axioms may be interpreted as an indication of the absence of structural change in demand. Within the literature on demand for food in the United States, GARP and WARP have been applied to demand for meat (Alston and Chalfant 1991a; Chalfant and Alston 1988; Moschini and Moro 1996) and to U.S. food demand and to the demand for all goods including food (Bergtold, Akobundu and Peterson 2004; Brester and Schroeder 1995; Brester and Wohlgenant 1991; Kastens and Brester 1996). These studies found that the data were consistent with WARP or GARP. However, various authors have suggested that these nonparametric tests tend to have low power (i.e., low odds of finding violations of WARP or GARP even when structural change is present) when applied to aggregate time-series data. In other words, the practitioner tends to under-reject the hypothesis of stable preferences (e.g., Alston and Chalfant 1991a).

[20] According to WARP, if a vector of goods, $\mathbf{q}_1(\mathbf{p}, M)$, at prices $\mathbf{p}$ and expenditure M is revealed to be preferred (R) to another bundle at the same prices and expenditure, $\mathbf{q}_2(\mathbf{p}, M)$, and $\mathbf{q}_1(\mathbf{p}, M) \neq \mathbf{q}_2(\mathbf{p}, M)$, then $\mathbf{q}_2(\mathbf{p}, M)$ cannot be revealed to be preferred to $\mathbf{q}_1(\mathbf{p}, M)$. Alternatively, $\mathbf{q}_1(\mathbf{p}, M)$ R $\mathbf{q}_2(\mathbf{p}, M) \leftrightarrow \mathbf{q}_1(\mathbf{p}, M)\cdot\mathbf{p}_1 \geq \mathbf{q}_2(\mathbf{p}, M)\cdot\mathbf{p}_1$. According to SARP, if $\mathbf{q}_1(\mathbf{p}, M)$ R $\mathbf{q}_2(\mathbf{p}, M)$ and $\mathbf{q}_2(\mathbf{p}, M)$ R $\mathbf{q}_3(\mathbf{p}, M)$ and so on until $\mathbf{q}_{n-1}(\mathbf{p}, M)$ R $\mathbf{q}_n(\mathbf{p}, M)$, then $\mathbf{q}_1(\mathbf{p}, M)$ is revealed to be preferred to $\mathbf{q}_n(\mathbf{p}, M)$. Under GARP, if $\mathbf{q}_1(\mathbf{p}, M)$ is strictly revealed to be preferred (RS) to another bundle, $\mathbf{q}_2(\mathbf{p}, M)$, and $\mathbf{q}_1(\mathbf{p}, M) \neq \mathbf{q}_2(\mathbf{p}, M)$, then $\mathbf{q}_2(\mathbf{p}, M)$ cannot be strictly revealed to be preferred to $\mathbf{q}_1(\mathbf{p}, M)$. Alternatively, $\mathbf{q}_1(\mathbf{p}, M)$ R $\mathbf{q}_2(\mathbf{p}, M) \leftrightarrow \mathbf{q}_1(\mathbf{p}, M)\cdot\mathbf{p}_1 > \mathbf{q}_2(\mathbf{p}, M)\cdot\mathbf{p}_1$.

In the parametric approach, demand functions are explicitly specified and their parameters estimated and tested for consistency with demand theory and stability. The first food demand studies that used flexible functional forms tested whether parameter estimates were consistent with negativity, homogeneity, and symmetry conditions (e.g., Blanciforti, Green and King 1986). A rejection of homogeneity, symmetry, or negativity restrictions could indicate a change in preferences. Testing for stability of parameters is another approach to detecting structural change. Tests for stable parameters, like the Chow test or the cumulative sum (CUSUM) test, have been applied to demand models to determine if structural change has occurred. Using these tests, several studies detected some parameter instability in models applied to meats as a separable group (e.g., Chavas 1983; Dahlgran 1988; Eales and Unnevehr 1988; Goodwin 1989; Menkhaus, Clair and Hallingbye 1985; Moschini and Meilke 1984; Nyankori and Miller 1982). Structural change can also be detected by explicitly modeling the structural changes. It is fairly conventional in models using time-series data to include a time trend to represent gradual changes over time and, for quarterly or monthly data, to include a set of dummy variables to capture seasonal changes. These can be interpreted as intercept shift variables—changes in the intercept parameter as a function of time. Likewise, a discrete-intercept-shift dummy variable can be used to measure changes after a particular point in the data. However, the use of a time trend or even a discrete intercept shift might be interpreted as an admission of ignorance of the true source or form of structural change. It is preferable if the relevant factors can be identified and measured and more-specific hypotheses about structural change can be devised and tested (Moschini and Moro 1996). Three specific sources of structural change that have been explored in the food demand literature are demographic changes, advertising, and changes in information about the health consequences of diet.

Diversity of preferences is supported by the significance of demographic effects (e.g., household size, age, region of residence) in cross-sectional studies. However, it has also been argued that relevant demographic variables also change over time, and demand systems that are estimated with time-series data will be affected by these changes. Relevant demographic changes include women's increased labor force participation with related increases in demand for convenience foods and changes in the age structure of the U.S. population. Many studies have argued that increases in the rate of women participating in the labor force have increased the demand for convenience foods because of the greater opportunity cost of women's time. Nayga and Capps (1992), Brown and Schrader (1990), Jones and Choi (1992), McGuirk et al. (1995), and Brown and Lee (1986) tested whether an increased demand for convenience manifested in increased demand for certain foods (FAFH, eggs, potatoes, meats, orange juice products). Changes in age structure and income distribution of the U.S. population have also been proposed as sources of structural change (Brown and Lee 1986; Capps and Havlicek 1984; Feng and Chern 2000). The effects of changes in age structure and income distribution may be difficult to distinguish from other smoothly changing and related variables, including changes in technology of food preparation (both at home and away from home), food products in the market, and the proportion of home-prepared meals, as well as women's wages and labor force participation.

Advertising has also been suggested as another source of structural change. Some questions addressed in the food demand literature include whether advertising changes consumers' buying behavior, whether advertising makes consumers more responsive or less responsive to price and income changes, and whether advertising for one commodity affects the demand for other commodities. Branded and generic advertising have been incorporated in single-equation models of food demand (e.g., Blisard, Sun and Blaylock 1991; Capps 1989; Chang, Green and Blaylock 1992) as well as in food demand systems (e.g., Brester and Schroeder 1995; Brown, Behr and Lee 1994; Brown and Lee 2000; Jones and Choi 1992; Kinnucan et al. 1997; Richards, Gao and Patterson 1999). The magnitude and significance of the estimated advertising effects have been mixed.[21]

Increasing attention has been devoted to the effects of information and health concerns on food demand. Scientific evidence has suggested that diets high in saturated fat and cholesterol are associated with greater risk of coronary heart disease, and such information has become more available to the public through popular media outlets (Brown and Schrader 1990). Specifically, certain foods like red meats and eggs have been associated with cholesterol and saturated fat. Some argue that increasing public awareness of these connections has led to changes in food consumption. Brown and Schrader (1990) introduced an index of cholesterol information to account for changes in consumer tastes and preferences for eggs, and that index was later extended to encompass general health information (Adhikari et al. 2007; Capps and Schmitz 1991; Chern, Loehman and Yen 1995; Feng and Chern 2000; Gao and Shonkwiler 1993; Kinnucan et al. 1997; McGuirk et al. 1995; Yen and Chern 1992) as well as a food scare information index (Piggott and Marsh 2004). Again, findings have been mixed concerning the magnitude and significance of the effects of information.

As noted, any particular findings of structural change in demand may reflect model specification error, such as a poor choice of functional form, rather than true structural change (Alston and Chalfant 1991a, 1991b; Chalfant and Alston 1988). The use of a flexible functional form specification does not eliminate this problem. Consequently, it often pays to examine the robustness of findings in terms of their sensitivity to changes in model specification or other aspects of the analysis.

4.2. Conditional versus Unconditional Elasticities of Demand

Two-stage budgeting is used in two ways in food demand analysis. Some studies specify the first and second stages to obtain unconditional demand elasticities (George and King 1971; Goddard and Glance 1989; Huang 1985, 1993; Seale, Regmi and Bernstein 2003; You, Epperson and Huang 1996). Because the number of observations in many time-series data sets is small, two-stage budgeting allows for estimation of disaggregated elasticities of demand. For example, the first-stage estimates of elasticities of demand could be based on aggregate groups like meats and eggs, vegetables and fruits, dairy products, and other foods. Assuming that each food group is weakly separable, the second-stage estimates can be based on specific foods within each group. Homogeneity and symmetry restrictions can be applied at either the first or second stage or both stages of estimation. Using (29) and (30), the unconditional elasticities of demand can be obtained from the first- and second-stage estimates.

[21] The studies listed here are a small sample of studies that address the effect of advertising on demand for food. For a more comprehensive list, see Kinnucan, Thompson, and Chang (1992) and Kaiser et al. (2005).

Alternatively, many studies model only the second stage of the two-stage budgeting process. This use of two-stage budgeting has been common in estimating demand for meat. Capps and Havlicek (1984) argued that the effects of prices of other foods and nonfoods on meat expenditure are relatively small; therefore, partial price elasticities are useful approximations of complete elasticities. In addition, Gao and Spreen (1994) and Heien and Pompelli (1988) argued that conditional meat elasticities are appropriate when the aggregate price elasticity of demand for meat is close to one in magnitude. However, as discussed in section 5, the average aggregate own-price elasticity of demand for meat is generally found to be considerably less than one in magnitude. In addition, many studies find large cross-price effects of prices of food and nonfood goods. Moschini, Moro, and Green (1994) tested whether food is weakly separable from nonfood and whether meat is weakly separable from nonmeat and found some support for the common practice of treating these goods as comprising separable groups. They argued, however, that, because of the endogeneity of group expenditure functions, estimates from a complete demand system may be more appropriate for policy analysis.

4.3. Type of Data and Statistical Considerations

Both cross-sectional and time-series data have been used in estimating U.S. food demand systems. Such data are available from public institutions like USDA and the Bureau of Labor Statistics (BLS) and from private institutions like A.C. Nielsen and Information Resource Inc. Each type of data has its own set of statistical problems and solutions. Quality-adjustment of prices and selection bias are the most common problems associated with estimation of demand models based on cross-sectional data, whereas autocorrelation and unit roots are commonly found in demand studies based on time-series data.

4.3.1. Cross-Sectional Data Sources

Survey data on cross sections of households have typically been used to study Engel relationships because the observed price variation is generally not meaningful or informative for estimating demand response to changes in prices of goods of constant quality (Chern, Huang and Lee 1993; George and King 1971). However, it has also been argued that prices may vary by region because of variations in supply and quality and that, by disentangling supply-induced price variation from quality-induced price variation, meaningful elasticities of demand with respect to price can be estimated using cross-sectional data (Cox and Wohlgenant 1986). Hence, increasingly, cross-sectional data are being used to estimate price elasticities (as well as income elasticities) by making use of the abundant information available about household characteristics and socioeconomic and demographic variables.

Surveys typically used in these analyses are the USDA Nationwide Food Consumption Survey (NFCS) and the BLS Consumer Expenditure Survey (CEX). Since the 1930s, the USDA has conducted seven nationally representative household food consumption surveys: 1936, 1942, 1948 (urban households only), 1955, 1965-66, 1977-78, and 1987-88. The 1977-78 and 1987-88 surveys contain data on expenditures on food and consumption of FAH by sample households (Buse, Eastwood and Wahl 1993).

The CEX is a nationwide household survey administered every year since 1984 and designed to represent the total U.S. civilian noninstitutionalized population. The CEX consists of two surveys: a diary and a quarterly interview survey. The purpose of the diary survey is to obtain detailed data on expenditures for small, frequently purchased items such as food and apparel while the interview survey obtains detailed data on expenditures for large items such as property, automobiles, and major appliances and on recurring expenses such as rent, utilities, and insurance premiums. Detailed data on expenditures on FAH and FAFH are collected in the diary survey for a two-week period. The interview survey contains data on expenditures on aggregate food categories like FAH and FAFH. The CEX diary data, in conjunction with consumer price indexes, can be used to estimate food demand systems. Some previous studies have utilized the CEX to estimate demand systems, treating the data as representing an annual cross section (Capps and Havlicek 1984; Kokoski 1986; Nelson 1991; Raper, Wanzala and Nayga 2002); others aggregated the data to form a time series (Chang and Green 1989, 1992; Feng and Chern 2000; Reed, Levedahl and Hallahan 2005; Reed, Levedahl and Clark 2003).

4.3.2. Time-Series Data Sources

Most studies that model demand for food in the United States are based on time-series data, such as per capita disappearance data from the USDA, aggregated CEX data from the BLS, Personal Consumption Expenditures (PCE) from the U.S. Department of Commerce's Bureau of Economic Analysis (BEA), and proprietary data from private companies. The USDA's disappearance data are constructed as a residual from available commodity supply less measurable nonfood uses. The commodity supply is based on records of annual commodity flows from production and consists of the sum of production, imports, and beginning stocks. For most commodity categories, measurable nonfood uses are farm inputs (feed and seed), exports, ending stocks, and industrial uses. These data do not distinguish between FAFH and FAH and do not measure food use of highly processed foods such as bakery products, frozen dinners, and soups in the finished product form (although the ingredients in those products are included as components of less highly processed foods such as sugar, flour, vegetables for processing, and fresh meat) (USDA, Economic Research Service 2009). Studies that utilize these quantity data for estimating demand parameters also use annual retail price indexes from the BLS. It should be noted, though, that the BLS price indexes distinguish between FAH and FAFH, so use of the BLS price indexes with the disappearance data may be inappropriate.

As previously discussed, the CEX diary and interview data are from cross sections of households, but these data can be aggregated to construct a weekly, monthly, quarterly, or annual time series of average expenditures per consuming unit. Since the observations occur on a weekly basis, assumptions need to be made in aggregating data to a monthly, quarterly, or annual basis. For example, how does one account for households that report expenditures for a week that straddles two months? The CEX expenditure data are usually used with price indexes from BLS.

A lesser known source of expenditure data is the PCE estimates from the BEA (U.S. Department of Commerce, BEA 2010). The detailed PCE estimates are extrapolations from

PCE benchmark levels that are estimated every five years using BEA's Benchmark Input-Output Accounts. The PCE data are estimated using the "commodity flow" method to develop estimates of the "best levels" for all final sales to consumers of goods and services by product category. The commodity flow method starts with total sales (or shipments) by producers of final goods and services. Then, using this estimate of total sales, BEA adds transportation costs, wholesale and retail trade margins, sales taxes, and imports and deducts changes in inventories, exports, sales to business, and sales to government. The method produces consistent estimates of the value of final sales to consumers and the allocation of those sales across product categories. Between benchmark years, the benchmark value for each PCE category is interpolated using annual, monthly, or quarterly retail or service trade sales data (Landefeld, Seskin and Fraumeni 2008). BEA also publishes price indexes that correspond to the PCE estimates. The indexes are constructed from the BLS's Consumer Price and Producer Price Indexes but are derived using the Fisher formula rather than the Laspeyres formula used by BLS.

4.3.3. Problems Encountered When Estimating Demand Using Cross-Sectional Data

Although cross-sectional data from surveys such as the CEX and NFCS capture demographic and socioeconomic characteristics of survey participants, several problems must be addressed when estimating demand models using cross-sectional data. First, unit costs in a cross section (household expenditure on a good divided by the quantity consumed) reflect more than spatial variation caused by supply shocks. Consumers choose the quality as well as the quantity of a good to purchase, and the calculated price reflects this choice. Cox and Wohlgenant (1986) suggested that unit costs should be adjusted for quality variation before substituting unit costs for prices in estimations of food demand functions. Usually, demographic, regional, and seasonal variables are used to proxy for quality and quality-adjusted prices (Gao, Wailes and Cramer 1995; Huang and Lin 2000).

The econometric treatment of zero consumption has also received considerable attention. In a cross section, especially if the data are highly disaggregated, some of the households surveyed will inevitably consume zero quantities of certain goods. If these observations are simply deleted, then selection bias is introduced into the estimation of the parameters of the demand system. A popular procedure to deal with zero consumption is to use a Heckman-type sample selection correction factor (Heien and Wessells 1990) or other similar two-step procedures (Yen, Kan and Su 2002; Yen, Lin and Davis 2008; Yen, Lin and Smallwood 2003).

4.3.4. Problems Encountered When Estimating Demand Using Time-Series Data

The main statistical problems with using time-series data in estimation are autocorrelation and nonstationarity. The error vector u_t is assumed to be an independent draw from a normal distribution with zero mean and temporally uncorrelated and to have a contemporaneous variance-covariance matrix Ω. Since $E(\mathbf{u}_t) = 0$ and $E(\mathbf{u}_t\mathbf{u}_t') = \boldsymbol{\delta}_{ii}'\Omega$ where δ_{ii} is the Kroenecker delta, $\boldsymbol{\Omega}$ is singular (Johnson, Hassan and Green 1984, p. 143).

The adding-up condition reflects the restriction that the sum of the expenditures for individual goods equals total expenditure. Thus, if the adding-up restriction is imposed in the estimation of a demand system, the variance-covariance matrix will be singular. Barten (1969) showed that the maximum likelihood estimator can still be obtained by arbitrarily deleting the *n*th equation of the system.[22] However, Berndt and Savin (1975) argued that this result does not hold for autoregressive errors, and a more reasonable assumption is that u_t follows an autoregressive process. One way to deal with first-order autocorrelation is by replacing the variables in the system with their first-order transforms and using feasible generalized least squares to solve for the parameters of the demand system (e.g., Chalfant 1987). Berndt and Savin (1975) showed that the adding-up property for expenditures implies that certain restrictions on the autoregressive parameter matrix, namely ρ, must be the same for each equation. Invariance of results can be achieved by a slightly modified seemingly-unrelated-regression (SUR) procedure using a consistent estimate of the variance-covariance matrix from an unrestricted equation-by-equation least-squares procedure in the first stage (e.g., Piggott et al. 1996; Yen and Chern 1992).

Several authors have argued that autocorrelation may be a symptom of model misspecification in that the dynamic effects of past consumption on current consumption are omitted from the model (e.g., Blanciforti, Green and King 1986; Deaton and Muellbauer 1980b, p. 77; Kesavan et al. 1993). Specifically, suppose the demand model can be specified as

$$w_i = \mathrm{f}(\mathbf{p}_t, M_t) + u_t, \tag{81}$$

where $u_t = \rho u_{t-1} + \varepsilon_t$, ρ is the autocorrelation coefficient and ε_t is a random error. u_{t-1} can be written as

$$u_{t-1} = w_{t-1} - \mathrm{f}(\mathbf{p}_{t-1}, M_{t-1}). \tag{82}$$

Substituting (82) into u_{t-1} and this into (81) yields the budget equation as a function of its lagged value:

$$w_t = \rho w_{t-1} + \mathrm{f}(p_t, M_t) - \rho \mathrm{f}(p_{t-1}, M_{t-1}) + \varepsilon_t .$$

Habit persistence is an extension of the preceding structural change discussion (see section 4.1). A static demand model assumes that tastes and preferences are constant. However, preferences may change as a result of consumers developing habits. For example, a consumer may become addicted to a certain product so that past consumption of a product will be associated with greater current consumption of it (Johnson, Hassan and Green 1984, p. 138). However, model misspecification other than omitted dynamic variables could lead to autocorrelation. Autocorrelation could reflect the use of an incorrect functional form (e.g., using a linear model when the true data-generating process is double-logarithmic) rather than omitted dynamic variables (Alston and Chalfant 1991a, 1991b).

Methods to specify a dynamic model of demand include the addition of an exogenous trend term that can be used to account for changing tastes and making the parameters of the demand system time-dependent. The second method is generally implemented by assuming that the intercept term in a static model, say α_i, depends linearly on previous consumption:

$$\alpha_i = \alpha_{i0} + \xi_i q_{i,t-1},$$

[22] The estimates will be invariant to what equation is dropped from the system so long as maximum likelihood estimation procedures are applied (Barten 1969). This is known as "Barten's invariance principle." Maximum likelihood estimates can be obtained by iterating over the variance-covariance matrix of the seemingly-unrelated-regression model (Greene 2003, p. 347).

where α_{i0} is constant, ξ_i is the habit parameter, and $q_{i,t-1}$ is the lagged quantity of the *i*th product (Blanciforti, Green and King 1986). Instead of lagged quantity, Manser (1976) suggested using lagged total expenditure while Kesavan et al. (1993) suggested incorporating dynamic behavior by adding lagged dependent and independent variables into demand models.[23]

One important issue when dealing with time-series data is whether the stochastic properties of economic time series can be characterized as nonstationary or as stationary around some deterministic trend. This issue is important because it indicates the nature of the response to a shock. If the underlying stochastic process is nonstationary, any shock has a permanent effect on the subsequent path of the variable. However, if it is stationary, the effect dies out and the variable converges toward its underlying trend. In other words, a stationary series yields consistent estimates whereas nonstationary series are asymptotically inconsistent. In addition, Granger and Newbold (1974) showed that inferences based on nonstationary data may be spurious. This means that the computed t-statistics and F-statistic may be significant, indicating a relationship between variables when, in fact, no relationship exists. Gao and Shonkwiler (1993) argued that, given the nature of most price and income time series, it is generally best to work with difference models rather than level-data models because the consequences of differencing when it is not needed are much less serious than those of failing to difference when it is appropriate.

[23] Incorporating dynamic variables through intercept shifts is known as translation and is commonly used to incorporate demographic and health information as preference shifters.

5. EVALUATION OF ESTIMATES OF ELASTICITIES OF DEMAND

Methods for quantifying the relationship between food prices, total expenditure, and food consumption are diverse, and the observed differences in estimates of elasticities of demand reflect this diversity among other things. Thus, it pays to scrutinize available elasticity estimates for their likely relevance and usefulness before using them in any particular analysis, with attention paid to aspects such as their consistency with economic theory and other priors and whether they are conditional on the appropriate concept of income. It is also desirable to have a sense of the likely accuracy of a given set of elasticities compared with other sets.

One way to evaluate the accuracy of demand elasticities from different studies is by comparing how well the elasticities predict past changes in food consumption given actual changes in prices and expenditures. Kastens and Brester (1996) found "conditional on price" consumption forecasts to be superior to direct statistical model forecasts.[24] In addition, conditional-on-price consumption forecasts can be used to compare the predictive performance of studies that vary greatly in terms of data, functional form, separability assumptions, and so on.

Kastens and Brester (1996) based their conditional-on-price consumption forecasts on the following model of demand, Q_n:

$$Q_n = \mathrm{Q}_n(\mathbf{p}, M), \forall n = 1, \ldots, N, \quad (83)$$

where the quantities consumed of N goods are a function of $\mathbf{p}$, a vector of food prices, and M, total expenditure on N goods. Taking the total derivative of (83) and converting the partial derivatives into elasticities yields

$$d \ln Q_n = \sum_{k=1}^{N} \eta_{nk} d \ln p_k + \eta_{nM} d \ln M, \forall n = 1, \ldots, N, \quad (84)$$

where $d \ln Q$, $d \ln p$, and $d \ln M$ are approximately the proportional changes in Q, p, and M for goods denoted by subscripts $n = 1, \ldots, N$, and η_{nk} and η_{nM} are price and income elasticities of demand.[25] Given the actual proportional changes in p and M, sets of elasticities of demand with respect to prices and expenditure can be evaluated by comparing the implied predictions of $d \ln Q$ from (84) with the actual proportional changes in Q.

Depending on the data source, the estimates of elasticities of demand may or may not allow for a distinction between FAFH and FAH. For example, per capita disappearance data from the USDA Economic Research Service make no distinction between FAFH and FAH.

[24] An anonymous reviewer pointed out that the forecasting method discussed and used in this study is actually conditional on prices and total expenditure. To be consistent with the naming convention introduced by Kastens and Brester (1996), we refer to this method of forecasting as "conditional on price" although we acknowledge that the forecasting method is conditional on prices and total expenditure.

[25] An anonymous reviewer pointed out that, when the basic conditional-on-price forecast presented in (84) is multiplied by w_n, which is the expenditure share for good n, then equation (84) becomes the Rotterdam demand system (i.e., equation (53)).

On the other hand, expenditures and prices from the CEX, the NFCS, and scanner data do make this distinction.[26] Thus, (84) is modified in two ways to reflect the distinction between FAH and FAFH (where NF denotes nonfood):

$$\widehat{d\ln Q_{nt}} = \sum_{k=1}^{N-2} \eta_{nk}^{FAH} d\ln p_{kt}^{FAH} + \eta_{nk}^{FAFH} d\ln p_{kt}^{FAFH} + \eta_{nk}^{NF} d\ln p_{kt}^{NF} + \eta_{nM} d\ln M, n = 1,\ldots,N, \quad (85)$$

$$\widehat{d\ln Q_{nt}} = \sum_{k=1}^{N-1} \eta_{nk} d\ln p_{kt} + \eta_{nk}^{NF} d\ln p_{kt}^{NF} + \eta_{nM} d\ln M, n = 1,\ldots,N, \quad (86)$$

where $\widehat{d\ln Q_{nt}}$ are predicted values of quantities demanded. Equation (85) is the conditional-on-price forecast model used for estimates of elasticities of demand based on price and expenditure data that distinguished between FAFH and FAH and, accordingly, included $N-2$ FAH products, an FAFH composite, and a nonfood composite. Equation (86) is the conditional-on-price forecast model used for estimates of elasticities of demand based on price and expenditure data that did not make this distinction and, accordingly, included $N-1$ food products and a nonfood composite.

To predict annual percentage changes in quantities of foods consumed using elasticities from different demand studies in equations (85) and (86), we require data on the annual proportional changes in prices and total expenditure. In section 4.3, we identified two sources of price and expenditure data available to the public: Fisher-Ideal price indexes and expenditures (PCE) from BEA and Laspeyres price indexes (the BLS consumer price index) and expenditures (CEX) from BLS. We used both sets of price and expenditure data to approximate $d\ln P$ and $d\ln M$.

The performance of the various demand systems can be assessed by calculating the mean absolute error (MAE) for each good, n in the system:

$$MAE_n = \frac{1}{T}\sum_{t=1}^{T}\left| d\ln Q_{nt} - \widehat{d\ln Q_{nt}} \right| \times 100\%, \forall n = 1,..,N, \quad (87)$$

where $\widehat{d\ln Q_{nt}}$ is the predicted annual percentage change in quantity consumed of good n for time period t from (85) or (86) and $d\ln Q_{nt}$ is the actual annual percentage change in quantity consumed of the good. The quantity changes were measured differently for demand systems based on sources of data that distinguished FAFH from FAH and those that did not. To evaluate estimates of elasticities of demand based on price and expenditure data that did not distinguish between FAFH and FAH, the Economic Research Service per capita disappearance data were used to proxy for the "actual" quantities in (87). To evaluate estimates of elasticities of demand based on price and expenditure data that did distinguish between FAFH

[26] The studies that use A.C. Nielsen or Information Research Inc.'s InfoScan data are based on price and quantity data for food purchased at retail establishments and exclude FAFH purchases (see Information Research Inc.'s InfoScan website at *www.symphonyiri.com/productsolutions/allproducts/allproductsdetail/tabid/159/productid/83/default.aspx* or the A.C. Nielsen website at *www.en-us.nielsen.com/content/nielsen/en_us/measurement/consumer_measurement.html*).

and FAH, we used implicit quantity indexes as proxies for the actual quantities in (87).[27] Two implicit quantity indexes were constructed: one using the BEA price indexes and expenditures and the other using the BLS price indexes and expenditures. While the BEA annual series is longer than the BLS annual series (1960–2007 versus 1984–2006), the BLS series includes expenditure estimates by income group.

Park et al. (1996), Raper, Wanzala, and Nayga (2002), and Huang and Lin (2000) presented elasticities of demand for food by income group. Hence, to evaluate elasticities from these models, we calculated implicit quantity indexes by income group. Using the BLS data, we first constructed expenditure series that closely match the income groups in each study. Park et al. (1996) and Raper, Wanzala, and Nayga (2002) estimated elasticities of demand for foods by "poverty" and "nonpoverty" groups, while Huang and Lin (2000) defined "low income" as income at 130% of the poverty line or lower and "high income" as income at 300% of the poverty line or higher. According to the U.S. Census Bureau (2010), the poverty threshold for a household of two individuals ranged from $6,000 in 1984 to $13,000 in 2006. Hence, we defined low-, middle-, and high-income groups relative to these thresholds and nonpoverty and poverty groups likewise. We then calculated implicit quantity indexes for each retail product by income group.

As previously discussed, conditional elasticities may differ from unconditional elasticities, so the evaluation of estimates of elasticities of demand using (87) is limited to estimates from demand systems that include all major food groups or all major food groups and nonfood (Tables 3 and 4). Appendix Tables A-2 and A-3 contain a list of studies in which the estimates are conditional on expenditure on one major food group (e.g., meats, dairy, fruits and vegetables, fats and oils).

The mean own-price elasticity estimates that we evaluated are reported in Tables 5 and 6. These tables illuminate some interesting differences in characteristics between studies that used data that distinguished between FAFH and FAH (Table 5) and those that used data that did not (Table 6). First, note that all of the estimates of own-price elasticities included in Table 6 (based on data that did not distinguish FAH from FAFH) were based on time-series data, while most of the estimates in Table 5 were based on cross-sectional data. The average estimates of own-price elasticities in Table 6 are consistently smaller in magnitude than their counterparts in Table 5 with the exception of the ones for beef. This is somewhat surprising in that three studies found FAFH to be more price and expenditure (income) elastic than FAH (Nayga and Capps 1992; Park et al. 1996; Piggott 2003; Raper, Wanzala and Nayga 2002), which would imply that the estimates in Table 6 would be larger in magnitude because these

[27] The product of a price index and a quantity index, $P = \mathrm{P}(\bar{p}, p, \bar{q}, q)$ and $Q = \mathrm{Q}(\bar{p}, p, \bar{q}, q)$, respectively, with base-year price $\bar{p}$ and base quantity $\bar{q}$ should be equal to the expenditure ($p \times q$) relative to that in the base year:

$$\mathrm{P}(\bar{p}, p, \bar{q}, q)\mathrm{Q}(\bar{p}, p, \bar{q}, q) = \frac{pq}{\bar{p}\bar{q}}.$$

This is known as the product test. Hence, the implicit quantity index is defined as

$$\mathrm{Q}(\bar{p}, p, \bar{q}, q) = \frac{pq}{\bar{p}\bar{q}} \frac{1}{\mathrm{P}(\bar{p}, p, \bar{q}, q)}$$

(Diewert 1993).

Table 3. Studies That Estimated Demand Systems Conditional on Expenditure on Food or on Food and Goods Based on Data That Distinguished FAH from FAFH

Study						
Author	Year	Table No.	Conditional On	Population	Data Frequency	Data Years
Capps & Havlicek	1984	2	Goods	United States	Cross section	1972–1974
		3	Goods	United States	Cross section	1972–1974
Feng & Chern	2000	3	Food	United States	Monthly	1981–1995
Heien & Wessells	1988	1	Food	United States	Cross section	1977–1978
Huang & Lin	2000	4	Food	United States	Cross section	1987–1988
		5	Food	High	Cross section	1987–1988
		6	Food	Middle	Cross section	1987–1988
		7	Food	Low	Cross section	1987–1988
Nayga & Capps	1992	3	Goods	United States	Monthly	1970–1989
Park, Holcombe, Raper & Capps	1996	7	Food	Nonpoverty	Cross section	1987–1988
		7	Food	Poverty	Cross section	1987–1988
Piggott	2003	4	Food	United States	Annual	1968–1999
		4	Food	United States	Annual	1968–1999
Raper, Wanzala & Nayga	2002	6	Food	Nonpoverty	Cross section	1992–1993
		6	Food	Poverty	Cross section	1992–1993
Reed, Levedahl & Hallahan	2005	3	Goods	United States	Quarterly	1982–2000
Yen, Lin & Smallwood	2003	2	Food	Food stamp	Cross section	1996–1997
Blanciforti	1984	10	Food	United States	Annual	1948–1978
		2	Food	United States	Annual	1948–1978
		3	Food	United States	Annual	1948–1978
		5	Food	United States	Annual	1948–1978
		6	Food	United States	Annual	1948–1978
		7	Food	United States	Annual	1948–1978
		8	Food	United States	Annual	1948–1978
		9	Food	United States	Annual	1948–1978

Notes: AIDS=almost ideal demand system (Deaton and Muellbauer 1980a); LAIDS=linearized AIDS (Deaton and Muellbauer1980a); GAIDS=generalized AIDS (Bollino 1987); GFGAIDS=globally, flexible, generalized AIDS (Piggott 2003); LES=linear expenditure system (Klein and Rubin 1947); ITL=indirect translog (Christensen, Jorgensen and Lau 1975); SAI=semiflexible AIDS (Moschini 1998).

† Dynamic means the authors of the study included a lagged dependent variable in their specification of demand.

‡ Autocorrelation means the authors of the study corrected the covariance-variance matrix for autocorrelation.

	Included Variables							Parameter Restrictions	
	Demand System	Advertising	Health Index	Demographic	Structural Change	Dynamic†	Autocorrelation‡	Symmetry	Homogeneity
	S1-Branch	No	No	Yes	No	No	Yes	Yes	Yes
	S1-Branch	No	No	Yes	No	No	No	Yes	Yes
	LAIDS	No	Yes	Yes	No	No	No	Yes	Yes
	LAIDS	No	No	Yes	No	No	No	Yes	Yes
	LAIDS	No	No	Yes	No	No	No	Yes	Yes
	LAIDS	No	No	Yes	No	No	No	Yes	Yes
	LAIDS	No	No	Yes	No	No	No	Yes	Yes
	LAIDS	No	No	Yes	No	No	No	Yes	Yes
	LAIDS	No	No	Yes	No	Yes	No	Yes	Yes
	LES	No	No	Yes	No	No	No	Yes	Yes
	LES	No	No	Yes	No	No	No	Yes	Yes
	GAIDS	No	No	No	No	No	No	Yes	Yes
	GFGAIDS	No	No	No	No	No	No	Yes	Yes
	LES	No	No	Yes	No	No	No	Yes	Yes
	LES	No	No	Yes	No	No	No	Yes	Yes
	SAI	No	No	No	No	No	Yes	Yes	Yes
	ITL	No	No	No	No	No	No	Yes	Yes
	AIDS	No	No	No	No	Yes	Yes	Yes	Yes
	LAIDS	No	No	No	No	No	No	No	No
	LAIDS	No	No	No	No	No	No	No	Yes
	LAIDS	No	No	No	No	Yes	No	No	No
	LAIDS	No	No	No	No	Yes	No	No	Yes
	AIDS	No	No	No	No	No	No	Yes	Yes
	AIDS	No	No	No	No	Yes	No	Yes	Yes
	AIDS	No	No	No	No	No	Yes	Yes	Yes

Table 4. Studies That Estimated Demand Systems Conditional on Expenditure on Food or on Food and Goods Based on Data That Did Not Distinguish FAH from FAFH

Study						
Author	Year	Table No.	Conditional On	Population	Data Frequency	Data Years
Blanciforti & Green	1983	1	Food	United States	Annual	1948–1978
Blanciforti, Green & King	1986	5.3	Food	United States	Annual	1948–1978
		5.3	Food	United States	Annual	1948–1978
Brester & Schroeder	1995	3	Goods	United States	Quarterly	1970–1993
Brester & Wohlgenant	1991	3	Goods	United States	Annual	1962–1989
Choi & Sosin	1990	2	Food	United States	Annual	1953–1984
Eales & Unnevehr	1988	4	Goods	United States	Annual	1965–1985
		5	Goods	United States	Annual	1965–1985
Eales & Unnevehr	1993	A2	Goods	United States	Annual	1962–1989
George & King	1971	5	Goods	United States	Annual	1946–1968
Heien	1982	3	Goods	United States	Annual	1947–1979
Heien	1983	3	Goods	United States	Quarterly	1967–1979
Huang	1985	2	Goods	United States	Annual	1953–1983
		D	Goods	United States	Annual	1953–1983
Huang	1993	1	Goods	United States	Annual	1953–1990
Kastens & Brester	1996	1	Goods	United States	Annual	1923–1992
		2	Goods	United States	Annual	1923–1992
		3	Goods	United States	Annual	1923–1992
Marsh, Schroeder & Mintert	2004	7	Goods	United States	Quarterly	1982–1998
Moschini, Moro & Green	1994	4	Goods	United States	Annual	1947–1978
Richards, Gao & Patterson	1999	3	Food	United States	Annual	1951–1994
Wang & Bessler	2003	1	Food	United States	Quarterly	1975–1989
You, Epperson & Huang	1996	1	Goods	United States	Annual	1960–1993

Notes: AIDS=almost ideal demand system (Deaton and Muellbauer 1980a); LAIDS=linearized AIDS (Deaton and Muellbauer 1980a); FDLAIDS=first-differenced LAIDS (Deaton and Muellbauer 1980a); LES=linear expenditure system (Klein and Rubin 1947); ACS=almost complete system (Heien 1982); ITL=indirect translog (Christensen, Jorgensen and Lau 1975); DL=double log; FDDL=first-differenced double log.

† Dynamic means the authors of the study included a lagged dependent variable in their specification of demand.

‡ Autocorrelation means the authors of the study corrected the covariance-variance matrix for autocorrelation.

	Included Variables						Parameter Restrictions	
Demand System	Advertising	Health Index	Demographic	Structural Change	Dynamic†	Autocorrelation‡	Symmetry	Homogeneity
LES	No	No	No	No	No	No	Yes	Yes
LAIDS	No	No	No	No	No	No	No	Yes
LAIDS	No	No	No	No	No	No	Yes	Yes
Rotterdam	Yes	No	No	No	No	No	Yes	Yes
Rotterdam	No	No	No	No	No	No	Yes	Yes
ITL	No	No	No	Yes	No	No	Yes	Yes
FDLAIDS	No	No	No	No	No	No	Yes	Yes
FDLAIDS	No	No	No	No	No	No	Yes	Yes
FDLAIDS	No	No	No	Yes	No	No	Yes	Yes
DL	No	No	No	No	No	No	Yes	Yes
ACS	No	No	No	No	No	No	Yes	Yes
ACS	No	No	No	No	Yes	Yes	Yes	Yes
Differential	No	No	No	No	No	No	Yes	Yes
Differential	No	No	No	No	No	No	Yes	Yes
Differential	No	No	No	No	No	No	Yes	Yes
FDLAIDS	No	No	No	No	No	No	Yes	Yes
FDLAIDS	No	No	No	No	No	No	Yes	Yes
FDDL	No	No	No	No	No	No	Yes	Yes
Rotterdam	No	Yes	No	No	No	Yes	Yes	Yes
Rotterdam	No	No	No	No	No	No	Yes	Yes
LAIDS	Yes	Yes	Yes	No	Yes	No	No	No
LAIDS	No	No	No	No	No	No	Yes	Yes
Differential	No	No	No	Yes	No	No	Yes	Yes

Table 5. Own-Price Elasticities of Demand for Selected Demand Systems Conditional on Expenditure on Food or on Food and Goods Based on Data That Distinguished FAH from FAFH

Food Category	Disaggregated Food Product	No. of Estimates	Own-Price Elasticity of Demand: Average	Standard Deviation	Min. Value	Max. Value
FAH	FAH	3	−0.48	0.06	−0.54	−0.43
Cereals and bakery products	Cereals and bakery products	3	−0.86	0.22	−1.00	−0.61
	Bakery products	8	−0.33	0.10	−0.49	−0.17
	Cereals	8	−0.41	0.26	−0.74	−0.09
Dairy products	Dairy products	8	−0.85	0.12	−1.07	−0.73
	Cheese	2	−0.13	0.17	−0.24	−0.01
	Fluid, evaporated, and dried milk	2	−0.50	0.04	−0.53	−0.47
Eggs	Eggs	5	−0.17	0.24	−0.59	0.02
Fats and oils	Fats and oils	9	−0.62	0.26	−1.00	−0.33
Fruits and vegetables	Fruits and vegetables	4	−0.91	0.14	−0.99	−0.71
	Fruits	6	−0.61	0.15	−0.75	−0.34
	Fruits, fresh	1	−0.82	–	−0.82	−0.82
	Fruits, processed	1	−0.27	–	−0.27	−0.27
	Vegetables	6	−0.61	0.18	−0.74	−0.32
	Vegetables, fresh	1	−0.61	–	−0.61	−0.61
	Vegetables, processed	1	−0.56	–	−0.56	−0.56
Meats	Meats	3	−0.86	0.22	−1.00	−0.61
	Beef	7	−0.42	0.15	−0.73	−0.26
	Pork	8	−0.78	0.36	−1.52	−0.45
	Meats other (including lamb/mutton)	5	−0.44	0.19	−0.75	−0.29
	Poultry	9	−0.67	0.31	−1.28	−0.22
	Fish	8	−0.73	0.59	−2.02	−0.24
Sugars and sweets	Sugars and sweets	2	−0.99	0.01	−1.00	−0.99
FAFH	FAFH	8	−1.02	0.28	−1.50	−0.69
Nonfood	Nonfood	2	−0.93	0.10	−1.00	−0.86

Table 6. **Own-Price Elasticities of Demand for Selected Demand Systems Conditional on Expenditure on Food or on Food and Goods Based on Data That Did Not Distinguish FAH from FAFH**

			Own-Price Elasticity of Demand			
Food Category	Disaggregated Food Product	No. of Estimates	Average	Standard Deviation	Min. Value	Max. Value
Cereals and bakery products	Cereals and bakery products	18	−0.51	0.21	−0.80	−0.15
	Bakery products	1	−0.15	NA	−0.15	−0.15
	Cereals	4	−0.27	0.09	−0.39	−0.18
	Flour	3	−0.07	0.25	−0.30	0.19
	Rice	2	−0.23	0.12	−0.32	−0.15
Dairy products	Dairy products	4	−0.10	0.07	−0.19	−0.04
	Cheese	3	−0.42	0.10	−0.52	−0.33
	Fluid, evaporated, and dried milk	3	−0.50	0.16	−0.63	−0.33
	Milk, fluid	2	−0.30	0.06	−0.35	−0.26
	Ice cream	2	−0.32	0.29	−0.53	−0.12
Eggs	Eggs	8	−0.18	0.09	−0.32	−0.08
Fats and oils	Fats and oils	6	−0.07	0.08	−0.14	0.09
	Butter	4	−0.85	0.76	−1.93	−0.17
	Margarine	4	−0.29	0.04	−0.35	−0.25
Fruits and vegetables	Fruits and vegetables	15	−0.38	0.24	−0.66	0.32
	Fruits	3	−0.42	0.36	−0.83	−0.20
	Fruits, fresh	2	−1.71	1.85	−3.02	−0.40
	Apples, fresh	3	−0.39	0.29	−0.72	−0.20
	Bananas, fresh	3	−0.47	0.12	−0.62	−0.40
	Oranges, fresh	3	−0.80	0.23	−1.00	−0.55
	Fruits, processed	2	−0.47	0.17	−0.59	−0.35
	Vegetables	2	−0.11	0.04	−0.14	−0.08
	Vegetables, fresh	2	−0.19	0.22	−0.35	−0.03
	Carrots, fresh	2	−0.27	0.32	−0.50	−0.04
	Lettuce, fresh	2	−0.14	0.00	−0.14	−0.14
	Onions, fresh	2	−0.22	0.04	−0.25	−0.20
	Tomatoes, fresh	2	−0.47	0.12	−0.56	−0.39
	Potatoes	3	−0.36	0.04	−0.39	−0.31
	Vegetables, processed	2	−0.50	0.51	−0.86	−0.14
	Tomatoes, canned	2	−0.28	0.15	−0.38	−0.18
	Peas, canned	2	−0.44	0.36	−0.69	−0.19
Meats	Meats	18	−0.63	0.24	−1.05	−0.34
	Red meats	1	−0.97	NA	−0.97	−0.97
	Beef	13	−0.70	0.20	−0.95	−0.28
	Pork	15	−0.68	0.14	−0.95	−0.41
	Meats, other (including lamb/mutton)	1	−1.37	NA	−1.37	−1.37
	Poultry and fish	4	−0.69	0.01	−0.70	−0.68
	Poultry	7	−0.37	0.28	−0.89	−0.08
	Chicken	4	−0.39	0.44	−0.80	0.23
	Turkey	2	−0.30	0.54	−0.68	0.08
	Fish	2	−0.11	0.17	−0.23	0.01
Sugars and sweets	Sugars and sweets	5	−0.03	0.14	−0.16	0.18
	Sugar	2	−0.15	0.13	−0.24	−0.05
	Sweets	2	0.03	0.05	−0.01	0.07
Nonfood	Nonfood	17	−1.10	0.25	−1.74	−0.98

estimates include FAFH and FAH. The average own-price elasticities tend to be more consistent (smaller standard deviation) across studies in Table 6 compared to those in Table 5.

Tables 7 and 8 present MAE estimates for a selected group of studies. In Table 7 (studies based on data that distinguished FAH from FAFH), the average MAE for the predictions of percentage changes in quantities across all commodities for a particular study is between 3% and 8%. The estimates of price and income elasticities of demand for "low income" and "poverty groups" have the greatest percentage error. The best-performing sets of estimates of elasticities of demand include those of Huang and Lin (2000) and Feng and Chern (2000) for the U.S. population as a whole and those of Raper, Wanzala, and Nayga (2002) for "nonpoverty" groups.

In Table 8 (studies based on data that did not distinguish between FAH and FAFH), the average MAE across all food products for a particular study ranges between 2% and 4%. Most of the estimated elasticities of demand can be used to predict the actual quantities for each food group with less than 5% error with the exception of Heien (1982, 1983), and Brester and Schroeter (1995). The results shown in Table 7 cannot be compared with those in Table 8 because the measures of actual quantities differ (the actual quantity estimates are based on Economic Research Service per capita disappearance data versus implicit quantity indexes derived from expenditures and price indexes).

Table 7. **Mean Absolute Error for Selected Studies Based on Data That Distinguished FAFH from FAH**

Table Number	Number of Goods	Implicit Quantity Indexes Based on BLS Data to Proxy for Actual Quantity‡: Percent of Goods with MAE >5%	Implicit Quantity Indexes Based on BLS Data to Proxy for Actual Quantity‡: Average MAE (percent)	Implicit Quantity Indexes Based on BEA Data to Proxy for Actual Quantity‡: Percent of Goods with MAE >5%	Implicit Quantity Indexes Based on BEA Data to Proxy for Actual Quantity‡: Average MAE (percent)
Study: Park et al. (1996)[a]					
7 – Nonpoverty†	12	17	4.10	–	–
7 – Poverty†	12	67	8.09	–	–
Study: Huang & Lin (2000)					
4 – United States	13	0	3.30	15.39	3.90
5 – High income*	13	15	3.88	–	–
6 – Middle income*	13	69	5.96	–	–
7 – Low income*	13	54	6.33	–	–
Study: Feng & Chern (2000)					
3 – United States	8	0	3.45	12.50	3.67
Study: Raper, Wanzala & Nayga (2002)[a]					
6 – Poverty†	9	89	6.91	–	–
6 – Nonpoverty†	9	0	3.50	–	–
Study: Reed, Levedahl & Hallahan (2005)					
3 – United States	7	14	3.61	28.57	4.02

Notes:

[a] Park et al. (1996) and Raper, Wanzala, and Nayga (2002) presented only own-price and expenditure elasticities of demand. We calculated the cross-price elasticities using estimates of parameters presented in the respective papers.

† The implicit quantity indexes for poverty and nonpoverty groups were based on CEX expenditures by group and the Consumer Price Index for each good. The poverty threshold varies by year and ranged between $6,000 and $13,000 between 1984 and 2006 (see *www.census.gov/hhes/www/poverty/histpov/hstpov1.html*).

* The implicit quantity indexes for low-, middle- and high-income groups were based on CEX expenditures by group and the Consumer Price Index for each good. Huang and Lin (2000) defined low income as being 130% or below the poverty threshold and high income as being 300% or above the poverty threshold. Hence, the expenditures used to calculate the implicit quantity indexes are based on these expenditure categories.

‡ Proportional changes in implicit quantity indexes based on BEA or BLS price and expenditure data were used as proxies for proportional changes in actual quantities in the MAE formula. Proportional changes in prices were estimated using BEA Fisher-Ideal or BLS Laspeyres Consumer Price Indexes.

Table 8. Mean Absolute Error for Selected Studies Based on Data That Did Not Distinguish FAFH from FAH

Study	Table Number	Number of Goods	Share (percent) of Goods with MAE >5%	Average MAE (percent)
Blanciforti (1984)	10	4	0	2.33
	7	4	0	2.51
	8	4	0	2.05
	9	4	0	2.09
Heien (1982)	3	13	31	5.93
Heien (1983)	3	5	20	2.92
Blanciforti & Green (1983)	1	4	0	2.32
Huang (1985)	2	8	0	2.23
Eales & Unnevehr (1988)	4	5	0	2.22
Choi & Sosin (1990)	2	3	0	2.84
Huang (1993)	1	8	0	2.16
Eales & Unnevehr (1993)	A2	5	0	2.03
Moschini, Moro & Green (1994)	4	7	0	2.10
Brester & Schroeder (1995)	3	4	25	3.01
You, Epperson & Huang (1996)	1	11	9	2.21
Kastens & Brester (1996)	1	7	0	2.36
	2	7	29	3.41
	3	7	0	2.34
Wang and Bessler (2003)	1	5	0	2.08

Note: Price indexes for FAH prices were used only to approximate the proportional change in price for the conditional-on-price forecast in equation (86).

6. NEW ESTIMATES OF ELASTICITIES OF DEMAND

As shown in the previous section, many studies based on time-series data did not separate FAFH from FAH. Since it is likely that FAFH products differ from FAH products in terms of the responsiveness of consumption to prices and expenditure, we used data sets that distinguish between the two product categories: (a) annual expenditure and price data from the BEA and (b) monthly expenditure and price data from the BLS. We used these data to construct implicit quantity indexes and budget shares for seven categories of FAH (cereals and bakery products, meat, eggs, dairy products, fruits and vegetables, other foods, and nonalcoholic beverages), FAFH, alcoholic beverages, and nonfood.

As suggested by Gao and Shonkwiler (1993), we tested the data for unit roots and found strong evidence supporting long-run unit roots in the annual BEA data and seasonal unit roots in the monthly BLS data. This suggests that demand should be modeled using a structural form that allows for first- and twelfth-differencing. Hence, in this section, we present new estimates of elasticities of demand using Barten's synthetic model (equation (78)). Because Barten's synthetic model nests four differential-type demand systems (i.e., Rotterdam, FDLAIDS, CBS, and NBR models), we also tested whether the data follow one of these more parsimonious forms.

In addition to presenting first-stage estimates of elasticities of demand for aggregate food categories and a nonfood composite, we present estimates of second-stage elasticities of demand for disaggregated fruits and vegetables. In the previous section we noted that studies that estimate elasticities of demand that distinguish FAFH from FAH are usually for aggregated food groups. To estimate elasticities of demand for disaggregated fruits and vegetables, we constructed monthly quantity indexes and budget shares for apples, bananas, citrus, other fresh fruit, potatoes, lettuce, tomatoes, other fresh vegetables, and processed fruits and vegetables, all from the expenditures reported in the BLS CEX diary for 1998–2009. We matched the expenditure data with Consumer Price Indexes from BLS. As in the first-stage estimates, we used Barten's synthetic model to model the second stage. Following Carpentier and Guyomard (2001), we approximated "unconditional" (i.e., conditional on total expenditures on all goods and services) elasticities by combining the first- and second-stage estimates.

6.1. Data for Estimating New Elasticities of Demand

In section 4.3, we discussed several types of data that have been used in estimating demand systems. We chose to use annual price indexes and the PCE per capita from the BEA. To our knowledge, the detailed data on PCE for food have been used only by Blanciforti, Green, and King (1986), and they did not include FAFH in their demand model. As a robustness check, we also used average household expenditures from the CEX that were aggregated to a monthly series and matched these expenditures with Consumer Price Indexes (CPIs). The data on the CEX and CPIs also allowed us to generate the disaggregated series necessary to estimate the second stage for fruits and vegetables. This section presents the summary statistics and unit root test statistics for these data.

6.1.1. Annual BEA Price Indexes and Expenditures

The estimates of PCE from the BEA represent total aggregate spending in the United States for each year. We converted these estimates to per capita expenditures per year by dividing total PCE for each food product by the population for each year. We constructed composite price indexes for each food category as a linear combination of disaggregated price indexes, each weighted by its expenditure share (Table 9). For example, the BEA publishes price indexes for alcoholic beverages for off-premise consumption ($p_{FAH\text{-}alcohol}$) and alcoholic beverages in purchased meals ($p_{FAFH\text{-}alcohol}$). The weighted average price index for the alcoholic beverage product ($p_{alcohol}$), which uses as weights the value of each as a share of total expenditure on both types of purchases ($w_{FAH\text{-}alcohol}$ and $w_{FAFH\text{-}alcohol}$), is

$$p_{alcohol} = w_{FAFH-alcohol}\, p_{FAFH-alcohol} + w_{FAH-alcohol}\, p_{FAH-alcohol}.$$

Implicit quantity indexes were estimated using the composite price indexes and per capita expenditures (see footnote 27).

Table 9. Annual BEA Price and Expenditure Data for Aggregate Products in First-Stage Estimation

Constructed Food Category	Components	PCE Series ID†	Fisher-Ideal Price Index Series ID†
Cereals and bakery	Cereals and bakery	DCBPRC0	DCBPRG3
Meat	Beef	DBEERC0	DBEERG3
	Pork	DPORRC0	DPORRG3
	Other red meats	DMEARC0	DMEARG3
	Poultry	DPOURC0	DPOURG3
	Seafood and fish	DFISRC0	DFISRG3
Eggs	Eggs	DGGSRC0	DGGSRG3
Dairy products	Fluid milk	DMILRC0	DMILRG3
	Processed dairy products	DDAIRC0	DDAIRG3
Fruits and vegetables	Fresh fruits and vegetables	DFAVRC0	DFAVRG3
	Processed fruits and vegetables	DPFVRC0	DPFVRG3
Other foods at home	Fats and oils	DFATRC0	DFATRG3
	Sweets and sugars	DSWERC0	DSWERG3
	Other food, not elsewhere classified	DOFDRC0	DOFDRG3
Nonalcoholic beverages	Nonalcoholic beverages	DNBVRC0	DNBVRG3
FAFH	Food in purchased meals	DMABRC0	DMABRG3
Alcoholic beverages	Alcoholic beverages for off-premise	DAOPRC0	DAOPRG3
	Alcohol in purchased meals	DAPMRC0	DAPMRG3
Nonfood	PCE excluding food	DPXFRC0	DTGDRG3

†PCE stands for Personal Consumption Expenditure. The entries in this column, for expenditures, and the next, price indexes, are identifying names for the different series in the BEA database. The aggregate price index for each food aggregate was constructed as a weighted average of the component price indexes with expenditure shares for each component good acting as weights.

Source: U.S. Department of Commerce, Bureau of Economic Analysis, National Income and Product Accounts, Supplemental Tables, Underlying Detail (2010).

Summary statistics for the expenditure shares, price indexes, and implicit quantity indexes are shown in Table 10. Nonfood constitutes the largest share of the budget with a mean value of 83.43%. Nonfood includes goods and services that are not food. The expenditure share for meat has been declining sharply since the 1970s, falling from a maximum of 4.3% of the average consumer's budget to a minimum of approximately 1.3% in 2009. The trend is similar for other food categories but smaller in magnitude. On the other hand, nonfood and FAFH gained a larger proportion of the average consumer's budget, although the budget share for FAFH dropped from its peak of 0.048 in the mid-1990s to 0.042 in 2009. The price indexes generally trend up with limited variation between years. The price indexes for FAFH, cereals and bakery products, and alcoholic beverages vary the least year to year.

We tested the annual series of budget shares and logged values of prices and quantities for stationarity. Tests for detecting unit roots include the augmented Dickey-Fuller (ADF)(1979), Phillips-Perron (PP) (1988), and Dickey-Fuller generalized least squares (DFGLS) (Elliott, Rothenberg and Stock 1996).[28] In all three tests the null hypothesis that the variable follows a unit root process is tested against the alternative hypothesis of stationarity. An alternative to the DFGLS test is the Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) (1992) test, which tests the null of trend stationarity against the alternative of a unit root. Using the DFGLS test, we could reject the null hypothesis of a unit root for a subset of the BEA series that included the logged price series for cereals and bakery products, eggs, fruits and vegetables, and alcoholic beverages; the logged quantity series for other food and nonalcoholic beverages; and the expenditure shares for meat. Thus, we failed to reject the null hypothesis of a unit root for the majority of the BEA data series (Table 11). With the KPSS test, we rejected the null hypothesis of trend stationarity in favor of a unit root process for all of the logged prices except eggs; all of the logged quantity indexes except meat, dairy products, fruits and vegetables, other foods, and nonalcoholic beverages; and all of the expenditure shares except nonfood. Detection of unit roots in these data suggests that a differencing approach to estimation is appropriate (Gao and Shonkwiler 1993).

6.1.2. Monthly BLS Price Indexes and Expenditures

The CEX diary data are from cross sections of households and can be aggregated to construct a weekly, monthly, quarterly, or annual time series of average expenditures per consuming unit. Since the observations are on a weekly basis, assumptions are necessary to aggregate the data. Because the CPIs are available monthly and annually, we aggregated the CEX diary data to create a monthly series (Table 12). When consuming units reported expenditures for a week that straddled two months, those expenditures were assigned to the month that included four or more of the days in question. These observations constitute approximately 20% of all observations for a given year. To extrapolate the sample observations to the population, we applied the sample weights calculated by the BLS.[29] The CEX public microdata

[28] Conventional unit root tests like ADF and PP tend to lose power when used on a series with a low-order moving-average process. DFGLS is similar to the ADF test statistic but "has substantially improved power when an unknown mean or trend is present" (Elliott, Rothenberg and Stock 1996, p. 813).

[29] The sample weights are inverse probability weights adjusted for oversampling of minorities and for nonresponse.

Table 10. Summary Statistics for BEA Data, Annual, 1960–2009

		Expenditure Shares				Composite Price Indexes				Implicit Quantity Indexes			
	Observations	Mean	Std. Dev.	Min.	Max.	Mean	Std. Dev.	Min.	Max.	Mean	Std. Dev.	Min.	Max.
Cereals and bakery	50	0.0147	0.0034	0.0107	0.0227	56.96	31.10	18.40	120.81	103.72	14.27	79.21	126.89
Meat	50	0.0263	0.0110	0.0131	0.0433	58.45	27.74	20.84	109.23	125.87	7.36	113.23	151.21
Eggs	50	0.0015	0.0009	0.0007	0.0035	73.87	26.79	39.25	154.49	93.11	12.51	69.98	122.68
Dairy	50	0.0118	0.0061	0.0051	0.0254	56.97	29.13	19.32	115.01	149.58	23.44	114.20	193.23
Fruits and vegetables	50	0.0138	0.0050	0.0083	0.0240	55.60	30.13	16.57	115.26	126.68	6.58	114.49	144.13
Other foods	50	0.0199	0.0026	0.0153	0.0244	59.18	31.62	18.13	115.34	91.66	17.67	61.67	121.28
Nonalcoholic beverages	50	0.0114	0.0024	0.0075	0.0148	63.90	34.11	15.89	113.67	99.53	12.34	73.38	118.69
FAFH	50	0.0443	0.0031	0.0393	0.0490	54.48	32.00	13.26	115.37	95.14	23.84	54.41	130.58
Alcoholic beverages	50	0.0220	0.0049	0.0159	0.0310	58.25	28.53	22.88	112.68	105.17	21.53	66.10	143.14
Nonfood	50	0.8343	0.0348	0.7720	0.8807	56.99	30.68	18.12	108.90	83.15	29.99	38.75	136.50

Note: Expenditure shares were calculated for each food as aggregate personal consumption expenditures (PCE) for each food divided by total personal consumption expenditures on food and nonfood goods. The implicit quantity indexes were calculated for each food as PCE per capita for each food product divided by the corresponding price index.

Source: U.S. Department of Commerce, Bureau of Economic Analysis, National Income and Product Accounts (2010).

Table 11. Tests for Unit Roots in Annual BEA Price Indexes, Implicit Quantity Indexes, and Expenditure Shares, 1960–2009

	Price Indexes			Implicit Quantity Indexes			Expenditure Shares		
	No. of Lags	Test Statistic	10% Critical Value	No. of Lags	Test Statistic	10% Critical Value	No. of Lags	Test Statistic	10% Critical Value
Dickey-Fuller Generalized Least Squares (DFGLS)									
Cereals and bakery	10	−2.56	−2.37	1	−1.98	−2.88	5	−1.92	−2.70
Meat	1	−1.44	−2.88	3	−1.87	−2.81	10	−2.56	−2.37
Eggs	7	−2.72	−2.58	1	−2.48	−2.88	6	−0.87	−2.64
Dairy products	1	−1.20	−2.88	1	−2.20	−2.88	1	−1.03	−2.88
Fruits and vegetables	10	−2.52	−2.37	1	−2.40	−2.88	9	−1.48	−2.44
Other foods	5	−2.13	−2.70	6	−3.20	−2.64	2	−2.39	−2.84
Nonalcoholic beverages	3	−2.17	−2.81	6	−2.93	−2.64	3	−2.24	−2.81
FAFH	3	−2.48	−2.81	10	−0.97	−2.37	1	−1.16	−2.88
Alcoholic beverages	10	−2.68	−2.37	4	−1.92	−2.76	8	−1.51	−2.51
Nonfood	5	−2.58	−2.70	1	−2.34	−2.88	4	−2.00	−2.76
Kwiatkowski, Phillips, Schmidt, and Shin (KPSS)									
Cereals and bakery	5	0.18	0.12	5	0.12	0.12	5	0.13	0.12
Meat	5	0.21	0.12	5	0.09	0.12	5	0.17	0.12
Eggs	3	0.07	0.07	5	0.14	0.12	5	0.24	0.12
Dairy products	5	0.19	0.12	5	0.09	0.12	5	0.20	0.12
Fruits and vegetables	5	0.20	0.12	5	0.09	0.12	5	0.21	0.12
Other foods	5	0.19	0.12	5	0.06	0.12	4	0.13	0.13
Nonalcoholic beverages	5	0.20	0.12	5	0.08	0.12	5	0.18	0.12
FAFH	5	0.21	0.12	5	0.22	0.12	5	0.23	0.12
Alcoholic beverages	5	0.17	0.12	5	0.17	0.12	5	0.14	0.12
Nonfood	5	0.19	0.12	5	0.16	0.12	5	0.10	0.12

Notes: DFGLS critical values reported in this table are linear interpolations between approximate critical values listed in Elliot, Rothenberg, and Stock (1996). The unit root tests were applied to the logarithmic transformations of the price and quantity indexes. Lag length was determined by the Ng-Perron sequential t-test procedure for the DFGLS test and by the automatic bandwidth selection procedure proposed by Newey and West (1994) as described by Hobijn, Franses, and Ooms (1998, p. 7) (Baum 2000) for the KPSS test.

Source: Authors' calculations using personal consumption expenditures and Fisher-Ideal price indexes (U.S. Department of Commerce, Bureau of Economic Analysis, National Income and Product Accounts 2010).

Table 12. Monthly BLS Price and Expenditure Data for Aggregate Products in First-Stage Estimation

	Expenditure†			Price	
Food Group	Variable Name/ Universal Classification Code (UCC)	Database	Availability	CPI, All Urban Consumers, Series ID	Availability
Cereals and bakery	CEREAL BAKEPROD	CEX Diary, FMLY files CEX Diary, FMLY files	1984–2009	CUUR0000SAF111	1960–2009 1960–2009
Meats	BEEF	CEX Diary, FMLY files	1984–2009	CUUR0000SEFC‡	1960–2009
	PORK	CEX Diary, FMLY files		CUUR0000SEFD‡	1960–2009
	OTHMEAT	CEX Diary, FMLY files		CUUR0000SEFE‡	1960–2009
	POULTRY	CEX Diary, FMLY files		CUUR0000SEFF‡	1960–2009
	SEAFOOD	CEX Diary, FMLY files		CUUR0000SEFG‡	1960–2009
Eggs	EGGS	CEX Diary, FMLY files		CUUR0000SEFH	1960–2007
Dairy products	MILKPROD OTHDAIRY	CEX Diary, FMLY files	1984–2009	CUUROOOOSEFJ	1960–2009
Fruits and vegetables	FRSHFRUT PROCFRUT FRSHVEG PROCVEG	CEX Diary, FMLY files	1984–2009	CUUR0000SAF113	1960–2009
Other foods	SWEETS OILS MISCFOOD	CEX Diary, FMLY files	1984–2009	CUUR0000SAF115	1967–2009
Nonalcoholic beverages	NONALBEV	CEX Diary, FMLY files	1984–2009	CUUR0000SAF114	1960–2009
FAFH	FOODAWAY	CEX Diary, FMLY files	1984–2009	CUUR0000SEFV	1960–2009
	200511 ≤ UCC ≤ 200536 (Alcoholic bev. away from home)	CEX Diary, EXPD files	1984–2009	CUUR0000SEFX‡	1967–2009
Alcoholic beverages	200111 ≤ UCC ≤ 200410 (alcoholic bev. at home)	CEX Diary, EXPD files	1984–2009	CUUR0000SEFW‡	1978–2009
Nonfood	UCC > 250110	CEX Diary, EXPD files	1986–2009*	CUUR0000SA0L1	1960–2009

†Monthly expenditure for each food product was calculated in two steps. First, we estimated the average weekly expenditure for each consumer unit for each food product and multiplied these expenditures by the number of days in each month to obtain average monthly expenditure for the consumer unit. Consumer units that reported expenditures for a week that straddled two months were assigned to the month that contributed four or more days to the consumer unit's week. Then, we estimated the sample average for each year using sample (inverse probability) weights to obtain the average monthly expenditure for the U.S. noninstitutionalized population.

‡The aggregate price indexes for meat and alcoholic beverages were constructed as a weighted average of the component price indexes with the expenditure shares for the components acting as weights.

*Between 1984 and 1986, the CEX diary survey collected limited nonfood expenditure data. After 1986, BLS expanded the collection of nonfood items in the diary survey.

are available from 1980 through 2009, but since the CPIs for some of the detailed fruit and vegetable series used to estimate the second stage are available starting only in 1998, we used a subset of the data.[30]

The budget shares calculated using the BLS expenditure data are quite different from the budget shares calculated using the BEA expenditure data. The mean budget share for non-food based on the CEX data is 81.6%, compared with 83.4% using the BEA data. However, both series appear to trend upward over the period of 1998–2009. The budget shares for FAFH derived from both BLS and BEA expenditure data appear to have moved in a similar pattern: slight growth between 1998 and 2000 and a decline thereafter. However, on average, the magnitude of the BLS-based budget share for FAFH is bigger than the BEA-based budget share (0.07 compared with 0.04, respectively). The movements of the budget shares for the other foods appear to be similar across data sources (Table 13). Seasonality also appears to exist in the monthly budget shares.

Because we aggregated the CEX into monthly observations, seasonality could be an issue. Hylleberg, Engle, Granger, and Yoo (1990) (HEGY) discussed three classes of time-series models commonly used to model seasonality: (a) a purely deterministic seasonal process, (b) a stationary seasonal process, and (c) an integrated seasonal process. A purely deterministic seasonal process allows the mean (or variance) of a series to vary by season; for example,

$$x_t = m_0 + \sum_{i=1}^{11} m_i S_{it} + \varepsilon_t,$$

where S_{it} is a monthly dummy at month i and time t, m_0 is a constant, and ε_t is white noise. A stationary seasonal process can be generated by an infinite autoregressive process in which the roots of the autoregressive polynomial lie outside the unit circle (e.g., $x_t = \rho x_{t-12} + \varepsilon_t$ where $\rho < 0$). Lastly, an integrated seasonal process is similar to the stationary seasonal process except at least one of the roots of the autoregressive polynomial is on the unit circle (e.g., $x_t = x_{t-12} + \varepsilon_t$). If seasonality is of this class, then the data are not stationary and, as discussed in section 4.3.4, the use of nonstationary data in the analysis may have troubling statistical consequences. Hence, we tested the series of logged prices, logged implicit quantities, and expenditure shares for seasonal as well as long-run unit roots.

Testing for unit roots in monthly data is made more complicated by the presence of seasonality.[31] Unlike annual data, monthly data could have a unit root at the zero frequency (i.e., a standard long-run unit root where first-differencing would have to be applied to render the series stationary) or at seasonal frequencies corresponding to the number of cycles per year. For example, the data-generating process may cycle every six months and be nonstationary, which implies that a unit root occurs at that frequency. HEGY developed an approach for detecting seasonal and long-run unit roots in quarterly data, which Beaulieu and Miron (1993) extended to monthly data. The goal of the HEGY test is to test hypotheses about a particular

[30] We tried estimating the first stage using aggregated BLS monthly data from 1986 through 2009 but some of the resulting estimates were nonsensical (for instance, a positive own-price elasticity for FAFH). Hence, we chose a subset of the data that yielded theoretically consistent estimates of elasticities of demand.

[31] However, it should be noted that Ghysels, Lee, and Noh (1994) showed that the Dickey-Fuller test can still be used to test for a unit root at the zero frequency to the extent that the model is augmented with appropriate autoregressive terms.

Table 13. Summary Statistics for BLS Monthly Data, 1998–2009

		Expenditure Shares				Consumer Price Indexes				Implicit Quantity Indexes			
	Obs.	Mean	Std. Dev.	Min.	Max.	Mean	Std. Dev.	Min.	Max.	Mean	Std. Dev.	Min.	Max.
Cereals and bakery	144	0.0151	0.0021	0.0108	0.0204	112.09	11.71	96.44	137.09	95.35	8.16	75.71	116.94
Meat	144	0.0252	0.0035	0.0178	0.0344	116.42	13.15	97.08	139.53	91.01	10.95	66.99	117.47
Eggs	144	0.0012	0.0002	0.0007	0.0018	118.10	23.03	89.25	179.29	98.03	10.38	75.02	137.26
Dairy	144	0.0117	0.0011	0.0080	0.0145	110.15	10.84	92.08	133.88	103.86	5.86	86.16	117.23
Fruits and vegetables	144	0.0183	0.0018	0.0136	0.0234	112.22	13.07	92.85	137.23	104.92	7.58	83.20	126.41
Other foods	144	0.0244	0.0029	0.0168	0.0319	107.64	7.61	96.37	124.75	111.83	13.30	85.99	142.46
Nonalcoholic beverages	144	0.0093	0.0010	0.0061	0.0124	105.27	6.89	96.06	120.83	110.38	12.31	75.50	146.20
FAFH	144	0.0666	0.0064	0.0513	0.0844	112.41	11.62	95.22	134.44	89.07	6.96	73.98	107.60
Alcoholic beverages	144	0.0119	0.0019	0.0071	0.0172	107.08	11.12	89.07	128.76	107.28	18.71	74.07	169.36
Nonfood	144	0.8162	0.0157	0.7779	0.8656	111.84	10.25	95.63	130.39	118.76	13.50	84.91	163.08

Note: Expenditure shares were calculated for each food as average monthly expenditure per household for each food divided by total expenditure on goods and services. The implicit quantity indexes were calculated for each food as average monthly expenditure per household for each food product divided by the corresponding price index.

Sources: Department of Labor, Bureau of Labor Statistics, Consumer Expenditure Survey (2010); Department of Labor, Bureau of Labor Statistics, Consumer Price Index Database (2010).

unit root without taking a stand on whether other seasonal or zero frequency (long-run) unit roots are present (see Technical Appendix A.1 for more details).

We applied the HEGY test to the CEX monthly data. The HEGY estimation equations included a constant, a time trend, and lagged dependent variables. The set of lags was determined using the Bayesian Information Criteria (BIC). We found evidence of a long-run unit root (i.e., $\pi_1 = 0$) for most of the logged price and quantity series and the expenditure shares. We generally could not reject the unit root hypothesis at the 5% level for most of the seasonal frequencies across all series (Table 14). In particular, we detected seasonal unit roots at most seasonal frequencies for most of the logged prices (e.g., cereals and bakery, eggs, fruits and vegetables, other food, nonalcoholic beverages, and alcoholic beverages). The evidence for seasonal unit roots in the series of expenditure shares and logged quantity indexes is less strong.[32] In the next section, we discuss our strategy for modeling the seasonality in the BLS data using Barten's synthetic model and the GODDS.

6.2. First-Stage Estimates of Elasticities of Demand

The price and expenditure shares in both data sets were found to be nonstationary. Therefore, we utilized Barten's synthetic model (Barten 1993) and the GODDS (Eales, Durham and Wessells 1997) to estimate elasticities of demand. This section presents estimates of demand parameters and price and expenditure elasticities obtained using Barten's synthetic model (equation (78)). Since the results from the GODDS (equation (80)) are almost identical to those from Barten's synthetic model, we present these results in the appendix in Tables A-4 through A-8.

The differential demand specifications discussed to this point have been in terms of infinitesimal changes. For application to discrete data, the continuous differentials in equations (78) and (80) are approximated with their discrete counterparts:

$$dw_n \approx \Delta w_n = w_{n,t} - w_{n,t-s}, \forall n = 1,\dots,N,$$

$$d\ln q_n \approx \Delta \ln q_n = \ln q_{n,t} - \ln q_{n,t-s}, \forall n = 1,\dots,N,$$

$$d\ln p_n \approx \Delta \ln p_n = \ln p_{n,t} - \ln p_{n,t-s}, \forall n = 1,\dots,N,$$

$$d\ln Q \approx \sum_{n=1}^{N} \bar{w}_n \Delta \ln q_n,$$

where $s = 1$ for the annual BEA data and $s = 12$ for the monthly CEX data and

$$\bar{w}_n = \tfrac{1}{2}(w_{n,t} + w_{n,t-1}), \forall n = 1,\dots,N.$$

We first-differenced the BEA data because we detected long-run unit roots using the DFGLS and KPSS tests. For the annual data, the Breusch-Godfrey test for higher-order serial correlation indicated autocorrelation at the 5% significance level in the equations for eggs, fruits and

[32] It should be noted that Ghysels, Lee, and Noh (1994) found that the HEGY test still suffered from severe size distortions of the test statistics when the true data-generating process followed a moving average process even though the HEGY test was the most useful at detecting unit roots at seasonal frequencies among alternative tests. In other words, under the HEGY the nominal size of the test (commonly 5% significance) seriously understates the actual size of the test. Hence, since the HEGY test is found to be unreliable, we cannot conclude that the BLS expenditure share and quantity series are stationary.

Table 14. Test for Seasonal Unit Roots for BLS Monthly Data, 1998–2009

		Seasonal Frequency (Test of Coefficients in Test Regression)						
	Lags	0 (π_1=0)	π (π_2=0)	π/2 (π_3=π_4=0)	2π/3 (π_5=π_6=0)	π/3 (π_7=π_8=0)	5π/6 (π_9=π_{10}=0)	π/6 (π_{11}=π_{12} = 0)
Prices								
Cereal and bakery	5	−2.18	−2.44	4.82	2.42	3.33	4.02	5.04
Meat	1	−2.58	−3.51	8.20	9.16	12.86	5.64	11.84
Eggs	4	−3.38	−5.12	2.03	4.99	4.64	8.64	0.99
Dairy	2	−3.80	−3.44	8.37	6.98	9.89	7.12	8.99
Fruits and vegetables	14	−1.15	−1.51	0.52	1.05	0.29	1.74	2.10
Other food	9	−2.77	−1.80	2.06	0.45	0.86	3.39	0.04
Nonalcoholic beverages	4	−5.06	−3.57	1.48	4.65	0.89	9.34	4.39
FAFH	0	−1.39	−3.54	8.74	10.32	8.10	15.55	17.60
Alcohol beverages	8	−2.50	−0.51	1.47	5.85	0.83	10.15	1.58
Nonfood	11	−4.44	−1.79	0.91	5.93	0.98	2.44	0.85
Expenditure Shares								
Cereal and bakery	4	−1.94	−2.42	9.33	6.20	5.23	11.33	8.79
Meat	1	−1.42	−3.68	8.06	12.50	8.23	12.19	9.07
Eggs	0	−3.12	−4.62	15.35	15.11	15.68	13.98	17.97
Dairy	0	−2.49	−4.35	10.60	16.80	8.21	14.93	10.22
Fruits and vegetables	3	−0.70	−1.76	14.93	3.14	5.34	16.52	12.64
Other food	7	−0.85	−4.29	2.72	6.88	3.28	4.84	3.88
Nonalcoholic beverages	1	−1.41	−3.31	10.59	9.23	2.74	9.83	6.49
FAFH	4	−1.51	−4.93	10.64	18.43	4.60	21.40	11.35
Alcoholic beverages	7	−2.00	−4.24	1.60	7.39	8.05	13.60	7.61
Nonfood	7	−2.25	−4.26	6.11	9.97	4.13	9.67	3.50

continued on following page

Table 14. Test for Seasonal Unit Roots for BLS Monthly Data, 1998–2009 (cont.)

		Seasonal Frequency (Test of Coefficients in Test Regression)						
	Lags	**0** (π_1=0)	**π** (π_2=0)	**π/2** (π_3=π_4=0)	**2π/3** (π_5=π_6=0)	**π/3** (π_7=π_8=0)	**5π/6** (π_9=π_{10}=0)	**π/6** (π_{11}=π_{12} = 0)
Implicit Quantity Indexes								
Cereal and bakery	5	−3.08	−3.75	2.60	4.53	6.15	10.21	11.00
Meat	0	−2.87	−2.64	10.88	7.13	10.60	9.18	18.47
Eggs	2	−1.73	−3.11	13.35	5.25	11.26	5.34	17.15
Dairy	1	−0.97	−2.62	9.35	5.51	11.99	8.22	12.36
Fruits and vegetables	8	0.58	−4.16	4.09	1.75	9.70	13.21	16.15
Other food	4	−0.01	−2.59	7.22	2.47	7.47	8.43	4.51
Nonalcoholic beverages	3	−0.45	−2.39	7.81	8.03	6.61	8.02	12.62
FAFH	0	−2.25	−2.98	10.24	14.44	11.60	12.93	9.50
Alcoholic beverages	3	−1.39	−2.96	8.66	10.49	9.67	13.62	10.65
Nonfood	5	−2.59	−3.64	17.89	4.87	2.76	24.46	9.49

Note: The HEGY test regressions included a trend, a constant, and and lagged dependent variables. Beaulieu and Miron (1993) derived the critical values from the distributions of the HEGY test statistics for monthly data. The critical values for the test regression with a trend and a constant and 240 observations for a 10% level of significance are: −2.99 for the test of the null hypothesis $\pi_1 = 0$ versus the alternative $\pi_1 < 0$ (test of long-run unit root), −2.47 for the test of the null hypothesis $\pi_2 = 0$ versus the alternative $\pi_2 < 0$ (test of unit root corresponding to a biannual cycle), and 5.25 for the joint test of the null hypothesis $\pi_n = \pi_{n-1} = 0$, n = 2,6,8,10,12 (test of unit root corresponding to seasonal frequencies π/2, 2π/3, π/3, 5π/6, and π/6).

Source: Authors' calculation of HEGY test for monthly data using aggregated average monthly household expenditures (U.S. Department of Labor, Bureau of Labor Statistics, Consumer Expenditure Survey 2010; Department of Labor, Bureau of Labor Statistics, Consumer Price Index Database 2010).

Table 15. **Autocorrelation Statistics for Barten's Synthetic and NBR Models Using BEA Annual Data, 1960–2009**

	AR(1) Coefficient	Durbin's h-statistic	p-value	Breusch-Godfrey Test Statistic	p-value
Barten's Synthetic Model					
Cereals and bakery	0.01	0.00	0.97	0.00	0.97
Meat	0.09	0.50	0.48	0.71	0.40
Eggs	−0.30	4.98	0.03	6.26	0.01
Dairy products	0.07	0.24	0.62	0.35	0.56
Fruits and vegetables	−0.24	3.23	0.07	4.25	0.04
Other foods	−0.06	0.15	0.70	0.21	0.65
Nonalcoholic beverages	−0.01	0.01	0.93	0.01	0.92
FAFH	0.33	5.38	0.02	6.69	0.01
Alcoholic beverages	0.23	2.42	0.12	3.26	0.07
NBR Model					
Cereals and bakery	0.01	0.00	0.97	0.00	0.97
Meat	0.09	0.50	0.48	0.71	0.40
Eggs	−0.30	4.98	0.03	6.26	0.01
Dairy products	0.07	0.24	0.62	0.35	0.56
Fruits and vegetables	−0.24	3.23	0.07	4.25	0.04
Other foods	−0.06	0.15	0.70	0.21	0.65
Nonalcoholic beverages	−0.01	0.01	0.93	0.01	0.92
FAFH	0.33	5.38	0.02	6.69	0.01
Alcoholic beverages	0.23	2.42	0.12	3.26	0.07

Source: Authors' calculations using annual personal consumption expenditures and Fisher-Ideal price indexes (U.S. Department of Commerce, Bureau of Economic Analysis, National Income and Product Accounts 2010).

vegetables, and FAFH. However, Durbin's h-test for serial autocorrelation indicated autocorrelation only in the equations for eggs and FAFH (Table 15).

We twelfth-differenced the BLS data because of evidence that the monthly data may be following a seasonal unit root data-generating process. As noted in section 6.1.2, using the HEGY test, we detected unit roots at seasonal frequencies for some of the series. To determine whether first- or twelfth-differencing would be appropriate, we first tested whether the seasonality was deterministic by estimating Barten's synthetic model and the GODDS using first-differenced monthly BLS data with the following adjustments to account for seasonality: (a) monthly dummies alone, (b) quarterly dummies alone, (c) monthly dummies and monthly dummies interacted with a linear time trend, and (d) quarterly dummies and quarterly dummies interacted with a linear time trend. We detected severe negative autocorrelation by applying the Breusch-Godfrey test and the Durbin's h-test to each equation in both demand systems with the four seasonal modeling strategies (for brevity, we present test results only for the models that included monthly dummies in Table 16).[33]

Detection of some autocorrelation in the residuals is expected in that differencing the data induces autocorrelation in the residuals (i.e., $\Delta\varepsilon_t = \varepsilon_t - \varepsilon_{t-1}$), but the detection of large first-order autocorrelation may be indicative of a model misspecification problem. We concluded that the severe autocorrelation that we detected may be a symptom of seasonal variation not captured by the deterministic seasonal models previously suggested. Hence, we also estimated Barten's synthetic model and the GODDS using twelfth-differenced rather than first-differenced BLS data, and autocorrelation did not appear to be as much of a problem (i.e., the Breusch-Godfrey and Durbin's h-test detected autocorrelation only in the equations for fruits and vegetables and alcoholic beverages when the data were twelfth-differenced).

We also augmented Barten's synthetic model and the GODDS by including a constant term in each equation that acts as a linear trend term in each demand system when modeling differenced data. The final models are

$$w_{nt}\Delta \ln q_{nt} = t_n + (a_n + \delta_1 w_{nt})\Delta \ln Q_t + \sum_{j=1}^{N}\left[b_{nj} - \delta_2 w_{nt}(\delta_{nj} - w_{jt})\right]\Delta \ln p_{jt} + v_t, \forall n = 1,\dots,N, \quad (88)$$

$$\Delta \mathrm{w}_{nt} = t_n + (c_n + \varphi_1 \mathrm{w}_{nt})\Delta \ln \mathrm{Q}_t + \sum_{k=1}^{N}\left[d_{nk} + \varphi_2 \mathrm{w}_{nt}(\delta_{nk} - \mathrm{w}_{kt})\right]\Delta \ln \mathrm{p}_{kt} + v_t, \forall n, \quad (89)$$

$$w_{nt}\Delta_{12} \ln q_{nt} = t_n + (a_n + \delta_1 w_{nt})\Delta_{12} \ln Q_t + \sum_{j=1}^{N}\left[b_{nj} - \delta_2 w_{nt}(\delta_{nj} - w_{jt})\right]\Delta_{12} \ln p_{jt} + v_t, \forall n, \quad (90)$$

$$\Delta_{12} \mathrm{w}_{nt} = t_n + (c_n + \varphi_1 \mathrm{w}_{nt})\Delta_{12} \ln \mathrm{Q}_t + \sum_{k=1}^{N}\left[d_{nk} + \varphi_2 \mathrm{w}_{nt}(\delta_{nk} - \mathrm{w}_{kt})\right]\Delta_{12} \ln \mathrm{p}_{kt} + v_t, \forall n, \quad (91)$$

where t_n is the constant term acting as a trend variable and Δ and Δ_{12} are the first- and twelfth-difference operators, respectively. Equations (88) and (89) are Barten's synthetic model and the GODDS model estimated with the BEA annual data. Equations (90) and (91) are Barten's

[33] The Breusch-Godfrey test is a Lagrange multiplier (*LM*) test of the null hypothesis of no autocorrelation versus the alternative that the error follows an AR(*P*) or MA(*P*) process. The test statistic is

$$LM = T\frac{\hat{\mathbf{e}}'\mathbf{X}_0(\mathbf{X}_0'\mathbf{X}_0)^{-1}\mathbf{X}_0'\hat{\mathbf{e}}}{\hat{\mathbf{e}}'\hat{\mathbf{e}}} \sim \chi^2(P),$$

where $\mathbf{X}_0$ is the original $\mathbf{X}$ matrix augmented by P additional columns containing lagged ordinary least square residuals ($\hat{e}_1,\dots,\hat{e}_{t-n}$). Durbin's h-test is a modification of the Breusch-Godfrey Lagrange multiplier test (Greene 2003, pp. 269–271).

Table 16. Autocorrelation Statistics for Barten's Synthetic and FDLAIDS Models Using BLS Monthly Data, 1998–2009

	First-difference					Twelfth-difference				
	AR(1) Coefficient	Durbin's h	p-value	Breusch-Godfrey	p-value	AR(1) Coefficient	Durbin's h	p-value	Breusch-Godfrey	p-value
Barten's Synthetic Model										
Cereals and bakery	−0.37	20.16	0.00	21.02	0.00	0.03	0.12	0.73	0.14	0.71
Meat	−0.45	31.69	0.00	30.48	0.00	0.12	1.90	0.17	2.11	0.15
Eggs	−0.40	25.28	0.00	25.41	0.00	0.11	1.69	0.19	1.88	0.17
Dairy products	−0.36	20.56	0.00	21.38	0.00	0.10	1.29	0.26	1.44	0.23
Fruits and vegetables	−0.40	25.41	0.00	25.52	0.00	0.26	9.27	0.00	9.69	0.00
Other foods	−0.48	37.58	0.00	34.76	0.00	−0.05	0.35	0.55	0.39	0.53
Nonalcoholic beverages	−0.47	37.59	0.00	34.77	0.00	0.05	0.27	0.60	0.31	0.58
FAFH	−0.44	30.60	0.00	29.64	0.00	−0.04	0.20	0.66	0.22	0.64
Alcoholic beverages	−0.29	11.65	0.00	12.95	0.00	0.26	8.54	0.00	8.98	0.00
FDLAIDS Model										
Cereals and bakery	−0.37	20.16	0.00	21.02	0.00	0.03	0.12	0.73	0.14	0.71
Meat	−0.45	31.69	0.00	30.48	0.00	0.12	1.90	0.17	2.11	0.15
Eggs	−0.40	25.28	0.00	25.41	0.00	0.11	1.69	0.19	1.88	0.17
Dairy products	−0.36	20.56	0.00	21.38	0.00	0.10	1.29	0.26	1.44	0.23
Fruits and vegetables	−0.40	25.41	0.00	25.52	0.00	0.26	9.27	0.00	9.69	0.00
Other foods	−0.48	37.58	0.00	34.76	0.00	−0.05	0.35	0.55	0.39	0.53
Nonalcoholic beverages	−0.47	37.59	0.00	34.77	0.00	0.05	0.27	0.60	0.31	0.58
FAFH	−0.44	30.60	0.00	29.64	0.00	−0.04	0.20	0.66	0.22	0.64
Alcoholic beverages	−0.29	11.65	0.00	12.95	0.00	0.26	8.54	0.00	8.98	0.00

Source: Authors' calculations using aggregated average monthly household expenditures and consumer price indexes (U.S. Department of Labor, Bureau of Labor Statistics, Consumer Expenditure Survey 2010; U.S. Department of Labor, Bureau of Labor Statistics, Consumer Price Index Database 2010).

synthetic model and the GODDS model estimated with BLS monthly data. Homogeneity and symmetry restrictions were incorporated and the nonfood category was left out of estimation to avoid singularity of the variance-covariance matrix. The adding-up condition was used to recover the parameter estimates of nonfood demand.[34] The demand systems were estimated using iterated seemingly unrelated regressions in Stata version 8.0.

Because the elasticities of demand were calculated as linear combinations of the parameter estimates, the standard errors for those estimates were calculated using

$$\widehat{\mathrm{V}}(aX+bY)=a^2\,\widehat{\mathrm{V}}(X)+b^2\,\widehat{\mathrm{V}}(Y)+2ab\,\widehat{\mathrm{Cov}}(X,Y),$$

where a and b are nonstochastic coefficients, X and Y are variables, and $\widehat{\mathrm{V}}(\cdot)$ and $\widehat{\mathrm{Cov}}(\cdot)$ denote estimated variance and covariance, respectively. For example, the estimated variances of the expenditure and own- and cross-price elasticities of demand for the nth food using Barten's synthetic model are

$$\widehat{\mathrm{V}}(\eta_{nM})=\left(1/\overline{w}_n\right)^2\widehat{\mathrm{V}}(a_n)+\widehat{\mathrm{V}}(\delta_1)+2\left(1/\overline{w}_n\right)^2\widehat{\mathrm{Cov}}(a_n,\delta_1),\forall n=1,\dots,N,$$

$$\begin{aligned}\widehat{\mathrm{V}}(\eta_{nk})=&\left(\overline{w}_k/\overline{w}_n\right)^2\widehat{\mathrm{V}}(a_n)+\widehat{\mathrm{V}}(\delta_1)+\left(1/\overline{w}_n\right)^2\widehat{\mathrm{V}}(b_{nk})+\left(\delta_{nk}-\overline{w}_k\right)^2\widehat{\mathrm{V}}(\delta_2)\\&+2(\overline{w}_k/\overline{w}_n)\widehat{\mathrm{Cov}}(a_n,\delta_1)+2(\overline{w}_k/\overline{w}_n^2)\widehat{\mathrm{Cov}}(a_n,b_{nk})\\&-2(\overline{w}_k/\overline{w}_n)(\delta_{nk}-\overline{w}_k)\widehat{\mathrm{Cov}}(a_n,\delta_2)+2\left(1/\overline{w}_n\right)\widehat{\mathrm{Cov}}(b_{nk},\delta_1)\\&-2(\delta_{nk}-\overline{w}_k)\widehat{\mathrm{Cov}}(\delta_1,\delta_2)-2(1/\overline{w}_n)(\delta_{nk}-\overline{w}_k)\widehat{\mathrm{Cov}}(b_{nk},\delta_2),\forall n,k=1,\dots,N,\end{aligned}$$

where $\overline{w}_n$ is the mean expenditure share for the nth good, a_n and b_{nk} are estimated coefficients on expenditure and prices, δ_1 and δ_2 are estimated nesting parameters, and δ_{nk} is the Kronecker delta.

Using the Wald and Likelihood Ratio tests, we found that the BEA data favored the NBR model over the Rotterdam, FDLAIDS, and CBS models (Table 18) and that the BLS data favored the FDLAIDS model (Table 18). For the Wald test, the joint null hypothesis that $\delta_1 = 0$ and $\delta_2 = 1$ cannot be rejected at the 5% level of significance using the BEA data (the probability of rejecting the NBR model restrictions when the restrictions are true is 0.35). Likewise, the joint null hypothesis that $\delta_1 = \delta_2 = 1$ cannot be rejected at the 5% level of significance using the BLS data (the p-value on the Wald statistic is 0.08). For the Likelihood Ratio test, the general model rejects all of the models except the NBR model at the 5% level of significance using the BEA data (the p-values on the Likelihood Ratio test statistics are 0.18). Using BLS data, the p-value on the Likelihood Ratio statistic for the FDLAIDS model is 0.11. Hence, the BEA-based estimates have marginal budget shares that are constant and Slutsky substitution

[34] An anonymous reviewer pointed out that the estimated system parameters may not add up because we approximated the Divisia volume index with discrete differences. To test whether our estimates violated the adding-up condition, we re-estimated Barten's synthetic model while leaving out a different equation (other than nonfood) and recovered the parameters for the missing equation using the adding-up restriction. We did this for all food products for Barten's synthetic model applied to the BEA and BLS data. We found our estimates to be invariant to any choice of equation omitted in estimation and recovered using the adding-up condition.

terms that vary with total expenditure, whereas the BLS-based estimates have marginal budget shares and Slutsky substitution terms that vary with total expenditure.

Since the NBR and FDLAIDS model were not rejected by Barten's synthetic model using the BEA and BLS data sets, respectively, the estimates of the demand system parameters and elasticities of demand from these models are presented and discussed. The results from the GODDS model are presented in the appendix (Table A-9 – Table A-11).

6.2.1. Estimates Using Annual BEA Data

A total of 64 parameters were estimated that represent demand responses to prices (9 own-price responses and 45 cross-price responses with symmetry) and expenditure using the NBR model and BEA annual data. Of these 64, 25 were statistically significantly different from zero at the 5% level of significance, including most of the own-price effects and the expenditure effects. Roughly half of the variation in each equation of the system can be explained by the model except for the equations for meat and eggs, which have R^2 statistics of 0.22 and 0.31, respectively.

All of the expenditure elasticities and uncompensated price elasticities of demand are evaluated at the sample means of the expenditure shares. The elasticity estimates based on the NBR model and using the BEA annual data are consistent with those in the literature and are consistent with demand theory. The own-price elasticity estimates are all negative and statistically significantly different from zero at 5%, which is consistent with the law of demand. All of the food expenditure elasticities are less than one, which is consistent with Engel's Law. Eggs are found to be inferior with an expenditure elasticity equal to −0.69; all of the other foods are normal. Our estimate of the expenditure elasticity for FAFH of 0.84

Table 17. Wald and Log-Likelihood Tests for Nested Models of Barten's Synthetic Model Using BEA Price and Expenditure Data, 1960–2009, Annual

	Likelihood Ratio Test	p-value	Wald Test	p-value
Rotterdam ($\delta_1 = \delta_2 = 0$)	20.63	0.00	28.67	0.00
FDLAIDS ($\delta_1 = \delta_2 = 1$)	12.07	0.00	18.59	0.00
CBS ($\delta_1 = 1, \delta_2 = 0$)	25.56	0.00	43.16	0.00
NBR ($\delta_1 = 0, \delta_2 = 1$)	2.12	0.35	3.53	0.17

Source: Authors' calculations based on Barten's synthetic model and using the annual personal consumption expenditures and Fisher-Ideal price indexes (U.S. Department of Commerce, Bureau of Economic Analysis, National Income and Product Accounts 2010).

Table 18. Wald and Log-Likelihood Tests for Nested Models of Barten's Synthetic Model Using BLS Data, 1998–2006, Monthly

	Likelihood Ratio Test	p-value	Wald Test	p-value
Rotterdam ($\delta_1 = \delta_2 = 0$)	10.53	0.0052	12.75	0.0017
FDLAIDS ($\delta_1 = \delta_2 = 1$)	4.35	0.1137	5.05	0.0801
CBS ($\delta_1 = 1, \delta_2 = 0$)	9.17	0.0102	10.68	0.0048
NBR ($\delta_1 = 0, \delta_2 = 1$)	5.22	0.0735	6.00	0.0497

Source: Authors' calculations based on Barten's synthetic model and using aggregated average monthly expenditures and consumer price indexes (U.S. Department of Labor, Bureau of Labor Statistics, Consumer Expenditure Survey 2010; U.S. Department of Labor, Bureau of Labor Statistics, Consumer Price Index Database 2010).

Table 19. **Parameter Estimates from the NBR Model Using BEA Data, 1960–2009, Annual**

	Demand For								
	Cereals and Bakery	Meat	Eggs	Dairy	Fruits and Vegetables	Other Foods	Nonalcoholic Beverages	FAFH	Alcoholic Beverages
Price of									
Cereals and bakery	0.0008	0.0004	0.0003	0.0019	0.0018	0.0065	−0.0007	−0.0067	−0.0012
	(0.0020)	(0.0014)	(0.0004)	(0.0013)	(0.0014)	(0.0014)	(0.0010)	(0.0028)	(0.0019)
Meat	0.0004	0.0156	0.0014	0.0000	0.0041	−0.0034	−0.0026	0.0057	0.0049
	(0.0014)	(0.0033)	(0.0005)	(0.0014)	(0.0014)	(0.0019)	(0.0014)	(0.0025)	(0.0016)
Eggs	0.0003	0.0014	0.0004	0.0010	−0.0007	−0.0009	0.0004	0.0003	−0.0004
	(0.0004)	(0.0005)	(0.0002)	(0.0004)	(0.0004)	(0.0005)	(0.0003)	(0.0008)	(0.0006)
Dairy	0.0019	0.0000	0.0010	0.0011	−0.0011	0.0030	0.0024	−0.0030	0.0020
	(0.0013)	(0.0014)	(0.0004)	(0.0016)	(0.0012)	(0.0014)	(0.0009)	(0.0024)	(0.0016)
Fruits and vegetables	0.0018	0.0041	−0.0007	−0.0011	0.0056	−0.0023	0.0015	0.0024	−0.0007
	(0.0014)	(0.0014)	(0.0004)	(0.0012)	(0.0019)	(0.0014)	(0.0009)	(0.0027)	(0.0018)
Other foods	0.0065	−0.0034	−0.0009	0.0030	−0.0023	0.0075	0.0009	0.0021	−0.0001
	(0.0014)	(0.0019)	(0.0005)	(0.0014)	(0.0014)	(0.0023)	(0.0012)	(0.0024)	(0.0017)
Nonalcoholic beverages	−0.0007	−0.0026	0.0004	0.0024	0.0015	0.0009	0.0026	−0.0010	0.0020
	(0.0010)	(0.0014)	(0.0003)	(0.0009)	(0.0009)	(0.0012)	(0.0012)	(0.0016)	(0.0011)
FAFH	−0.0067	0.0057	0.0003	−0.0030	0.0024	0.0021	−0.0010	0.0197	−0.0053
	(0.0028)	(0.0025)	(0.0008)	(0.0024)	(0.0027)	(0.0024)	(0.0016)	(0.0088)	(0.0040)
Alcoholic beverages	−0.0012	0.0049	−0.0004	0.0020	−0.0007	−0.0001	0.0020	−0.0053	0.0106
	(0.0019)	(0.0016)	(0.0006)	(0.0016)	(0.0018)	(0.0017)	(0.0011)	(0.0040)	(0.0036)
Nonfood	−0.0032	−0.0262	−0.0018	−0.0072	−0.0106	−0.0133	−0.0055	−0.0142	−0.0119
	(0.0041)	(0.0058)	(0.0013)	(0.0039)	(0.0039)	(0.0044)	(0.0033)	(0.0086)	(0.0058)
Expenditure	0.0041	0.0168	−0.0010	0.0114	0.0037	0.0158	0.0099	0.0374	0.0110
	(0.0038)	(0.0085)	(0.0014)	(0.0040)	(0.0037)	(0.0056)	(0.0042)	(0.0059)	(0.0041)
δ_1	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
δ_2	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Intercept	0.0001	−0.0003	0.0000	−0.0003	−0.0001	−0.0001	−0.0001	0.0001	0.0001
	(0.0001)	(0.0002)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0001)
R^2	0.5913	0.2245	0.3054	0.4210	0.5566	0.5529	0.6304	0.6507	0.5311

Note: Standard errors are in parentheses.

Source: Authors' calculations based on NBR model and using the annual personal consumption expenditures and Fisher-Ideal price indexes (U.S. Department of Commerce, Bureau of Economic Analysis, National Income and Product Accounts 2010).

is smaller than what is generally reported in the literature.[35] Similarly, our estimate of the own-price elasticity of demand for FAFH (−0.55) is smaller than the average found in the literature (−1.02, as shown in Table 5). Our estimates of the own-price elasticities of demand for cereals and bakery products (−0.93) and dairy (−0.91) seem consistent with estimates from previous studies that used similar data (average values of −0.86 for cereals and bakery products and −0.85 for dairy are listed in Table 5). However, our estimates of the own-price elasticities of demand for meat (−0.40) and fruits and vegetables (−0.58) are much smaller in magnitude than those found typically in the literature; the smallest own-price elasticities of demand found for meats and fruits and vegetables in other studies were −0.61 and −0.71, respectively (Table 5).

Many of our estimates of the cross-price elasticities of demand are statistically significantly different from zero. In particular, nonalcoholic beverages and dairy are gross substitutes (the elasticity of demand for dairy with respect to the price of nonalcoholic beverages is 0.20 and the elasticity of demand for nonalcoholic beverages with respect to the price of dairy is 0.21). This result seems sensible. Somewhat unexpected results included the cross-price relationships for other food and FAFH. Other food was found to be a gross substitute for cereals and bakery products and for dairy but was found to be a gross complement for nonfood. FAFH, on the other hand was found to be a gross complement for cereals and bakery products and a gross substitute for meat.

6.2.2. Estimates Using Monthly BLS Data

The parameter estimates from the FDLAIDS model using BLS monthly data are presented in Table 21. Of all of the price and expenditure parameters, 28 were found to be statistically significant at the 5% level, including most of the coefficients on the own-price and expenditure variables. The R^2 values for each equation using the monthly BLS data are much smaller than the R^2 values using the annual BEA data and range between 0.00 for the alcoholic beverage equation and 0.20 for the cereal and bakery product equation. Hence, the explanatory power of the FDLAIDS model is much smaller when using the BLS data than when using the BEA data.

The elasticities of demand based on models estimated using the BLS monthly data are quite different from those based on models estimated using the BEA annual data. The estimates of the own-price elasticities of demand using the monthly data are significantly smaller in magnitude for cereals and bakery products (−0.30), meats (−0.12), dairy (−0.02), and eggs (−0.22) than the estimates using the annual data (Table 22). However, the estimated own-price elasticity for other foods and FAFH are double the own-price elasticity based on BEA data (−1.54 versus −0.62 for other foods and −1.19 versus −0.55 for FAFH). Compared with the BEA data, the BLS data yielded smaller-sized estimates of elasticities of demand with respect to total expenditure on goods. Using either data set, the elasticity of demand for eggs with respect to expenditure is negative. Excluding eggs and nonfood, the expenditure elasticities

[35] Piggott (2003), Raper, Wanzala, and Nayga (2002), Park et al. (1996), and Reed, Levedahl, and Hallahan (2005) reported estimates of the elasticity of demand for FAFH with respect to expenditure (and in some cases income) to be greater than one, but Nayga and Capps (1992) estimated that the elasticity of demand for FAFH with respect to expenditure was 0.81.

Table 20. First-Stage Uncompensated Elasticities of Demand from the NBR Model Using BEA Data, 1960–2009, Annual

	With Respect to Price of										
Elasticity of Demand For	Cereals and Bakery	Meat	Eggs	Dairy	Fruits and Vegetables	Other Foods	Nonalcoholic Beverages	FAFH	Alcoholic Beverages	Nonfood	Expenditure
Cereals and bakery	−0.93	0.04	0.02	0.14	0.13	0.45	−0.04	−0.42	−0.06	0.39	0.28
	(0.13)	(0.10)	(0.03)	(0.09)	(0.10)	(0.10)	(0.07)	(0.19)	(0.13)	(0.38)	(0.26)
Meat	0.02	−0.40	0.05	0.00	0.16	−0.12	−0.09	0.23	0.20	−0.69	0.64
	(0.05)	(0.13)	(0.02)	(0.05)	(0.05)	(0.07)	(0.05)	(0.10)	(0.06)	(0.33)	(0.32)
Eggs	0.24	1.00	−0.73	0.66	−0.47	−0.54	0.27	0.25	−0.20	0.22	−0.69
	(0.29)	(0.36)	(0.14)	(0.28)	(0.30)	(0.32)	(0.22)	(0.54)	(0.37)	(1.25)	(0.95)
Dairy	0.16	0.00	0.08	−0.91	−0.09	0.26	0.20	−0.26	0.17	−0.59	0.97
	(0.11)	(0.13)	(0.04)	(0.14)	(0.11)	(0.11)	(0.08)	(0.21)	(0.14)	(0.46)	(0.34)
Fruits and vegetables	0.14	0.32	−0.05	−0.07	−0.58	−0.15	0.11	0.20	−0.03	−0.16	0.27
	(0.11)	(0.11)	(0.03)	(0.09)	(0.14)	(0.10)	(0.07)	(0.19)	(0.13)	(0.38)	(0.26)
Other foods	0.33	−0.17	−0.04	0.15	−0.11	−0.62	0.05	0.12	0.00	−0.50	0.79
	(0.07)	(0.10)	(0.02)	(0.07)	(0.07)	(0.11)	(0.06)	(0.12)	(0.08)	(0.34)	(0.28)
Nonalcoholic beverages	−0.06	−0.22	0.03	0.21	0.13	0.08	−0.77	−0.08	0.18	−0.37	0.86
	(0.08)	(0.12)	(0.03)	(0.08)	(0.08)	(0.10)	(0.10)	(0.14)	(0.10)	(0.42)	(0.36)
FAFH	−0.15	0.13	0.01	−0.07	0.06	0.05	−0.02	−0.55	−0.12	−0.19	0.84
	(0.06)	(0.06)	(0.02)	(0.05)	(0.06)	(0.05)	(0.04)	(0.20)	(0.09)	(0.24)	(0.13)
Alcoholic beverages	−0.05	0.24	−0.02	0.10	−0.02	0.00	0.10	−0.22	−0.50	−0.13	0.50
	(0.09)	(0.08)	(0.03)	(0.07)	(0.08)	(0.08)	(0.05)	(0.18)	(0.16)	(0.34)	(0.19)
Nonfood	0.00	−0.03	0.00	−0.01	−0.01	−0.02	−0.01	−0.02	−0.02	−0.94	1.07
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.03)	(0.02)

Notes: Estimates of elasticities of demand were computed at the mean of the data. Standard errors are in parentheses.

Source: Authors' calculations based on NBR model and using the annual personal consumption expenditures and Fisher-Ideal price indexes (U.S. Department of Commerce, Bureau of Economic Analysis, National Income and Product Accounts 2010).

Table 21. **Parameter Estimates from the FDLAIDS Model Using BLS Data, 1998–2009, Monthly**

	Demand For								
	Cereals and Bakery	**Meat**	**Eggs**	**Dairy**	**Fruits and Vegetables**	**Other Foods**	**Nonalcoholic Beverages**	**FAFH**	**Alcoholic Beverages**
Price of									
Cereals and bakery	0.0104	0.0001	0.0004	0.0052	−0.0028	0.0039	−0.0018	−0.0070	0.0013
	(0.0040)	(0.0022)	(0.0003)	(0.0011)	(0.0019)	(0.0051)	(0.0027)	(0.0066)	(0.0026)
Meat	0.0001	0.0216	0.0010	0.0011	0.0010	0.0089	0.0023	−0.0079	−0.0041
	(0.0022)	(0.0056)	(0.0004)	(0.0017)	(0.0030)	(0.0037)	(0.0020)	(0.0100)	(0.0048)
Eggs	0.0004	0.0010	0.0010	0.0001	0.0009	−0.0001	0.0008	−0.0026	0.0002
	(0.0003)	(0.0004)	(0.0001)	(0.0002)	(0.0003)	(0.0005)	(0.0003)	(0.0010)	(0.0004)
Dairy	0.0052	0.0011	0.0001	0.0113	−0.0010	−0.0052	−0.0030	0.0023	−0.0019
	(0.0011)	(0.0017)	(0.0002)	(0.001)	(0.0013)	(0.0019)	(0.0011)	(0.0041)	(0.0019)
Fruits and vegetables	−0.0028	0.0010	0.0009	−0.0010	0.0052	0.0095	0.0031	0.0013	−0.0032
	(0.0019)	(0.0030)	(0.0003)	(0.0013)	(0.0032)	(0.0032)	(0.0018)	(0.0073)	(0.0035)
Other foods	0.0039	0.0089	−0.0001	−0.0052	0.0095	−0.0136	0.0000	0.0257	−0.0021
	(0.0051)	(0.0037)	(0.0005)	(0.0019)	(0.0032)	(0.0092)	(0.0041)	(0.0115)	(0.0043)
Nonalcoholic beverages	−0.0018	0.0023	0.0008	−0.0030	0.0031	0.0000	0.0000	−0.0007	−0.0026
	(0.0027)	(0.0020)	(0.0003)	(0.0011)	(0.0018)	(0.0041)	(0.0037)	(0.0061)	(0.0023)
FAFH	−0.0070	−0.0079	−0.0026	0.0023	0.0013	0.0257	−0.0007	−0.0162	0.0132
	(0.0066)	(0.0100)	(0.0010)	(0.0041)	(0.0073)	(0.0115)	(0.0061)	(0.0337)	(0.0119)
Alcoholic beverages	0.0013	−0.0041	0.0002	−0.0019	−0.0032	−0.0021	−0.0026	0.0132	0.0011
	(0.0026)	(0.0048)	(0.0004)	(0.0019)	(0.0035)	(0.0043)	(0.0023)	(0.0119)	(0.0080)
Nonfood	−0.0096	−0.0240	−0.0016	−0.0090	−0.0140	−0.0270	0.0020	−0.0081	−0.0018
	(0.0050)	(0.0119)	(0.0008)	(0.0036)	(0.0070)	(0.0078)	(0.0042)	(0.0288)	(0.0131)
Expenditure	−0.0154	−0.0246	−0.0014	−0.0102	−0.0170	−0.0220	−0.0089	−0.0499	−0.0123
	(0.0007)	(0.0018)	(0.0001)	(0.0005)	(0.0010)	(0.0011)	(0.0006)	(0.0040)	(0.0018)
δ_1	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
δ_2	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Intercept	−0.0002	−0.0004	0.0000	−0.0001	0.0001	0.0002	0.0001	0.0000	0.0000
	(0.0001)	(0.0002)	(0.0000)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0005)	(0.0002)
R^2	0.2024	0.0303	0.0549	0.1106	0.1833	0.1412	0.0950	0.1658	−0.0066

Note: Standard errors are in parentheses.

Source: Authors' calculations from FDLAIDS and using aggregated monthly average household expenditures and consumer price indexes (U.S. Department of Labor, Bureau of Labor Statistics, Consumer Expenditure Survey 2010; U.S. Department of Labor, Bureau of Labor Statistics, Consumer Price Index Database 2010).

Table 22. First-Stage Uncompensated Elasticities of Demand from the FDLAIDS Model Using BLS Data, 1998–2009, Monthly

Elasticity of Demand For	With Respect to Price of: Cereals and Bakery	Meat	Eggs	Dairy	Fruits and Vegetables	Other Foods	Nonalcoholic Beverages	FAFH	Alcoholic Beverages	Nonfood	Expenditure
Cereals and bakery	−0.30	0.03	0.03	0.36	−0.17	0.28	−0.11	−0.39	0.09	0.19	−0.02
	(0.27)	(0.15)	(0.02)	(0.08)	(0.13)	(0.34)	(0.18)	(0.44)	(0.17)	(0.33)	(0.05)
Meat	0.02	−0.12	0.04	0.05	0.06	0.38	0.10	−0.25	−0.15	−0.15	0.02
	(0.09)	(0.22)	(0.01)	(0.07)	(0.12)	(0.15)	(0.08)	(0.40)	(0.19)	(0.48)	(0.07)
Eggs	0.34	0.84	−0.22	0.10	0.75	−0.05	0.63	−2.05	0.16	−0.37	−0.12
	(0.27)	(0.31)	(0.06)	(0.15)	(0.25)	(0.44)	(0.27)	(0.82)	(0.35)	(0.65)	(0.09)
Dairy	0.46	0.11	0.01	−0.02	−0.07	−0.42	−0.24	0.26	−0.15	−0.06	0.13
	(0.10)	(0.14)	(0.02)	(0.09)	(0.11)	(0.16)	(0.09)	(0.35)	(0.16)	(0.31)	(0.04)
Fruits and vegetables	−0.14	0.08	0.05	−0.04	−0.70	0.54	0.18	0.13	−0.16	−0.01	0.07
	(0.11)	(0.16)	(0.02)	(0.07)	(0.17)	(0.17)	(0.10)	(0.40)	(0.19)	(0.39)	(0.05)
Other foods	0.17	0.39	0.00	−0.20	0.41	−1.54	0.01	1.12	−0.07	−0.37	0.10
	(0.21)	(0.15)	(0.02)	(0.08)	(0.13)	(0.38)	(0.17)	(0.47)	(0.18)	(0.33)	(0.04)
Nonalcoholic beverages	−0.18	0.27	0.08	−0.30	0.35	0.02	−0.99	−0.01	−0.27	0.99	0.05
	(0.29)	(0.21)	(0.04)	(0.12)	(0.19)	(0.44)	(0.39)	(0.66)	(0.24)	(0.45)	(0.06)
FAFH	−0.09	−0.10	−0.04	0.04	0.03	0.40	0.00	−1.19	0.21	0.49	0.25
	(0.10)	(0.15)	(0.02)	(0.06)	(0.11)	(0.17)	(0.09)	(0.51)	(0.18)	(0.44)	(0.06)
Alcoholic beverages	0.12	−0.32	0.02	−0.14	−0.25	−0.15	−0.21	1.17	−0.89	0.69	−0.04
	(0.21)	(0.40)	(0.04)	(0.16)	(0.29)	(0.36)	(0.19)	(1.00)	(0.68)	(1.12)	(0.15)
Nonfood	−0.01	−0.03	0.00	−0.01	−0.02	−0.04	0.00	−0.02	0.00	−1.05	1.20
	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.04)	(0.02)	(0.06)	(0.01)

Notes: Estimates of elasticities of demand were evaluated at the mean of the data. Standard errors are in parentheses.

Source: Authors' calculations based on FDLAIDS and using aggregated monthly average household expenditures and consumer price indexes (U.S. Department of Labor, Bureau of Labor Statistics, Consumer Expenditure Survey 2010; U.S. Department of Labor, Bureau of Labor Statistics, Consumer Price Index Database 2010).

Table 23. **Mean Absolute Error for Conditional-on-Price Forecasts by Data Type**

	Percent MAE	
	BEA	BLS
Cereals and bakery	2.06	7.22
Meat	2.19	8.68
Eggs	6.50	10.57
Dairy	3.51	5.90
Fruits and vegetables	1.94	6.60
Other foods	1.95	7.24
Nonalcoholic beverages	3.19	7.51
FAFH	1.09	7.30
Alcoholic beverages	1.65	14.59
Nonfood	0.19	1.25
Average	2.43	7.69

Source: Authors' calculations based on elasticities of demand derived from NBR model using annual BEA data and from FDLAIDS model using monthly BLS data.

range between 0.28 and 0.97 for the BEA-data-based estimates and −0.04 and 0.25 for the BLS-data-based estimates.

6.3. Conditional-on-Price Forecasts for First-Stage Estimates

We used conditional-on-price forecasts (equation (85)) to test the forecasting ability of the estimates of elasticities of demand from Barten's synthetic model across the alternative data sets. Implicit quantity indexes were used as proxies for the actual quantities. Hence, the conditional-on-price forecasts we made with our estimates of elasticities of demand are in-sample.[36] The MAE was calculated for each food product. With the exception of eggs, the MAE for all products based on the annual BEA data is less than 5% (Table 23). The BLS-data-based estimates do not forecast as well as the BEA-data-based estimates; the MAE for each product ranged between 1.25% and 14.59%. The BEA-data-based estimates of elasticities forecast just as well if not better than both the BLS-data-based counterparts and estimates of elasticities from the literature based on data that distinguished FAFH from FAH (Table 7).

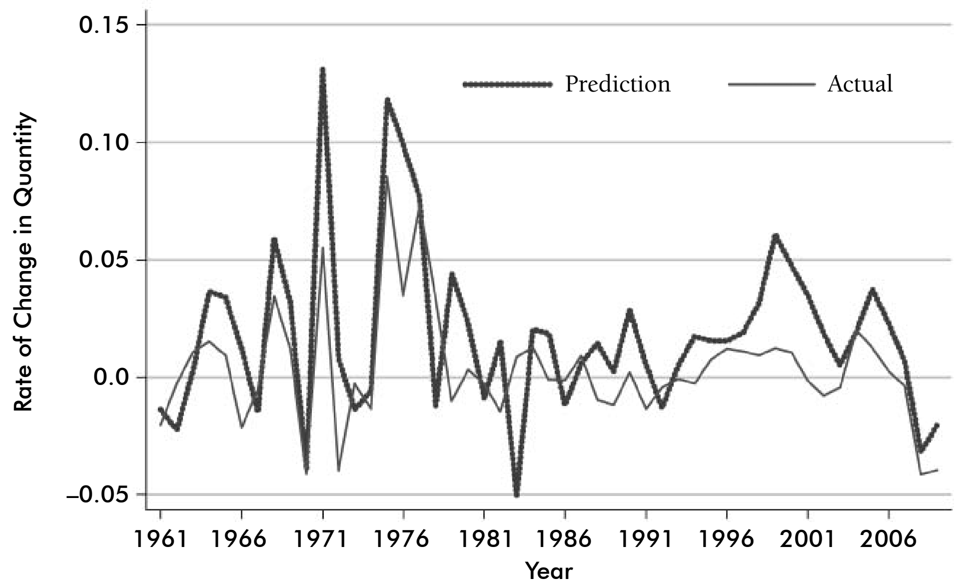
Over time, the conditional-on-price predicted rates of change in quantities closely mirror the rates of change in actual quantities as measured by the quantity indexes (Figures 2–11) for the BEA-data-based estimates. The predicted rates of change in consumption of nonalcoholic beverages and FAFH are close to the actual rates of change over most of the time period with the exception of the period 1970–1979. The predicted rates of change in consumption seem to be generally lower than the actual rates of change for meat and dairy from 1980 through 2009 but generally higher than the actual rates of change for cereals and bakery products for the same period.

6.4. Second-Stage Estimates of Elasticities of Demand for Fruits and Vegetables

The BEA-data-based estimates of elasticities of demand from Barten's synthetic model are better for forecasting quantity changes than the BLS-data-based estimates. For this reason, we used the BEA-data-based estimates of elasticities for the first-stage allocations, combined with second-stage estimates of elasticities of demand for disaggregated fruits and vegetables, to estimate disaggregated elasticities of demand for fruits and vegetables conditional on expenditure on all goods. We used the BLS data on prices and expenditures to estimate the second-stage elasticities of demand for apples, bananas, citrus, other fresh fruits, potatoes,

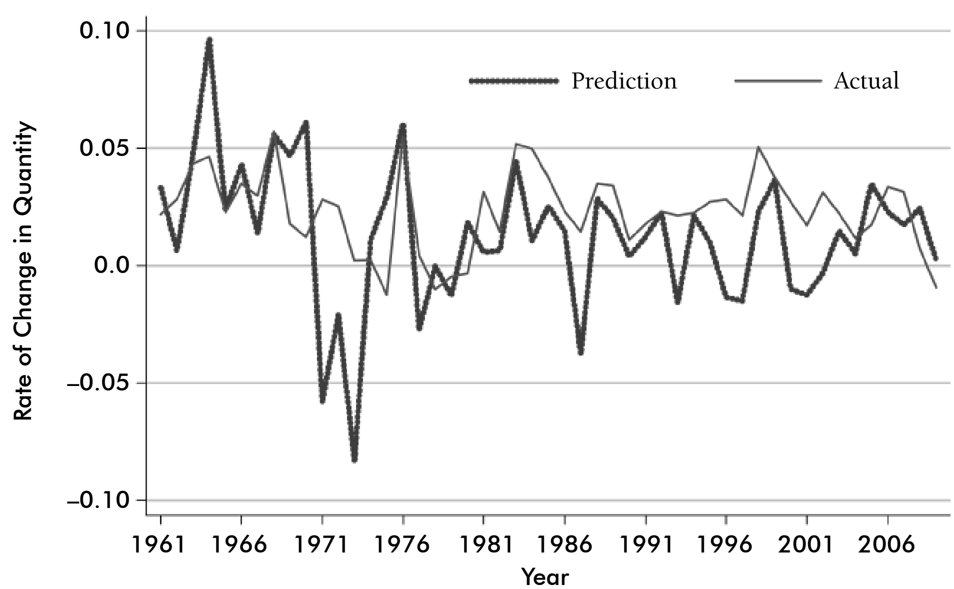
[36] The conditional-on-price forecasts using estimates of elasticities of demand from the literature are out-of-sample.

Figure 2. Predicted and Actual Rates of Change in Quantity for Cereals and Bakery Products Using the NBR Model, Annual, 1960–2009



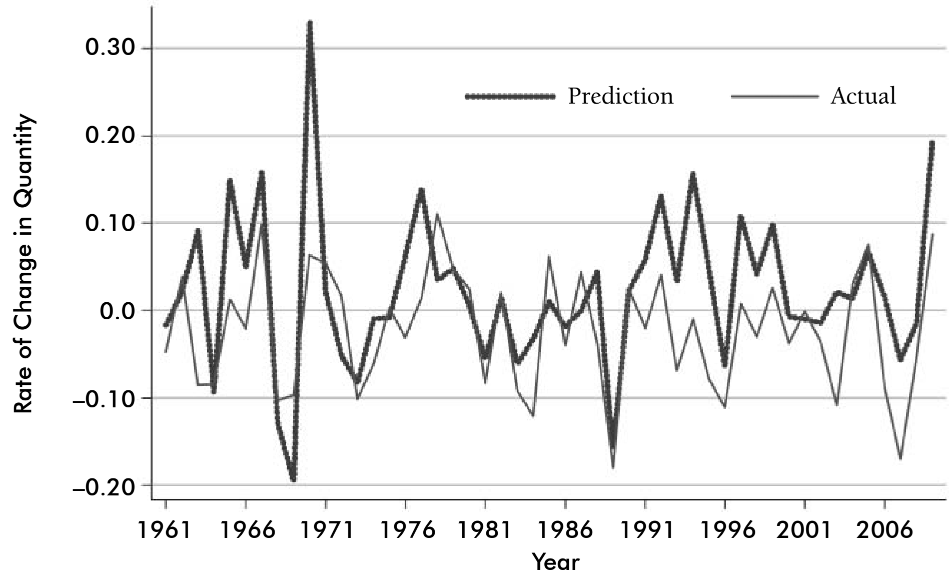
Source: Authors' calculations based on conditional-on-price forecasts using elasticities of demand based on NBR model with annual personal consumption expenditure and price data (U.S. Department of Commerce, Bureau of Economic Analysis 2010).

Figure 3. Predicted and Actual Rates of Change in Quantity for Meat Using the NBR Model, Annual, 1960–2009



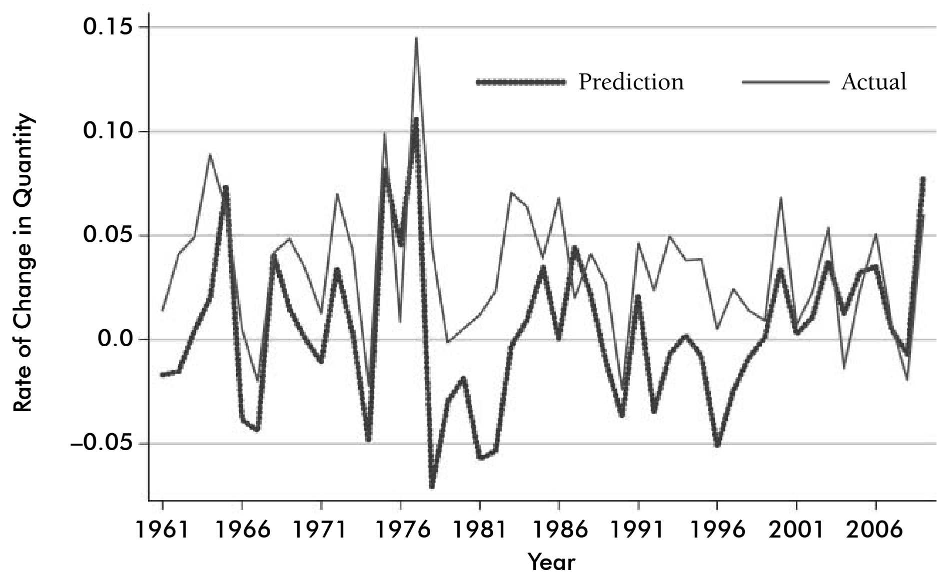
Source: Authors' calculations based on conditional-on-price forecasts using elasticities of demand based on NBR model with annual personal consumption expenditure and price data (U.S. Department of Commerce, Bureau of Economic Analysis 2010).

Figure 4. **Predicted and Actual Rates of Change in Quantity for Eggs Using the NBR Model, Annual, 1960–2009**



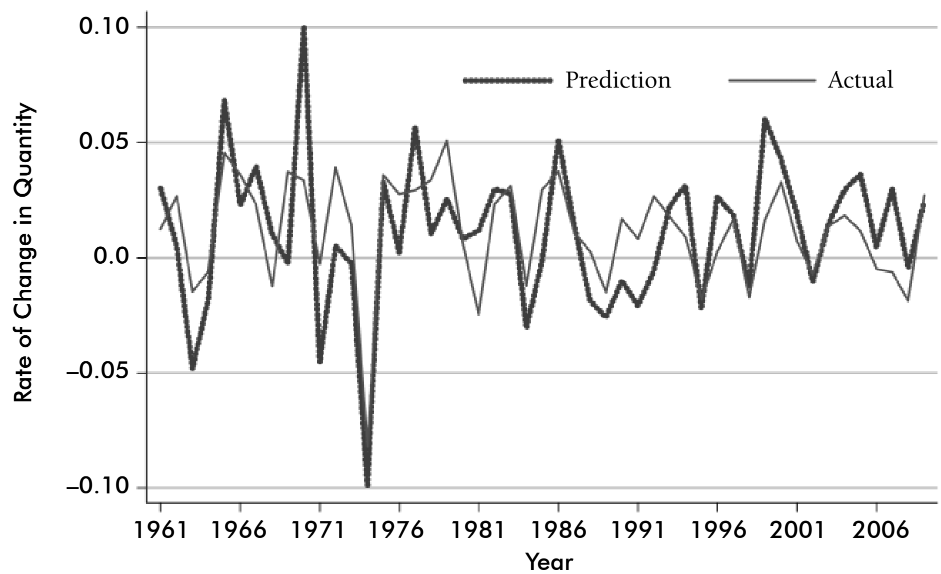
Source: Authors' calculations based on conditional-on-price forecasts using elasticities of demand based on NBR model with annual personal consumption expenditure and price data (U.S. Department of Commerce, Bureau of Economic Analysis 2010).

Figure 5. **Predicted and Actual Rates of Change in Quantity for Dairy Products Using the NBR Model, Annual, 1960–2009**



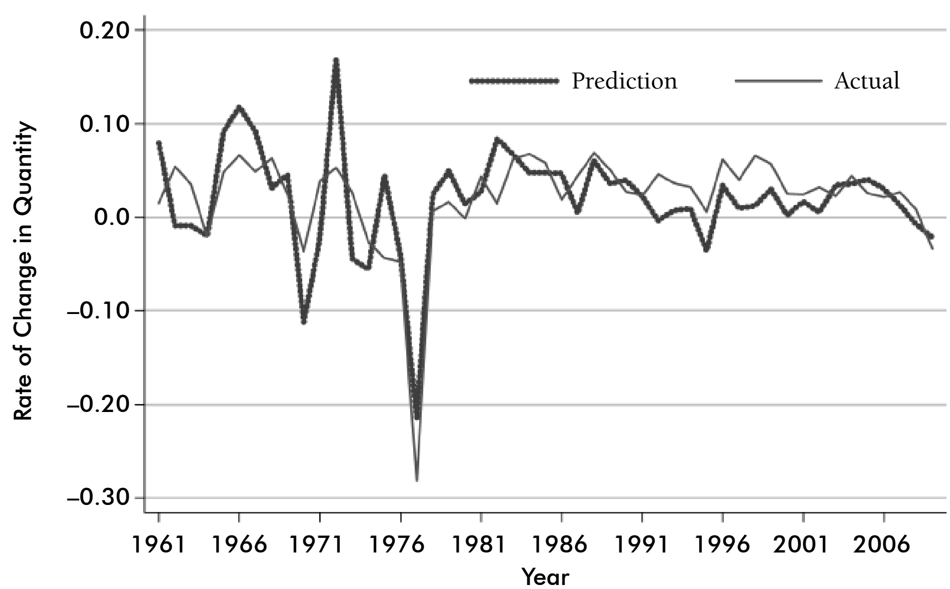
Source: Authors' calculations based on conditional-on-price forecasts using elasticities of demand based on NBR model with annual personal consumption expenditure and price data (U.S. Department of Commerce, Bureau of Economic Analysis 2010).

Figure 6. **Predicted and Actual Rates of Change in Quantity for Fruits and Vegetables Using the NBR Model, Annual, 1960–2009**



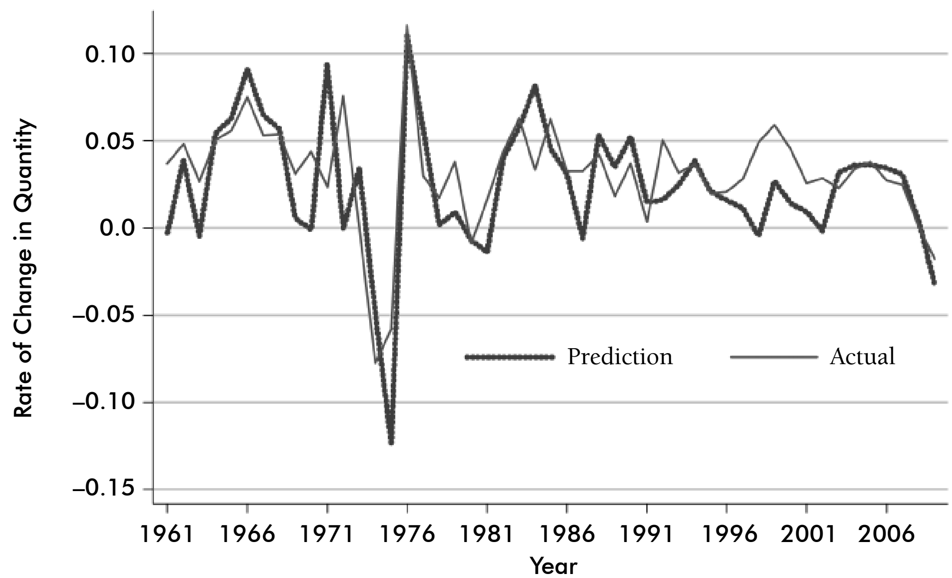
Source: Authors' calculations based on conditional-on-price forecasts using elasticities of demand based on NBR model with annual personal consumption expenditure and price data (U.S. Department of Commerce, Bureau of Economic Analysis 2010).

Figure 7. **Predicted and Actual Rates of Change in Quantity for Nonalcoholic Beverages Using the NBR Model, Annual, 1960–2009**



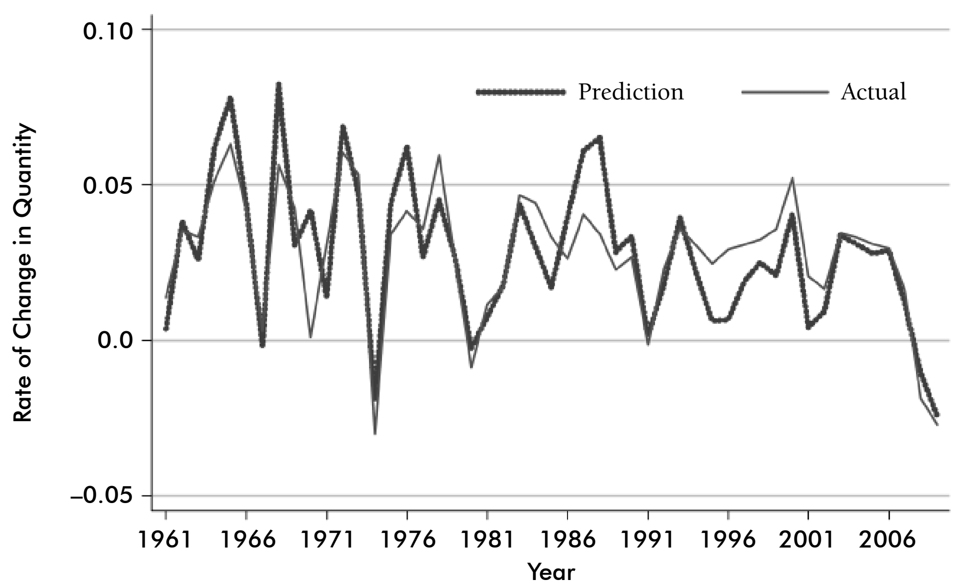
Source: Authors' calculations based on conditional-on-price forecasts using elasticities of demand based on NBR model with annual personal consumption expenditure and price data (U.S. Department of Commerce, Bureau of Economic Analysis 2010).

Figure 8. **Predicted and Actual Rates of Change in Quantity for Other Food Using the NBR Model, Annual, 1960–2009**



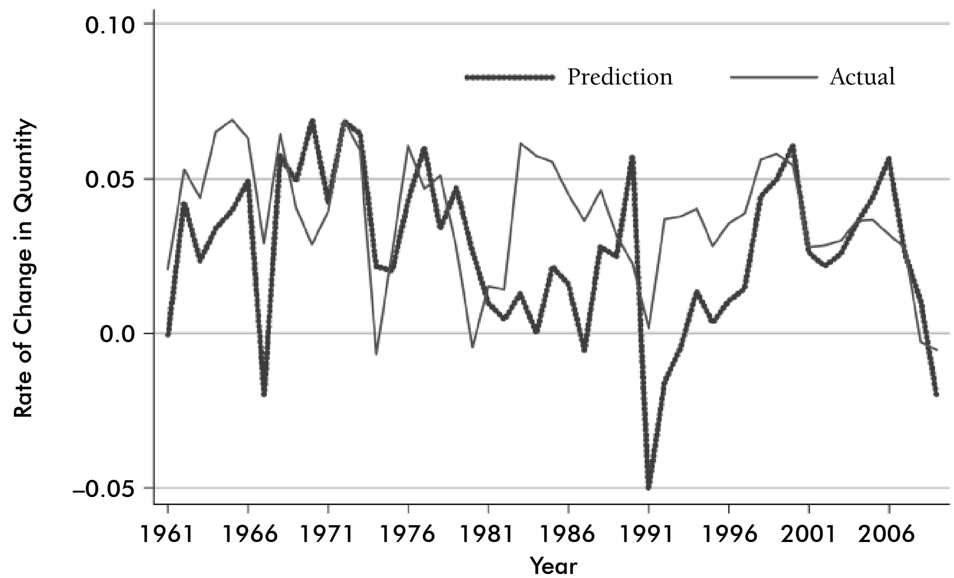
Source: Authors' calculations based on conditional-on-price forecasts using elasticities of demand based on NBR model with annual personal consumption expenditure and price data (U.S. Department of Commerce, Bureau of Economic Analysis 2010).

Figure 9. **Predicted and Actual Rates of Change in Quantity for FAFH Using the NBR Model, Annual, 1960–2009**



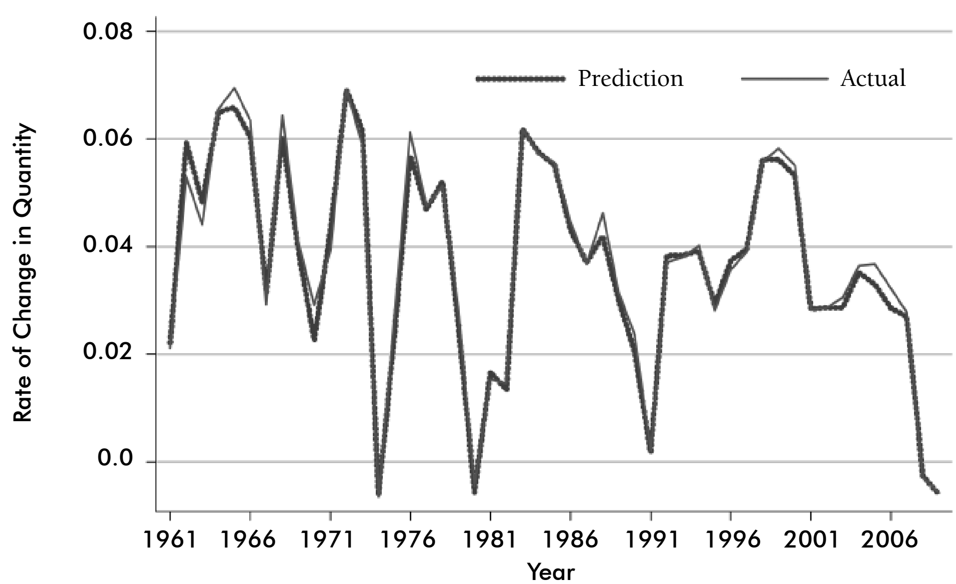
Source: Authors' calculations based on conditional-on-price forecasts using elasticities of demand based on NBR model with annual personal consumption expenditure and price data (U.S. Department of Commerce, Bureau of Economic Analysis 2010).

Figure 10. **Predicted and Actual Rates of Change in Quantity for Alcoholic Beverages Using the NBR Model, Annual, 1960–2009**



Source: Authors' calculations based on conditional-on-price forecasts using elasticities of demand based on NBR model with annual personal consumption expenditure and price data (U.S. Department of Commerce, Bureau of Economic Analysis 2010).

Figure 11. **Predicted and Actual Rates of Change in Quantity for Nonfood Using the NBR Model, Annual, 1960–2009**



Source: Authors' calculations based on conditional-on-price forecasts using elasticities of demand based on NBR model with annual personal consumption expenditure and price data (U.S. Department of Commerce, Bureau of Economic Analysis 2010).

lettuce, tomatoes, other fresh vegetables, and processed fruits and vegetables using Barten's synthetic model (equation (90)) (Table 24).[37] Consumer Price Indexes for processed fruits and vegetables and other fresh fruits are available only from 1998, so we estimated Barten's synthetic model with the BLS monthly data from 1998 through 2009. We included a linear time trend in the model as well as a constant and imposed symmetry and homogeneity on the estimates.

At the 5% level of significance, we reject all nested models. Matsuda (2005) and Eales, Durham, and Wessells (1997) argued that Barten's synthetic model and its reparameterization, the GODDS, are not merely artificial composites of known differential demand systems but can be viewed as demand systems in their own right. Hence, we present the estimated parameters and elasticities of demand for the second-stage disaggregated fruit and vegetable products based on Barten's synthetic model.

The estimates of parameters and elasticities based on the application of Barten's synthetic model using the monthly BLS data are presented in Tables 27 and 28. The estimated elasticities of demand for individual fruits and vegetables conditional on total expenditure on fruits and vegetables are consistent with demand theory. The estimated elasticities of demand with respect to total expenditure on fruits and vegetables are greater than one for bananas, citrus, other fresh fruits, lettuce, tomatoes, and other fresh vegetables. In comparison, the demand for the processed fruit and vegetable composite is more inelastic with respect to total expenditure, which is consistent with other studies reported in Tables 5 and 6.

6.5. Estimates of Elasticities of Demand for Fruits and Vegetables Conditional on Expenditure on Goods

Using equations (29) and (30), we approximated the elasticities of demand for fruits and vegetables conditional on expenditure on goods. For the first stage, we used the estimated elasticities of demand based on the NBR model and the annual BEA data (Table 20) for several reasons. First, the estimates of the elasticities of demand based on the BEA annual data resulted in smaller forecasting errors than the elasticities of demand based on the BLS data. Second, the NBR model using the annual BEA data seemed to fit the data better in terms of R^2 than the FDLAIDS model using the monthly BLS data.

The own-price elasticities of demand for the individual fruits and vegetables conditional on expenditure on all goods are similar to the own-price elasticities of demand conditional on expenditure on fruits and vegetables. The demands for apples (−0.57), potatoes (−0.45), and processed fruits and vegetables (−0.58) are the most price inelastic (Table 29). Citrus is the only category of fruits and vegetables for which demand is elastic with respect to its own price (−1.11). The expenditure elasticities range from 0.17 for potatoes and processed fruits and vegetables to 0.40 for tomatoes.

The estimated own-price and expenditure elasticities presented in Table 29 are compared with elasticities of demand from You, Epperson, and Huang (1996) and from Huang (1993) (Table 30). These studies estimated elasticities of demand using a two-stage budgeting procedure similar to that of George and King (1971) in which first-stage effects were subtracted

[37] We used the BLS data for the second stage because we used the finest level of disaggregation of the BEA data for our first-stage estimates.

Table 24. BLS Price and Expenditure Data for Fruits and Vegetables in the Second-Stage Estimation

	Price			Expenditure†		
Food	Database	Series ID	Availability	Database	Universal Classification Code	Availability
Apples	CPI, All Urban Consumers	CUUR0000SEFK01	1980–Present	CEX Diary, EXPN files	110110	1986–2009
Bananas	CPI, All Urban Consumers	CUUR0000SEFK02	1980–Present	CEX Diary, EXPN files	110210	1986–2009
Citrus	CPI, All Urban Consumers	CUUR0000SEFK03	1998–Present	CEX Diary, EXPN files	110310	1986–2009
Other fresh fruits	CPI, All Urban Consumers	CUUR0000SEFK04	1998–Present	CEX Diary, EXPN files	110410	1986–2009
Potatoes	CPI, All Urban Consumers	CUUR0000SEFL01	1986–Present	CEX Diary, EXPN files	120110	1986–2009
Lettuce	CPI, All Urban Consumers	CUUR0000SEFL02	1989–Present	CEX Diary, EXPN files	120210	1986–2009
Tomatoes	CPI, All Urban Consumers	CUUR0000SEFL03	1980–Present	CEX Diary, EXPN files	120310	1986–2009
Other fresh vegetables	CPI, All Urban Consumers	CUUR0000SEFL04	1998–Present	CEX Diary, EXPN files	120410	1986–2009
Processed fruits and vegetables	CPI, All Urban Consumers	CUUR0000SEFM	1998–Present	CEX Diary, EXPN files	130310–140340	1986–2009

†See notes to Table 12.

from the second-stage expenditures for each subgroup estimated. Compared to these other studies, the present study finds fruits and vegetables to be generally more price elastic and more expenditure inelastic, with the exception of apples.

6.6. Conditional-on-Price Forecasts for Fruits and Vegetables

Conditional-on-price forecasts were also performed on both sets of estimated elasticities of demand for fruits and vegetables (Table 31). The MAE of predictions of price-induced quantity changes for the elasticities of demand for fruits and vegetables conditional on total expenditure on all goods ranged between 8% and 16% over the period from 1998 through 2009. These large MAEs on the conditional-on-price forecasts can be attributed to the large MAEs on the conditional-on-price forecasts for the second-stage estimates of elasticities of demand for fruits and vegetables and errors in the approximation used to compute the elasticities of demand for fruits and vegetables conditional on total expenditure on all goods. The MAEs for the conditional-on-price forecasts for disaggregated fruits and vegetables, conditional on total expenditure on fruits

Table 25. Wald and Log-Likelihood Tests for Nested Models of Barten's Synthetic Model Using Aggregated BLS Data for Fruits and Vegetables, 1998–2009, Monthly

	Likelihood Ratio Test	p-value	Wald Test	p-value
Rotterdam ($\delta_1=\delta_2=0$)	51.69	0.00	68.53	0.00
FDLAIDS ($\delta_1=\delta_2=1$)	10.51	0.01	12.87	0.00
CBS ($\delta_1=1$, $\delta_2=0$)	15.39	0.00	19.07	0.00
NBR ($\delta_1=0$, $\delta_2=1$)	47.17	0.00	60.40	0.00

Source: Authors' calculations based on Barten's synthetic model and using aggregated average monthly expenditures and consumer price indexes (U.S. Department of Labor, Bureau of Labor Statistics, Consumer Expenditure Survey 2010; U.S. Department of Labor, Bureau of Labor Statistics, Consumer Price Index Database 2010).

Table 26. Autocorrelation Statistics for Barten's Model Using Aggregated Data from the BLS for Fruits and Vegetables, 1998–2009, Monthly

	AR(1) Coefficient	Durbin's h	p-value	Breusch-Godfrey	p-value
Apples	−0.04	0.16	0.69	0.18	0.67
Bananas	−0.01	0.02	0.89	0.02	0.88
Citrus	−0.06	0.45	0.50	0.50	0.48
Other fresh fruit	0.33	14.91	0.00	14.81	0.00
Potatoes	0.05	0.31	0.58	0.35	0.56
Lettuce	−0.09	0.96	0.33	1.06	0.30
Tomatoes	0.05	0.33	0.57	0.36	0.55
Other fresh vegetables	0.04	0.18	0.67	0.20	0.66

Source: Authors' calculations based on Barten's model and using aggregated average monthly expenditures and consumer price indexes (U.S. Department of Labor, Bureau of Labor Statistics, Consumer Expenditure Survey 2010; U.S. Department of Labor, Bureau of Labor Statistics, Consumer Price Index Database 2010).

Table 27. Second-Stage Parameter Estimates for Fruits and Vegetables from Barten's Model Using BLS Data, 1998–2009, Monthly

	Demand For							
	Apples	Bananas	Citrus	Other Fresh Fruit	Potatoes	Lettuce	Tomatoes	Other Fresh Vegetables
Price of								
Apples	0.0145 (0.0252)	−0.0066 (0.0077)	−0.0022 (0.0058)	−0.0036 (0.0113)	−0.0045 (0.0076)	0.0018 (0.0043)	−0.0037 (0.0054)	0.0169 (0.0127)
Bananas	−0.0066 (0.0077)	0.0009 (0.025)	−0.0029 (0.0054)	0.0105 (0.0105)	0.0048 (0.0075)	−0.0065 (0.0041)	−0.0025 (0.0047)	0.0014 (0.0118)
Citrus	−0.0022 (0.0058)	−0.0029 (0.0054)	−0.0220 (0.0259)	0.0027 (0.0099)	−0.0006 (0.0056)	0.0047 (0.0036)	0.0085 (0.0047)	0.0000 (0.0101)
Other fresh fruits	−0.0036 (0.0113)	0.0105 (0.0105)	0.0027 (0.0099)	−0.0262 (0.0553)	−0.0003 (0.0112)	−0.0102 (0.0068)	−0.0052 (0.0094)	0.0041 (0.0201)
Potatoes	−0.0045 (0.0076)	0.0048 (0.0075)	−0.0006 (0.0056)	−0.0003 (0.0112)	0.0214 (0.0251)	−0.0027 (0.0042)	0.0066 (0.0052)	−0.0261 (0.0119)
Lettuce	0.0018 (0.0043)	−0.0065 (0.0041)	0.0047 (0.0036)	−0.0102 (0.0068)	−0.0027 (0.0042)	0.0015 (0.0176)	0.0024 (0.0032)	0.0048 (0.0076)
Tomatoes	−0.0037 (0.0054)	−0.0025 (0.0047)	0.0085 (0.0047)	−0.0052 (0.0094)	0.0066 (0.0052)	0.0024 (0.0032)	0.0244 (0.0245)	0.0058 (0.0094)
Other fresh vegetables	0.0169 (0.0127)	0.0014 (0.0118)	0.0000 (0.0101)	0.0041 (0.0201)	−0.0261 (0.0119)	0.0048 (0.0076)	0.0058 (0.0094)	0.0136 (0.0625)
Processed fruits and vegetables	−0.0125 (0.0151)	0.0009 (0.0171)	0.0119 (0.0126)	0.0282 (0.0248)	0.0014 (0.0148)	0.0042 (0.0089)	−0.0362 (0.0116)	−0.0204 (0.0276)
Expenditure	−0.0770 (0.0190)	−0.0425 (0.0171)	−0.0431 (0.0210)	−0.1248 (0.0454)	−0.0804 (0.0183)	−0.0383 (0.0126)	−0.0238 (0.0191)	−0.1385 (0.0485)
δ_1	1.8487 (0.2379)	1.8487 (0.2379)	1.8487 (0.2379)	1.8487 (0.2379)	1.8487 (0.2379)	1.8487 (0.2379)	1.8487 (0.2379)	1.8487 (0.2379)
δ_2	0.8114 (0.3641)	0.8114 (0.3641)	0.8114 (0.3641)	0.8114 (0.3641)	0.8114 (0.3641)	0.8114 (0.3641)	0.8114 (0.3641)	0.8114 (0.3641)
Intercept	−0.0007 (0.0007)	−0.0012 (0.0006)	−0.0002 (0.0007)	0.0027 (0.0014)	−0.0008 (0.0007)	−0.0001 (0.0004)	0.0000 (0.0007)	0.0008 (0.0012)
R^2	0.2679	0.5336	0.7539	0.6134	0.2698	0.6135	0.5744	0.6836

Note: Standard errors are in parentheses.

Source: Authors' calculations based on Barten's model and using aggregated average monthly expenditures and Consumer Price Indexes (U.S. Department of Labor, Bureau of Labor Statistics, Consumer Expenditure Survey 2010; U.S. Department of Labor, Bureau of Labor Statistics, Consumer Price Index Database 2010).

Table 28. Second-Stage Estimates of Uncompensated Elasticities of Demand for Fruits and Vegetables from Barten's Model Using BLS Data, 1998–2009, Monthly

	With Respect to Price of									
Elasticity of Demand For	Apples	Bananas	Citrus	Other Fresh Fruit	Potatoes	Lettuce	Tomatoes	Other Fresh Vegetables	Processed Fruits and Vegetables	Expenditure on Fruits and Vegetables
Apples	−0.60	−0.09	−0.03	−0.04	−0.06	0.03	−0.05	0.25	−0.16	0.75
	(0.15)	(0.11)	(0.08)	(0.15)	(0.11)	(0.06)	(0.07)	(0.16)	(0.21)	(0.13)
Bananas	−0.13	−0.82	−0.07	0.09	0.05	−0.12	−0.06	−0.05	−0.08	1.20
	(0.12)	(0.19)	(0.08)	(0.15)	(0.11)	(0.06)	(0.07)	(0.17)	(0.25)	(0.11)
Citrus	−0.06	−0.07	−1.13	−0.05	−0.04	0.04	0.08	−0.09	0.04	1.29
	(0.07)	(0.07)	(0.08)	(0.12)	(0.07)	(0.04)	(0.06)	(0.11)	(0.15)	(0.12)
Other fresh fruits	−0.04	0.04	−0.01	−1.02	−0.02	−0.07	−0.05	−0.04	0.08	1.14
	(0.06)	(0.05)	(0.05)	(0.12)	(0.06)	(0.03)	(0.05)	(0.09)	(0.12)	(0.10)
Potatoes	−0.06	0.08	0.00	0.03	−0.48	−0.03	0.11	−0.36	0.06	0.64
	(0.11)	(0.11)	(0.08)	(0.15)	(0.14)	(0.06)	(0.07)	(0.16)	(0.21)	(0.13)
Lettuce	0.02	−0.15	0.08	−0.25	−0.07	−0.79	0.03	0.05	0.03	1.06
	(0.09)	(0.08)	(0.07)	(0.12)	(0.08)	(0.07)	(0.06)	(0.14)	(0.17)	(0.11)
Tomatoes	−0.10	−0.08	0.07	−0.20	0.05	0.00	−0.51	−0.05	−0.68	1.51
	(0.07)	(0.06)	(0.06)	(0.12)	(0.07)	(0.04)	(0.08)	(0.12)	(0.15)	(0.13)
Other fresh vegetables	0.06	−0.01	−0.03	−0.04	−0.16	0.01	0.01	−0.81	−0.18	1.14
	(0.06)	(0.06)	(0.04)	(0.08)	(0.06)	(0.03)	(0.04)	(0.12)	(0.12)	(0.07)
Processed fruits and vegetables	−0.04	0.02	0.07	0.16	0.02	0.03	−0.14	−0.05	−0.67	0.63
	(0.06)	(0.07)	(0.05)	(0.09)	(0.06)	(0.03)	(0.04)	(0.09)	(0.16)	(0.09)

Note: Estimates of elasticities of demand evaluated at the mean of data. Standard errors are in parentheses.

Source: Authors' calculations based on Barten's model and using aggregated average monthly expenditures and consumer price indexes (U.S. Department of Labor, Bureau of Labor Statistics, Consumer Expenditure Survey 2010; U.S. Department of Labor, Bureau of Labor Statistics, Consumer Price Index Database 2010).

Table 29. Estimates of Elasticities of Demand for Fruits and Vegetables Conditional on Expenditure on Goods, 1998–2009

Elasticity of Demand For	With Respect to Price of									
	Apples	Bananas	Citrus	Other Fresh Fruits	Potatoes	Lettuce	Tomatoes	Other Fresh Vegetables	Processed Fruits & Vegetables	Expenditure on Goods
Apples	−0.57	−0.07	−0.01	0.00	−0.03	0.04	−0.04	0.30	−0.05	0.20
Bananas	−0.08	−0.80	−0.05	0.16	0.10	−0.10	−0.05	0.02	0.10	0.32
Citrus	−0.01	−0.04	−1.11	0.03	0.01	0.06	0.09	−0.01	0.23	0.35
Other fresh fruits	0.00	0.06	0.01	−0.95	0.02	−0.05	−0.04	0.03	0.25	0.31
Potatoes	−0.03	0.10	0.02	0.06	−0.45	−0.02	0.12	−0.32	0.15	0.17
Lettuce	0.06	−0.13	0.10	−0.19	−0.03	−0.77	0.04	0.12	0.18	0.28
Tomatoes	−0.04	−0.05	0.10	−0.11	0.11	0.03	−0.50	0.05	−0.46	0.40
Other fresh vegetables	0.11	0.01	0.00	0.03	−0.11	0.03	0.02	−0.73	−0.01	0.31
Processed fruits and vegetables	−0.02	0.03	0.08	0.19	0.04	0.04	−0.14	−0.01	−0.58	0.17

Source: Authors' calculations based on first- and second-stage elasticities of demand. First-stage estimates of elasticities of demand based on the NBR model using annual BEA price and expenditure data for 1960–2009 (see Table 20). Second-stage estimates of elasticities of demand based on Barten's model using monthly BLS price and expenditure data for 1998–2009 (see Table 28).

and vegetables, are also very large, ranging between 7% and 13%. The elasticities of demand for disaggregated fruits and vegetables conditional on expenditure on all goods are approximated using the second-stage elasticities of demand, which yield predictions of quantities with large error. Hence, it is not surprising to find large MAEs for the conditional-on-price forecasts for the elasticities of demand for disaggregated fruits and vegetables conditional on total expenditure on goods.

Table 30. **Comparison of Own-Price and Expenditure Elasticities of Demand for Fruits and Vegetables Conditional on Expenditure on Goods, Estimates from Selected Studies**

	This Study	You, Epperson & Huang (1998)	Huang (1993)
Own-Price Elasticity of Demand			
Apples	−0.57	−0.17	−0.19
Bananas	−0.80	−0.42	−0.50
Citrus†	−1.11	−1.14	−0.85
Other fresh fruit	−0.95	−0.03 to −0.10	−1.18 to −0.42
Potatoes	−0.45	−0.18	−0.10
Lettuce	−0.77	−0.01	−0.10
Tomatoes	−0.50	−0.41	−0.62
Other fresh vegetables	−0.73	0.03 to −0.58	−0.08 to −0.54
Processed fruits and vegetables	−0.58	−0.14 to −0.35	−0.17 to −0.15
Elasticity of Demand with Respect to Expenditure on All Goods			
Apples	0.20	−0.19	−0.36
Bananas	0.32	0.63	0.09
Citrus†	0.35	0.89	−0.17
Other fresh fruit	0.31	−1.80 to 0.93	−0.49 to 0.12
Potatoes	0.17	0.29	0.11
Lettuce	0.28	0.64	0.37
Tomatoes	0.40	0.80	0.92
Other fresh vegetables	0.31	0.08 to 1.21	0.08 to 1.29
Processed fruits and vegetables	0.17	0.28 to 0.34	0.02 to 0.87

† The own-price elasticity of demand for oranges from You, Epperson, and Huang (1998) and Huang (1993) was reported for citrus.

Sources: Authors' calculations of estimates of own-price elasticities of demand using two-stage budgeting from Table 29 and similar estimates from the literature (You, Epperson and Huang 1998; Huang 1993).

Table 31. Mean Absolute Error for Conditional-on-Price Forecasts of Disaggregated Demand for Fruits and Vegetables

	Percent Mean Absolute Error	
	Estimates Conditional on Expenditures on Goods	**Estimates Conditional on Expenditures on Fruits and Vegetables**
Apples	13.09	13.43
Bananas	8.40	8.37
Citrus	12.78	13.06
Other fresh vegetables	13.37	15.79
Potatoes	9.10	9.90
Lettuce	9.01	10.17
Tomatoes	8.56	11.25
Other fresh vegetables	6.80	8.02
Processed fruits and vegetables	8.15	9.31
Average	9.92	11.04

Source: Authors' calculations based on elasticities of demand derived from NBR model using annual BEA data and Barten's model using monthly BLS data (see Table 29).

7. SUMMARY AND CONCLUSION

In this study, we have contributed to the professional literature on the demand for food in the United States in five ways. First, we reviewed and summarized previous work on estimating demand for food in the United States. This included a review of the underlying consumer theory and how it is connected to alternative approaches to the specification of systems of demand equations. In light of this review and the nature of the data to be modeled, for our new estimation work we chose to use models based on differential approximations of reduced-form demand equations, one of several approaches to modeling systems of demand that allow some properties of demand—homogeneity, symmetry, and adding-up—to be imposed directly on parameters while using flexible functional forms.

Second, we discussed the implications of different ways to structure models of preferences to limit the number of goods to be modeled. Assumptions about how goods are aggregated and separated into groups can be used to limit the number of goods included in econometric models. The assumption of weakly separable preferences is often invoked to justify estimation of demand for a subset of goods. However, estimates of elasticities of demand conditional on expenditure on a group of goods are quite different from their "unconditional" counterparts. Since there appears to be considerable substitution between aggregate groups of foods, elasticities of demand conditional on total expenditure on food or on all goods are more appropriate for food policy analysis. We showed how elasticities of demand conditional on total expenditure for a group of goods (second-stage elasticities of demand) can be used in conjunction with first-stage estimates of elasticities of demand to approximate unconditional elasticities of demand.

Third, we evaluated estimates of elasticities of demand from selected studies using the MAE from conditional-on-price forecasts. Because estimates of own-price, cross-price, and expenditure elasticities of demand depend on assumptions made about the nature of separability, we limited our analysis to estimates of elasticities of demand that are conditional on total expenditure on food or total expenditure on all goods. The average MAE for conditional-on-price forecasts across all of the demand equations ranged between 2% and 4% in the selected studies that did not separate consumption of FAFH and FAH (all time-series data sets). The average MAE for conditional-on-price forecasts across all demand equations ranged between 4% and 8% in the selected studies that did separate consumption of FAFH and FAH.

Fourth, we used two sets of time-series data to estimate the elasticities of demand for nine retail food products and a nonfood composite. Since the annual BEA and monthly BLS price and expenditure data appear to follow unit root processes, we opted to use a differential demand system for estimating the demands for the ten retail food products. Barten's synthetic model (and its reparameterization, the GODDS) nests four differential demand systems: the Rotterdam model, the FDLAIDS, the CBS model, and the NBR model. The estimates are constrained a priori to satisfy homogeneity and symmetry restrictions. The BEA data favored the NBR model while the BLS data favored the FDLAIDS model. The first-stage own-price elasticities of demand based on both data sets are negative and the cross-price elasticities of demand are generally statistically insignificant, although there is some evidence of cross-price relationships between other foods and FAFH. The first-stage own-price elasticities of demand based on the BLS monthly data are smaller in magnitude than the elasticities of demand based on the annual data with the exception of other foods, nonalcoholic beverages, FAFH, and alcoholic beverages.

We compared our estimates of the own-price elasticities of demand with comparable estimates from the literature. Our own BEA-data-based elasticity of demand for FAFH is found to be smaller than the average own-price elasticity found in the literature (−0.50 compared to −1.02). However, the own-price elasticities of demand for foods other than FAFH included in the study seemed to be consistent with the own-price elasticities of demand typically found in the literature. The BLS-data-based own-price elasticity for FAFH seemed more consistent with previous estimates. We also tested our estimated elasticities of demand for forecasting accuracy by calculating the MAE from conditional-on-price forecasts using our elasticities of demand and compared it with the MAEs from the selected studies. The BEA-data-based estimates of elasticities had a lower average MAE across all demand equations than the BLS-data-based estimates. In addition, the average MAE from the conditional-on-price forecasts based on the BEA data was smaller than the average MAE from conditional-on-price quantity forecasts based on elasticities of demand from the studies that separated consumption of FAFH and FAH.

Lastly, we demonstrated how the first-stage elasticities of demand could be used in conjunction with second-stage elasticities of demand for disaggregated fruits and vegetables to approximate elasticities of demand for disaggregated fruits and vegetables conditional on expenditure on goods. We used the BEA-data-based elasticities of demand for the first stage because they were theoretically consistent, somewhat comparable to what was found in the literature, and better at forecasting changes in quantities resulting from changes in prices. The elasticities of demand for processed fruits and vegetables conditional on expenditures on goods are found to be more inelastic with respect to total expenditure than elasticities for any of the disaggregated fresh fruits and vegetables. This finding is consistent with previous work. The own-price elasticities of demand for disaggregated fruits and vegetables conditional on expenditure on all goods are comparable to those found previously in the literature except for those for apples and processed fruits and vegetables. The average MAE for conditional-on-price forecasts using the approximated elasticities of demand for disaggregated fruits and vegetables conditional on total expenditure on goods is large, ranging between 8% and 16%. This result is most likely driven by large errors in the conditional-on-price forecasts for the second-stage elasticities of demand for disaggregated fruits and vegetables.

A.1. TECHNICAL APPENDIX ON TESTING FOR SEASONAL UNIT ROOTS

Beaulieu and Miron's (1993) test for seasonal stationarity for monthly data is an extension of a test developed by Hylleberg, Engle, Granger, and Yoo (1990) (HEGY) for quarterly data. HEGY stated that the standard autoregressive model that gives rise to unit roots is

$$y_t = \varphi_{1s} y_{t-s} + \varepsilon_t,$$

where $s = 4$ for quarterly data. If $\varphi_{1s} = 1$, then there is a unit root at the sth seasonal frequency and the appropriate filter for data following this process is to fourth-difference y_t (i.e., $\Delta_4 y_t$). Bringing the dependent variable to the left-hand side with $\varphi_{1s} = 1$, the quarterly seasonally integrated process takes the form

$$\Delta_4 = y_t - y_{t-s} = \varepsilon_t.$$

HEGY stated that a unit root at the quarterly frequency can be factored as

$$\begin{aligned}\Delta_4 &= \left(1 - L^4\right) = \left(1 - L\right)\left(1 + L + L^2 + L^3\right) \\ &= (1-L)(1+L)(1-iL)(1+iL),\end{aligned}$$

where L^k for all $k = 1,\ldots, 4$ is a standard lag operator such that $L^k y_t = y_t - y_{t-k}$. The roots of the polynomial in the backshift operator (e.g., the filter) are +1, –1,+i, and –i. HEGY used this factorization to develop a test regression of the form

$$\Delta_4 y_t = \pi_1 y_{t-1}^{(1)} + \pi_2 y_{t-1}^{(2)} + \pi_3 y_{t-2}^{(3)} - \pi_4 y_{t-1}^{(4)} + \varepsilon_t, \tag{A.1}$$

where

$$y_t^{(1)} = \left(1 + L + L^2 + L^3\right) y_t = y_t + y_{t-1} + y_{t-2} + y_{t-3},$$

$$y_t^{(2)} = -\left(1 - L + L^2 - L^3\right) y_t = -y_t + y_{t-1} - y_{t-2} + y_{t-3},$$

$$y_t^{(3)} = \left(1 - L^2\right) y_t = y_t - y_{t-2},$$

$$y_t^{(4)} = \left(1 - L^4\right) y_t = y_t - y_{t-4}.$$

To test various hypotheses about unit roots, equation (A.1) can be estimated using ordinary least squares and then those test statistics can be compared to the appropriate finite sample distributions based on Monte Carlo simulations. When $\pi_1 = 0$, the series contains a long-run unit root; when $\pi_2 = 0$, the series contains a biannual unit root; and when $\pi_3 = \pi_4 = 0$, the series contains an annual unit root. Equation (A.1) is usually augmented with a constant, quarterly dummies, and a time trend and estimated using ordinary least squares. If $\pi_1 = \pi_2 = \pi_3 = \pi_4 = 0$, then $\Delta_4 = (1 - L^4)$ is the appropriate filter (i.e., the data should be fourth-differenced to become stationary). The nonstandard critical values were derived by HEGY and Ghysels, Lee, and Noh (1994).

Beaulieu and Miron's (1993) test isolates each of the unit roots relating to the zero and seasonal frequencies for the nonstationary polynomial:

$$\Delta_{12} = 1 - L^{12} = (1-L)(1+L)(1+L^2)(1+L+L^2)(1-L+L^2) \times (1+\sqrt{3}L+L^2)(1-\sqrt{3}L+L^2). \tag{A.2}$$

The eleven seasonal unit roots that correspond to (A.2) are five pairs of complex roots on the unit circle, together with the real root, –1 (Table A-1). Following HEGY, Beaulieu and Miron (1993) used the factorization in (A.2) to develop a regression for testing for seasonal unit roots using monthly data:

$$\Delta_{12} y_t = \sum_{k=1}^{12} \pi_k y_{t-1}^{(k)} + \varepsilon_t, \tag{A.3}$$

where

$$y_t^{(1)} = (1+L+L^2+\ldots+L^{11})y_t,$$

$$y_t^{(2)} = -(1-L+L^2-L^3+L^4-L^5+L^6-L^7+L^8-L^9+L^{10}-L^{11})y_t,$$

$$y_t^{(3)} = -(L-L^3+L^5-L^7+L^9-L^{11})y_t,$$

$$y_t^{(4)} = -(1-L^2+L^4-L^6+L^8-L^{10})y_t,$$

$$y_t^{(5)} = -\tfrac{1}{2}(1+L-2L^2+L^3+L^4-2L^5+L^6+L^7-2L^8+L^9+L^{10}-2L^{11})y_t,$$

$$y_t^{(6)} = \sqrt{3/2}(1-L+L^3-L^4+L^6-L^7+L^9-L^{10})y_t,$$

$$y_t^{(7)} = \tfrac{1}{2}(1-L-2L^2-L^3+L^4+2L^5+L^6-L^7-2L^8+L^9+L^{10}+2L^{11})y_t,$$

$$y_t^{(8)} = -\sqrt{3/2}(1+L-L^3-L^4+L^6+L^7-L^9-L^{10})y_t,$$

$$y_t^{(9)} = -\tfrac{1}{2}(\sqrt{3}-L+L^3-\sqrt{3}L^3+L^4-L^6+\sqrt{3}L^7+L^9+\sqrt{3}L^{10}+2L^{11})y_t,$$

$$y_t^{(10)} = \tfrac{1}{2}(1-\sqrt{3}L+2L^2-\sqrt{3}L^3+L^4-L^6+\sqrt{3}L^7-2L^8+\sqrt{3}L^{10}+2L^{11})y_t,$$

$$y_t^{(11)} = \tfrac{1}{2}(\sqrt{3}+L-L^3-\sqrt{3}L^4-2L^6-L^7+L^9+\sqrt{3}L^9-L^{10})y_t,$$

$$y_t^{(12)} = -\tfrac{1}{2}(1+\sqrt{3}L+2L^2+\sqrt{3}L^3+L^4-L^6-\sqrt{3}L^7-2L^8-\sqrt{3}L^9-L^{10})y_t.$$

Like the HEGY test, a joint test of $\pi_{k-1} = \pi_k$ vs. $\pi_k \neq 0, \pi_{k-1} < 0$, for even values of $k > 2$ is a test for unit roots at seasonal frequencies. A long-run unit root is present if $\pi_1 = 0$. The nonstandard distributions for this test can be found in Beaulieu and Miron (1993).

Table A-1. The HEGY Test Extended to Monthly Data

Cycle (months)	Root	Test	Filter
0	0	$\pi_1 = 0$	$1 - L$
6	–1	$\pi_2 = 0$	$1 + L$
3,9	$\pm i$	$\pi_3 = \pi_4 = 0$	$1 + L^2$
8,4	$-\frac{1}{2}(1 \pm \sqrt{3}i)$	$\pi_5 = \pi_6 = 0$	$1 + L + L^2$
2,10	$\frac{1}{2}(1 \pm \sqrt{3}i)$	$\pi_7 = \pi_8 = 0$	$1 - L + L^2$
7,5	$-\frac{1}{2}(\sqrt{3} \pm i)$	$\pi_9 = \pi_{10} = 0$	$1 + \sqrt{3}L + L^2$
1,11	$\frac{1}{2}(\sqrt{3} \pm i)$	$\pi_{11} = \pi_{12} = 0$	$1 - \sqrt{3}L + L^2$

Source: Rodrigues and Franses (2003).

A.2. APPENDIX TABLES

Table A-2. Studies of Demand for Food Conditional on Expenditure on Subgroups of Foods Based on Data That Distinguished FAFH from FAH

Study							
Author	Year	Table No.	Conditional On	Population	Data Frequency	Data Years	Demand System
Gao, Wailes & Cramer	1994	1	Cereals/bakery	United States	Cross section	1987–1988	Barten
Yen & Chern	1992	1	Fats/oils	United States	Annual	1950–1986	AIDS
		1	Fats/oils	United States	Annual	1950–1986	AITL
		1	Fats/oils	United States	Annual	1950–1986	ITL
Yen, Kan & Su	2002	5	Fats/oils	United States	Cross section	1987–1988	ITL
Brown	1986	2	Juice	United States	Monthly	1978–1985	Double Log
Brown & Lee	2000	3	Juice	United States	Weekly	1998	Barten
Brown, Behr & Lee	1994	3	Juice	United States	Weekly	1987–1993	Rotterdam
Brown, Lee & Seale	1994	3	Juice	United States	Weekly	1988–1992	CBS
Arnade & Gopinath	2004	3	Meat/cheese	United States	Monthly	1998–2000	1st-order approx.
Chang & Green	1989	1	Meats	United States	Quarterly	1980–1984	LES
		2	Meats	United States	Quarterly	1980–1984	LES
Davis, Yen & Lin	2007	4	Meats	Low	Cross section	2004	ITL
		6	Meats	High	Cross section	2004	ITL
Gao & Spreen	1994	2	Meats	United States	Cross section	1987–1988	GADS/CBS Rotterdam
		3	Meats	Central	Cross section	1987–1988	GADS/CBS Rotterdam
		3	Meats	Northeast	Cross section	1987–1988	GADS/CBS Rotterdam
		3	Meats	South	Cross section	1987–1988	GADS/CBS Rotterdam
		3	Meats	West	Cross section	1987–1988	GADS/CBS Rotterdam
Reed, Clark & Levedahl	2003	2	Meats	United States	Annual	1980–2000	GADS
Wellman	1992	5	Meats	United States	Cross section	1977–1978	LAIDS
Yen & Huang	2002	3	Meats	United States	Cross section	1987–1988	ITL
Gould	1996	4	Milk	United States	Monthly	1991–1992	ITL
Cox & Wohlgenant	1986	3	Vegetables	West	Cross section	1977–1978	Linear / Tobit
Yen, Lin, Harris & Ballenger	2004	4	Vegetables	Low	Cross section	1999	ITL
		5	Vegetables	High	Cross section	1999	ITL

Notes: AIDS=almost ideal demand system (Deaton and Muellbauer 1980a); LAIDS=linearized AIDS (Deaton and Muellbauer 1980a); CBS=Central Bureau of Statistics (Netherlands) demand system (Keller and van Driel 1985); GADS=generalized Addilog demand system (Bewley and Young 1987); LES=linear expenditure system (Klein and Rubin 1947); ITL=indirect translog (Christensen, Jorgensen and Lau 1975); AITL=almost ideal translog demand system (Lewbel 1989).

†Dynamic means the authors of the study included a lagged dependent variable in their specification of demand.

‡Autocorrelation means the authors of the study corrected the covariance-variance matrix for autocorrelation.

Included Variables						Parameter Restrictions	
Advertising	Health Index	Demographic	Structural Change	Dynamic†	Autocorrelation‡	Symmetry	Homogeneity
No	No	Yes	No	No	No	Yes	Yes
No	Yes	Yes	No	Yes	Yes	Yes	Yes
No	Yes	Yes	No	Yes	Yes	Yes	Yes
No	Yes	Yes	No	Yes	Yes	Yes	Yes
No	No	Yes	No	No	No	Yes	Yes
No	No	No	No	Yes	No	No	Yes
Yes	No	No	No	Yes	No	Yes	Yes
Yes	No	No	No	Yes	No	Yes	Yes
No	No	No	No	No	No	Yes	Yes
No	No	Yes	No	Yes	No	Yes	Yes
Yes	No	No	No	Yes	Yes	Yes	Yes
Yes	No	No	No	Yes	Yes	Yes	Yes
No	No	Yes	No	No	No	Yes	Yes
No	No	Yes	No	No	No	Yes	Yes
No	No	Yes	No	No	No	Yes	Yes
No	No	Yes	No	No	No	Yes	Yes
No	No	Yes	No	No	No	Yes	Yes
No	No	Yes	No	No	No	Yes	Yes
No	No	Yes	No	No	No	Yes	Yes
No	No	No	No	Yes	No	Yes	Yes
No	No	Yes	No	No	No	Yes	Yes
No	No	Yes	No	No	No	Yes	Yes
No	No	Yes	No	No	No	No	Yes
No	No	Yes	No	No	No	No	Yes
No	No	Yes	No	No	No	Yes	Yes
No	No	Yes	No	No	No	Yes	Yes

Table A-3. Studies of Demand for Food Conditional on Expenditure on Subgroups of Foods Based on Data That Did Not Distinguish FAFH from FAH

Study							
Author	Year	Table No.	Conditional On	Population	Data Frequency	Data Years	Demand System
Chern, Loeman & Yen	1995	4	Fats/Oils	United States	Annual	1950–1988	AITL
Goddard & Glance	1989	5	Fats/Oils	United States	Annual	1962–1988	ITL
Gould, Cox & Perali	1991	2	Fats/Oils	United States	Quarterly	1962–1987	LAIDS
Henneberry et al.	1999	5	Fruits	United States	Annual	1970–1992	LAIDS
You, Epperson & Huang	1996	2	Fruits	United States	Annual	1960–1993	Differential Form
Alston & Chalfant	1993	5	Meats	United States	Quarterly	1967–1988	FDLAIDS
		5	Meats	United States	Quarterly	1967–1988	Rotterdam
Alston, Piggot & Chalfant	2002	1	Meats	United States	Quarterly	1970–1995	Double Log
		1	Meats	United States	Quarterly	1970–1995	Double Log
Capps & Schmitz	1991	4	Meats	United States	Annual	1966–1988	Rotterdam
	1991	4	Meats	United States	Annual	1966–1988	Rotterdam
Chalfant	1987	3	Meats	United States	Annual	1947–1978	AIDS
		3	Meats	United States	Annual	1947–1978	GFAIDS
Chen	1998	1	Meats	United States	Annual	1958–1985	AIDS
		1	Meats	United States	Annual	1958–1985	AIDS
		1	Meats	United States	Annual	1958–1985	LAIDS
		1	Meats	United States	Annual	1958–1985	LAIDS
Christensen & Manser	1977	8a	Meats	United States	Quarterly	1947–1971	DTL
		8a	Meats	United States	Quarterly	1947–1971	ITL
Clements	1987	4.4	Meats	United States	Annual	1950–1972	Rotterdam
Gao & Shonkwiler	1993	3	Meats	United States	Annual	1956–1987	Rotterdam
Hahn	1988	1	Meats	United States	Annual	1960–1984	Double Log
Hahn	1994	3	Meats	United States	Monthly	1980–1992	CBS
Hahn	2001	1	Meats	United States	Monthly	1979–1996	CBS
Kesavan et al.	1993	3	Meats	United States	Quarterly	1965–1988	AIDS
		3	Meats	United States	Quarterly	1965–1988	AIDS
		3	Meats	United States	Quarterly	1965–1988	AIDS
Kinnucan et al.	1997	5	Meats	United States	Quarterly	1975–1991	Rotterdam
McGuirk et al.	1995	3	Meats	United States	Annual	1960–1988	LAIDS
		3	Meats	United States	Annual	1960–1988	LAIDS
Moschini & Meilke	1989	4	Meats	United States	Quarterly	1967–1987	FDLAIDS
Piggott & Marsh	2004	4	Meats	United States	Quarterly	1982–1999	GAIDS
		4	Meats	United States	Quarterly	1982–1999	GAIDS
Piggott et al.	2007	4	Meats	United States	Quarterly	1982–2005	GAIDS

Included Variables						Parameter Restrictions	
Advertising	Health Index	Demographic	Structural Change	Dynamic†	Autocorrelation‡	Symmetry	Homogeneity
No	Yes	No	No	No	No	Yes	Yes
No	No	No	No	Yes	No	Yes	Yes
No	No	Yes	No	No	No	Yes	Yes
No	No	No	Yes	No	No	Yes	Yes
No	No	No	Yes	No	No	Yes	Yes
No	No	No	No	No	No	No	Yes
No	No	No	No	No	No	No	Yes
No	No	No	No	No	No	No	Yes
No	No	No	No	No	Yes	No	Yes
No	No	No	No	Yes	No	Yes	Yes
No	Yes	Yes	No	Yes	No	Yes	Yes
No	No	No	No	No	Yes	Yes	Yes
No	No	No	No	No	Yes	Yes	Yes
No	No	No	No	No	No	No	Yes
No	No	No	No	No	No	Yes	Yes
No	No	No	No	No	No	No	Yes
No	No	No	No	No	No	Yes	Yes
No	No	No	No	No	No	No	Yes
No	No	No	No	No	No	No	Yes
No	No	No	No	No	No	Yes	Yes
No	Yes	Yes	No	No	No	Yes	Yes
No	No	No	No	No	No	No	No
No	No	No	No	No	No	Yes	Yes
No	No	No	No	No	No	Yes	Yes
No	No	No	No	No	Yes	Yes	Yes
No	No	No	No	Yes	No	Yes	Yes
No	No	No	No	Yes	Yes	Yes	Yes
Yes	Yes	No	No	Yes	Yes	Yes	Yes
No	No	No	No	No	No	Yes	Yes
No	Yes	Yes	No	No	No	Yes	Yes
No	No	No	Yes	Yes	No	Yes	Yes
No	No	No	No	Yes	No	Yes	Yes
No	No	No	No	Yes	Yes	Yes	Yes
Yes	No	No	No	Yes	Yes	Yes	Yes

continued on page 108–109

Table A-3. Studies of Demand for Food Conditional on Expenditure on Subgroups of Foods Based on Data That Did Not Distinguish FAFH from FAH (cont.)

Study							
Author	Year	Table No.	Conditional On	Population	Data Frequency	Data Years	Demand System
Pope, Green & Eales	1980	3	Meats	United States	Annual	1950–1975	Box-Cox
		3	Meats	United States	Annual	1950–1975	Box-Cox
Thurman	1989	1	Meats	United States	Annual	1955–1983	Quadratic Double Log
Adhikari et al.	2007	1	Vegetables	United States	Annual	1980–2003	LAIDS
Henneberry et al.	1999	2	Vegetables	United States	Annual	1970–1992	LAIDS
You, Epperson & Huang	1996	3	Vegetables	United States	Annual	1960–1993	Differential Form

Note: AIDS=almost ideal demand system (Deaton and Muellbauer 1980a); LAIDS=linearized AIDS (Deaton and Muellbauer 1980a); FDLAIDS=first-differenced LAIDS (Deaton and Muellbauer 1980a); GAIDS=generalized AIDS (Bollino 1987); GFAIDS=generalized flexible AIDS (Chalfant 1987); ITL=indirect translog (Christensen, Jorgensen and Lau 1975); AITL=almost ideal translog demand system (Lewbel 1989); DTL=direct translog; CBS=Central Bureau of Statistics (Netherlands) demand system (Keller and van Driel 1985).

†Dynamic means the authors of the study included a lagged dependent variable in their specification of demand.

‡Autocorrelation means the authors of the study corrected the covariance-variance matrix for autocorrelation.

Included Variables						Parameter Restrictions	
Advertising	Health Index	Demographic	Structural Change	Dynamic†	Autocorrelation‡	Symmetry	Homogeneity
No	No	No	No	Yes	No	No	No
No	No	No	No	Yes	No	No	Yes
No	No	No	No	No	No	Yes	Yes
No	Yes	No	No	No	Yes	Yes	Yes
No	No	No	Yes	No	No	Yes	Yes
No	No	No	Yes	No	No	Yes	Yes

Table A-4. Wald and Log-Likelihood Tests for Nested Models of GODDS Using BEA Data, 1960–2009, Annual

	Likelihood Ratio Test	p-value	Wald Test	p-value
Rotterdam ($\varphi_1 = -1$, $\varphi_2 = 1$)	20.71	0.00	28.77	0.00
FDLAIDS ($\varphi_1 = \varphi_2 = 0$)	12.07	0.00	18.59	0.00
CBS ($\varphi_1 = 0$, $\varphi_2 = 1$)	25.62	0.00	43.27	0.00
NBR ($\varphi_1 = -1$, $\varphi_2 = 0$)	2.11	0.35	3.52	0.17

Source: Authors' calculations based on GODDS and using annual personal consumption expenditures and Fisher-ideal price indexes (U.S. Department of Commerce, Bureau of Economic Analysis, National Income and Product Accounts 2010).

Table A-5. Parameter Estimates from GODDS Using BEA Data, 1960–2009, Annual

	Demand For								
	Cereals and Bakery	Meat	Eggs	Dairy	Fruits and Vegetables	Other Foods	Nonalcoholic Beverages	FAFH	Alcoholic Beverages
Price of									
Cereals and bakery	−0.0022 (0.0031)	0.0004 (0.0014)	0.0004 (0.0004)	0.0018 (0.0014)	0.0016 (0.0015)	0.0065 (0.0014)	−0.0006 (0.001)	−0.0062 (0.0028)	−0.0010 (0.0019)
Meat	0.0004 (0.0014)	0.0092 (0.0058)	0.0013 (0.0005)	0.0000 (0.0015)	0.0041 (0.0014)	−0.0033 (0.0019)	−0.0024 (0.0014)	0.0059 (0.0025)	0.0051 (0.0016)
Eggs	0.0004 (0.0004)	0.0013 (0.0005)	0.0001 (0.0003)	0.0010 (0.0004)	−0.0008 (0.0005)	−0.0008 (0.0005)	0.0004 (0.0003)	0.0003 (0.0008)	−0.0003 (0.0006)
Dairy	0.0018 (0.0014)	0.0000 (0.0015)	0.0010 (0.0004)	−0.0011 (0.0024)	−0.0011 (0.0013)	0.0033 (0.0014)	0.0023 (0.0009)	−0.0038 (0.0025)	0.0021 (0.0016)
Fruits and vegetables	0.0016 (0.0015)	0.0041 (0.0014)	−0.0008 (0.0005)	−0.0011 (0.0013)	0.0030 (0.003)	−0.0022 (0.0014)	0.0011 (0.0009)	0.0023 (0.0026)	−0.0010 (0.0018)
Other foods	0.0065 (0.0014)	−0.0033 (0.0019)	−0.0008 (0.0005)	0.0033 (0.0014)	−0.0022 (0.0014)	0.0031 (0.0041)	0.0011 (0.0012)	0.0021 (0.0024)	0.0003 (0.0017)
Nonalcoholic beverages	−0.0006 (0.0010)	−0.0024 (0.0014)	0.0004 (0.0003)	0.0023 (0.0009)	0.0011 (0.0009)	0.0011 (0.0012)	0.0001 (0.0023)	−0.0009 (0.0016)	0.0021 (0.0011)
FAFH	−0.0062 (0.0028)	0.0059 (0.0025)	0.0003 (0.0008)	−0.0038 (0.0025)	0.0023 (0.0026)	0.0021 (0.0024)	−0.0009 (0.0016)	0.0135 (0.0109)	−0.0055 (0.0041)
Alcoholic beverages	−0.0010 (0.0019)	0.0051 (0.0016)	−0.0003 (0.0006)	0.0021 (0.0016)	−0.0010 (0.0018)	0.0003 (0.0017)	0.0021 (0.0011)	−0.0055 (0.0041)	0.0066 (0.0049)
Nonfood	−0.0007 (0.0045)	−0.0203 (0.0069)	−0.0016 (0.0013)	−0.0047 (0.0043)	−0.0072 (0.0045)	−0.0101 (0.0052)	−0.0032 (0.0036)	−0.0078 (0.0102)	−0.0083 (0.0063)
Expenditure	0.0001 (0.0048)	0.0084 (0.0100)	−0.0014 (0.0014)	0.0084 (0.0047)	−0.0005 (0.0047)	0.0104 (0.0067)	0.0068 (0.0047)	0.0263 (0.0100)	0.0054 (0.0059)
φ_1	−0.7487 (0.1824)	−0.7487 (0.1824)	−0.7487 (0.1824)	−0.7487 (0.1824)	−0.7487 (0.1824)	−0.7487 (0.1824)	−0.7487 (0.1824)	−0.7487 (0.1824)	−0.7487 (0.1824)
φ_2	0.1991 (0.1549)	0.1991 (0.1549)	0.1991 (0.1549)	0.1991 (0.1549)	0.1991 (0.1549)	0.1991 (0.1549)	0.1991 (0.1549)	0.1991 (0.1549)	0.1991 (0.1549)
Intercept	0.0001 (0.0001)	−0.0003 (0.0002)	0.0000 (0.0000)	−0.0003 (0.0001)	−0.0001 (0.0001)	−0.0001 (0.0001)	−0.0001 (0.0001)	0.0000 (0.0002)	0.0001 (0.0001)
R^2	0.5783	0.4500	0.4167	0.3578	0.4118	0.5184	0.0575	0.3215	0.3257

Note: Standard errors are in parentheses.

Source: Authors' calculations based on GODDS and using the annual personal consumption expenditures and Fisher-Ideal price indexes (U.S. Department of Commerce, Bureau of Economic Analysis, National Income and Product Accounts 2010).

Table A-6. First-Stage Uncompensated Elasticities of Demand from GODDS Using BEA Data, 1960–2009, Annual

Elasticity of Demand For	With Respect to Price of										
	Cereals and Bakery	Meat	Eggs	Dairy	Fruits and Vegetables	Other Foods	Nonalcoholic Beverages	FAFH	Alcoholic Beverages	Nonfood	Expenditure
Cereals and bakery	−0.94	0.04	0.03	0.13	0.12	0.46	−0.04	−0.39	−0.06	0.40	0.26
	(0.13)	(0.10)	(0.03)	(0.09)	(0.10)	(0.10)	(0.07)	(0.19)	(0.13)	(0.39)	(0.26)
Meat	0.02	−0.45	0.05	0.00	0.16	−0.12	−0.09	0.23	0.20	−0.58	0.57
	(0.05)	(0.13)	(0.02)	(0.06)	(0.05)	(0.07)	(0.05)	(0.10)	(0.06)	(0.33)	(0.32)
Eggs	0.28	0.91	−0.73	0.69	−0.49	−0.51	0.27	0.27	−0.16	0.18	−0.71
	(0.3)	(0.36)	(0.14)	(0.28)	(0.31)	(0.32)	(0.22)	(0.54)	(0.37)	(1.23)	(0.93)
Dairy	0.15	0.00	0.08	−0.90	−0.09	0.28	0.19	−0.33	0.18	−0.54	0.97
	(0.11)	(0.13)	(0.04)	(0.14)	(0.11)	(0.12)	(0.08)	(0.21)	(0.14)	(0.46)	(0.34)
Fruits and vegetables	0.13	0.31	−0.05	−0.07	−0.58	−0.15	0.09	0.20	−0.06	−0.03	0.22
	(0.10)	(0.10)	(0.03)	(0.09)	(0.14)	(0.10)	(0.07)	(0.19)	(0.13)	(0.39)	(0.28)
Other foods	0.33	−0.17	−0.04	0.17	−0.11	−0.65	0.05	0.11	0.01	−0.48	0.77
	(0.07)	(0.10)	(0.02)	(0.07)	(0.07)	(0.11)	(0.06)	(0.12)	(0.08)	(0.34)	(0.28)
Nonalcoholic beverages	−0.06	−0.21	0.03	0.20	0.10	0.09	−0.79	−0.08	0.18	−0.32	0.84
	(0.08)	(0.12)	(0.03)	(0.08)	(0.08)	(0.10)	(0.10)	(0.14)	(0.10)	(0.42)	(0.36)
FAFH	−0.14	0.13	0.01	−0.09	0.05	0.05	−0.02	−0.50	−0.13	−0.21	0.84
	(0.06)	(0.06)	(0.02)	(0.06)	(0.06)	(0.05)	(0.04)	(0.20)	(0.09)	(0.23)	(0.13)
Alcoholic beverages	−0.04	0.24	−0.01	0.10	−0.04	0.02	0.10	−0.24	−0.49	−0.13	0.50
	(0.09)	(0.08)	(0.03)	(0.07)	(0.08)	(0.08)	(0.05)	(0.18)	(0.16)	(0.34)	(0.19)
Nonfood	0.00	−0.03	0.00	−0.01	−0.01	−0.02	−0.01	−0.02	−0.02	−0.95	1.07
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.03)	(0.02)

Notes: Estimates of elasticities of demand were evaluated at the mean of the data. Standard errors are in parentheses.

Source: Authors' calculations based on GODDS and using the annual personal consumption expenditures and Fisher-Ideal price indexes (U.S. Department of Commerce, Bureau of Economic Analysis, National Income and Product Accounts 2010).

Table A-7. Parameter Estimates from GODDS Using BLS Data, 1998–2009, Monthly

	Demand For								
	Cereals and Bakery	Meat	Eggs	Dairy	Fruits and Vegetables	Other Foods	Nonalcoholic Beverages	FAFH	Alcoholic Beverages
Price of									
Cereals and bakery	0.0095 (0.0066)	0.0000 (0.0022)	0.0004 (0.0003)	0.0050 (0.0011)	−0.0027 (0.0019)	0.0038 (0.005)	−0.0018 (0.0027)	−0.0066 (0.0066)	0.0010 (0.0025)
Meat	0.0000 (0.0022)	0.0200 (0.0108)	0.0010 (0.0004)	0.0009 (0.0017)	0.0009 (0.0030)	0.0084 (0.0036)	0.0022 (0.002)	−0.0065 (0.0099)	−0.0045 (0.0047)
Eggs	0.0004 (0.0003)	0.0010 (0.0004)	0.0009 (0.0005)	0.0001 (0.0002)	0.0009 (0.0003)	−0.0001 (0.0005)	0.0008 (0.0003)	−0.0026 (0.0010)	0.0002 (0.0004)
Dairy	0.0050 (0.0011)	0.0009 (0.0017)	0.0001 (0.0002)	0.0107 (0.0045)	−0.0010 (0.0013)	−0.0049 (0.0019)	−0.0028 (0.0011)	0.0020 (0.0041)	−0.0018 (0.0019)
Fruits and vegetables	−0.0027 (0.0019)	0.0009 (0.0030)	0.0009 (0.0003)	−0.0010 (0.0013)	0.0044 (0.0075)	0.0096 (0.0031)	0.0030 (0.0018)	0.0009 (0.0073)	−0.0035 (0.0035)
Other foods	0.0038 (0.0050)	0.0084 (0.0036)	−0.0001 (0.0005)	−0.0049 (0.0019)	0.0096 (0.0031)	−0.0136 (0.0132)	0.0002 (0.0040)	0.0229 (0.0113)	−0.0013 (0.0042)
Nonalcoholic beverages	−0.0018 (0.0027)	0.0022 (0.0020)	0.0008 (0.0003)	−0.0028 (0.0011)	0.0030 (0.0018)	0.0002 (0.0040)	−0.0006 (0.0051)	−0.0010 (0.0061)	−0.0027 (0.0023)
FAFH	−0.0066 (0.0066)	−0.0065 (0.0099)	−0.0026 (0.0010)	0.0020 (0.0041)	0.0009 (0.0073)	0.0229 (0.0113)	−0.0010 (0.0061)	−0.0167 (0.0409)	0.0132 (0.0118)
Alcoholic beverages	0.0010 (0.0025)	−0.0045 (0.0047)	0.0002 (0.0004)	−0.0018 (0.0019)	−0.0035 (0.0035)	−0.0013 (0.0042)	−0.0027 (0.0023)	0.0132 (0.0118)	0.0003 (0.0091)
Nonfood	−0.0086 (0.0069)	−0.0224 (0.0139)	−0.0015 (0.0009)	−0.0082 (0.0052)	−0.0124 (0.0092)	−0.0250 (0.0111)	0.0027 (0.0052)	−0.0056 (0.0352)	−0.0008 (0.0135)
Expenditure	−0.0081 (0.0033)	−0.0125 (0.0056)	−0.0008 (0.0003)	−0.0048 (0.0025)	−0.0084 (0.0039)	−0.0107 (0.0051)	−0.0046 (0.0020)	−0.0186 (0.0145)	−0.0066 (0.0031)
φ_1	−0.4760 (0.2123)	−0.4760 (0.2123)	−0.4760 (0.2123)	−0.4760 (0.2123)	−0.4760 (0.2123)	−0.4760 (0.2123)	−0.4760 (0.2123)	−0.4760 (0.2123)	−0.4760 (0.2123)
φ_2	0.0485 (0.3834)	0.0485 (0.3834)	0.0485 (0.3834)	0.0485 (0.3834)	0.0485 (0.3834)	0.0485 (0.3834)	0.0485 (0.3834)	0.0485 (0.3834)	0.0485 (0.3834)
Intercept	−0.0002 (0.0001)	−0.0003 (0.0002)	0.0000 (0.0000)	0.0000 (0.0001)	0.0001 (0.0001)	0.0002 (0.0002)	0.0001 (0.0001)	0.0000 (0.0005)	0.0000 (0.0002)
R^2	0.7909	0.6094	0.7109	0.7839	0.6948	0.7814	0.6728	0.5571	0.2584

Note: Standard errors are in parentheses.

Source: Authors' calculations from GODDS and using aggregated monthly average household expenditures and consumer price indexes (U.S. Department of Labor, Bureau of Labor Statistics, Consumer Expenditure Survey 2010; U.S. Department of Labor, Bureau of Labor Statistics, Consumer Price Index Database 2010).

Table A-8. First-Stage Uncompensated Elasticities of Demand from GODDS Using BLS Data, 1998–2009, Monthly

	With Respect to Price of										
Elasticity of Demand For	Cereals and Bakery	Meat	Eggs	Dairy	Fruits and Vegetables	Other Foods	Nonalcoholic Beverages	FAFH	Alcoholic Beverages	Nonfood	Expenditure
Cereals and bakery	−0.31	0.03	0.03	0.34	−0.16	0.28	−0.11	−0.37	0.08	0.22	−0.01
	(0.26)	(0.15)	(0.02)	(0.08)	(0.13)	(0.33)	(0.18)	(0.44)	(0.17)	(0.34)	(0.05)
Meat	0.02	−0.13	0.04	0.05	0.05	0.35	−0.10	−0.20	−0.17	−0.13	0.03
	(0.09)	(0.22)	(0.01)	(0.07)	(0.12)	(0.14)	(0.08)	(0.39)	(0.19)	(0.48)	(0.07)
Eggs	0.35	0.80	−0.23	0.12	0.74	−0.07	0.62	−2.04	0.15	−0.31	−0.12
	(0.27)	(0.30)	(0.06)	(0.15)	(0.25)	(0.43)	(0.26)	(0.81)	(0.35)	(0.65)	(0.09)
Dairy	0.44	0.10	0.01	−0.03	−0.07	−0.40	−0.23	0.23	−0.15	−0.02	0.12
	(0.10)	(0.14)	(0.02)	(0.09)	(0.11)	(0.16)	(0.09)	(0.35)	(0.16)	(0.31)	(0.05)
Fruits and vegetables	−0.13	0.07	0.05	−0.05	−0.70	0.55	0.17	0.11	−0.18	0.05	0.07
	(0.11)	(0.16)	(0.02)	(0.07)	(0.17)	(0.17)	(0.10)	(0.40)	(0.19)	(0.39)	(0.06)
Other foods	0.17	0.36	0.00	−0.19	0.41	−1.49	0.02	1.00	−0.04	−0.32	0.08
	(0.21)	(0.15)	(0.02)	(0.08)	(0.13)	(0.37)	(0.17)	(0.46)	(0.17)	(0.32)	(0.04)
Nonalcoholic beverages	−0.18	0.26	0.08	−0.29	0.34	0.04	−1.00	−0.05	−0.28	1.04	0.03
	(0.28)	(0.21)	(0.03)	(0.12)	(0.19)	(0.43)	(0.39)	(0.65)	(0.24)	(0.45)	(0.06)
FAFH	−0.09	−0.08	−0.04	0.04	0.03	0.36	−0.01	−1.15	0.21	0.49	0.25
	(0.10)	(0.15)	(0.02)	(0.06)	(0.11)	(0.17)	(0.09)	(0.50)	(0.18)	(0.44)	(0.06)
Alcoholic beverages	0.10	−0.35	0.02	−0.14	−0.27	−0.09	−0.21	1.17	−0.92	0.74	−0.03
	(0.21)	(0.40)	(0.04)	(0.16)	(0.29)	(0.36)	(0.19)	(0.99)	(0.67)	(1.10)	(0.15)
Nonfood	−0.01	−0.03	0.00	−0.01	−0.02	−0.04	0.00	−0.02	0.00	−1.05	1.20
	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.03)	(0.02)	(0.06)	(0.01)

Notes: Estimates of elasticities of demand were evaluated at the mean of the data. Standard errors are in parentheses.

Source: Authors' calculations based on GODDS and using aggregated monthly average household expenditures and consumer price indexes (U.S. Department of Labor, Bureau of Labor Statistics, Consumer Expenditure Survey 2010; U.S. Department of Labor, Bureau of Labor Statistics, Consumer Price Index Database 2010).

Table A-9. First-Stage Parameter Estimates from Barten's Synthetic Model Using BEA Annual Price and Expenditure Data, 1960–2009

	Demand For								
	Cereals and Bakery	Meat	Eggs	Dairy	Fruits and Vegetables	Other Foods	Nonalcoholic Beverages	FAFH	Alcoholic Beverages
Price of									
Cereals and bakery	−0.0022 (0.0031)	0.0004 (0.0014)	0.0004 (0.0004)	0.0018 (0.0014)	0.0016 (0.0015)	0.0065 (0.0014)	−0.0006 (0.0010)	−0.0062 (0.0028)	−0.0010 (0.0019)
Meat	0.0004 (0.0014)	0.0092 (0.0058)	0.0013 (0.0005)	0.0000 (0.0015)	0.0041 (0.0014)	−0.0033 (0.0019)	−0.0024 (0.0014)	0.0059 (0.0025)	0.0051 (0.0016)
Eggs	0.0004 (0.0004)	0.0013 (0.0005)	0.0001 (0.0003)	0.0010 (0.0004)	−0.0008 (0.0005)	−0.0008 (0.0005)	0.0004 (0.0003)	0.0003 (0.0008)	−0.0003 (0.0006)
Dairy	0.0018 (0.0014)	0.0000 (0.0015)	0.0010 (0.0004)	−0.0011 (0.0024)	−0.0011 (0.0013)	0.0034 (0.0014)	0.0023 (0.0009)	−0.0038 (0.0025)	0.0021 (0.0016)
Fruits and vegetables	0.0016 (0.0015)	0.0041 (0.0014)	−0.0008 (0.0005)	−0.0011 (0.0013)	0.0030 (0.0030)	−0.0022 (0.0014)	0.0011 (0.0009)	0.0023 (0.0026)	−0.0010 (0.0018)
Other foods	0.0065 (0.0014)	−0.0033 (0.0019)	−0.0008 (0.0005)	0.0034 (0.0014)	−0.0022 (0.0014)	0.0031 (0.0041)	0.0011 (0.0012)	0.0021 (0.0024)	0.0003 (0.0017)
Nonalcoholic beverages	−0.0006 (0.0010)	−0.0024 (0.0014)	0.0004 (0.0003)	0.0023 (0.0009)	0.0011 (0.0009)	0.0011 (0.0012)	0.0001 (0.0023)	−0.0009 (0.0016)	0.0021 (0.0011)
FAFH	−0.0062 (0.0028)	0.0059 (0.0025)	0.0003 (0.0008)	−0.0038 (0.0025)	0.0023 (0.0026)	0.0021 (0.0024)	−0.0009 (0.0016)	0.0135 (0.0109)	−0.0055 (0.0041)
Alcoholic beverages	−0.0010 (0.0019)	0.0051 (0.0016)	−0.0003 (0.0006)	0.0021 (0.0016)	−0.0010 (0.0018)	0.0003 (0.0017)	0.0021 (0.0011)	−0.0055 (0.0041)	0.0066 (0.0049)
Nonfood	−0.0007 (0.0045)	−0.0203 (0.0069)	−0.0016 (0.0013)	−0.0047 (0.0043)	−0.0072 (0.0045)	−0.0101 (0.0052)	−0.0032 (0.0036)	−0.0078 (0.0102)	−0.0083 (0.0063)
Total expenditure on goods	0.0001 (0.0048)	0.0084 (0.0100)	−0.0014 (0.0014)	0.0084 (0.0047)	−0.0005 (0.0047)	0.0104 (0.0067)	0.0068 (0.0047)	0.0263 (0.0100)	0.0054 (0.0059)
δ_1	0.2513 (0.1824)	0.2513 (0.1824)	0.2513 (0.1824)	0.2513 (0.1824)	0.2513 (0.1824)	0.2513 (0.1824)	0.2513 (0.1824)	0.2513 (0.1824)	0.2513 (0.1824)
δ_2	0.8004 (0.1550)	0.8004 (0.1550)	0.8004 (0.1550)	0.8004 (0.1550)	0.8004 (0.1550)	0.8004 (0.1550)	0.8004 (0.1550)	0.8004 (0.1550)	0.8004 (0.1550)
Intercept	0.0001 (0.0001)	−0.0003 (0.0002)	0.0000 (0.0000)	−0.0003 (0.0001)	−0.0001 (0.0001)	−0.0001 (0.0001)	−0.0001 (0.0001)	0.0000 (0.0002)	0.0001 (0.0001)
R^2	0.5821	0.2660	0.3308	0.4079	0.5177	0.5575	0.6421	0.6590	0.5362

Note: Standard errors are in parentheses.

Source: Authors' calculations based on Barten's synthetic model and using annual personal consumption expenditures and price indexes (U.S. Department of Commerce, Bureau of Economic Analysis, National Income and Product Accounts 2010).

Table A-10. First-Stage Uncompensated Elasticities of Demand from Barten's Synthetic Model Using BEA Data, 1960–2009, Annual

Elasticity of Demand For	With Respect to Price of										
	Cereals and Bakery	Meat	Eggs	Dairy	Fruits and Vegetables	Other Foods	Nonalcoholic Beverages	FAFH	Alcoholic Beverages	Nonfood	Expenditure
Cereals and bakery	−0.94	0.04	0.03	0.13	0.12	0.46	−0.04	−0.39	−0.06	0.40	0.26
	(0.13)	(0.10)	(0.03)	(0.09)	(0.10)	(0.10)	(0.07)	(0.19)	(0.13)	(0.39)	(0.26)
Meat	0.02	−0.45	0.05	0.00	0.16	−0.12	−0.09	0.23	0.20	−0.58	0.57
	(0.05)	(0.13)	(0.02)	(0.06)	(0.05)	(0.07)	(0.05)	(0.10)	(0.06)	(0.33)	(0.32)
Eggs	0.28	0.92	−0.72	0.69	−0.49	−0.51	0.27	0.27	−0.16	0.18	−0.72
	(0.30)	(0.36)	(0.14)	(0.28)	(0.31)	(0.32)	(0.22)	(0.54)	(0.37)	(1.24)	(0.93)
Dairy	0.15	0.00	0.08	−0.90	−0.09	0.28	0.19	−0.33	0.18	−0.54	0.97
	(0.12)	(0.13)	(0.04)	(0.14)	(0.11)	(0.12)	(0.08)	(0.21)	(0.14)	(0.46)	(0.34)
Fruits and vegetables	0.13	0.31	−0.05	−0.07	−0.58	−0.15	0.09	0.20	−0.06	−0.03	0.22
	(0.10)	(0.10)	(0.03)	(0.09)	(0.14)	(0.10)	(0.07)	(0.19)	(0.13)	(0.39)	(0.28)
Other foods	0.33	−0.17	−0.04	0.17	−0.11	−0.64	0.05	0.11	0.01	−0.48	0.77
	(0.07)	(0.10)	(0.02)	(0.07)	(0.07)	(0.12)	(0.06)	(0.12)	(0.08)	(0.34)	(0.28)
Nonalcoholic beverages	−0.06	−0.21	0.03	0.20	0.10	0.09	−0.79	−0.08	0.18	−0.32	0.84
	(0.08)	(0.12)	(0.03)	(0.08)	(0.08)	(0.10)	(0.10)	(0.14)	(0.10)	(0.42)	(0.36)
FAFH	−0.14	0.13	0.01	−0.09	0.05	0.05	−0.02	−0.50	−0.13	−0.21	0.84
	(0.06)	(0.06)	(0.02)	(0.06)	(0.06)	(0.05)	(0.04)	(0.20)	(0.09)	(0.23)	(0.13)
Alcoholic beverages	−0.04	0.24	−0.01	0.10	−0.04	0.02	0.10	−0.24	−0.49	−0.13	0.50
	(0.09)	(0.08)	(0.03)	(0.07)	(0.08)	(0.08)	(0.05)	(0.18)	(0.16)	(0.34)	(0.19)
Nonfood	0.00	−0.03	0.00	−0.01	−0.01	−0.02	−0.01	−0.02	−0.02	−0.95	1.07
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.03)	(0.02)

Notes: Estimates of elasticities of demand were evaluated at the mean of the data. Standard errors are in parentheses.

Source: Authors' calculations based on Barten's synthetic model and using aggregated monthly average household expenditures and consumer price indexes (U.S. Department of Labor, Bureau of Labor Statistics, Consumer Expenditure Survey 2010; U.S. Department of Labor, Bureau of Labor Statistics, Consumer Price Index Database 2010).

Table A-11. First-Stage Parameter Estimates from Barten's Synthetic Model Using BLS Data, 1998–2009, Monthly

	Demand For								
	Cereals and Bakery	Meat	Eggs	Dairy	Fruits and Vegetables	Other Foods	Nonalcoholic Beverages	FAFH	Alcoholic Beverages
Price of									
Cereals and bakery	0.0097	0.0000	0.0004	0.0050	−0.0027	0.0038	−0.0018	−0.0066	0.0010
	(0.0066)	(0.0022)	(0.0003)	(0.0011)	(0.0019)	(0.0050)	(0.0027)	(0.0066)	(0.0026)
Meat	0.0000	0.0204	0.0010	0.0009	0.0009	0.0084	0.0022	−0.0066	−0.0046
	(0.0022)	(0.0109)	(0.0004)	(0.0017)	(0.0030)	(0.0036)	(0.002)	(0.01)	(0.0048)
Eggs	0.0004	0.0010	0.0009	0.0001	0.0009	−0.0001	0.0008	−0.0026	0.0002
	(0.0003)	(0.0004)	(0.0005)	(0.0002)	(0.0003)	(0.0005)	(0.0003)	(0.0010)	(0.0004)
Dairy	0.0050	0.0009	0.0001	0.0108	−0.0010	−0.0049	−0.0028	0.0020	−0.0018
	(0.0011)	(0.0017)	(0.0002)	(0.0046)	(0.0013)	(0.0019)	(0.0011)	(0.0041)	(0.0019)
Fruits and vegetables	−0.0027	0.0009	0.0009	−0.0010	0.0046	0.0097	0.0030	0.0009	−0.0035
	(0.0019)	(0.0030)	(0.0003)	(0.0013)	(0.0075)	(0.0031)	(0.0018)	(0.0073)	(0.0035)
Other foods	0.0038	0.0084	−0.0001	−0.0049	0.0097	−0.0133	0.0002	0.0229	−0.0013
	(0.0050)	(0.0036)	(0.0005)	(0.0019)	(0.0031)	(0.0133)	(0.0041)	(0.0114)	(0.0043)
Nonalcoholic beverages	−0.0018	0.0022	0.0008	−0.0028	0.0030	0.0002	−0.0004	−0.0011	−0.0027
	(0.0027)	(0.0020)	(0.0003)	(0.0011)	(0.0018)	(0.0041)	(0.0052)	(0.0061)	(0.0023)
FAFH	−0.0066	−0.0066	−0.0026	0.0020	0.0009	0.0229	−0.0011	−0.0161	0.0133
	(0.0066)	(0.0100)	(0.0010)	(0.0041)	(0.0073)	(0.0114)	(0.0061)	(0.0411)	(0.0119)
Alcoholic beverages	0.0010	−0.0046	0.0002	−0.0018	−0.0035	−0.0013	−0.0027	0.0133	0.0004
	(0.0026)	(0.0048)	(0.0004)	(0.0019)	(0.0035)	(0.0043)	(0.0023)	(0.0119)	(0.0092)
Nonfood	−0.0088	−0.0227	−0.0015	−0.0083	−0.0126	−0.0253	0.0026	−0.0062	−0.0009
	(0.0070)	(0.014)	(0.0009)	(0.0052)	(0.0093)	(0.0112)	(0.0052)	(0.0354)	(0.0137)
Expenditure	−0.0082	−0.0126	−0.0008	−0.0048	−0.0084	−0.0108	−0.0046	−0.0186	−0.0068
	(0.0033)	(0.0056)	(0.0003)	(0.0025)	(0.0040)	(0.0051)	(0.0020)	(0.0146)	(0.0031)
δ_1	0.5227	0.5227	0.5227	0.5227	0.5227	0.5227	0.5227	0.5227	0.5227
	(0.2133)	(0.2133)	(0.2133)	(0.2133)	(0.2133)	(0.2133)	(0.2133)	(0.2133)	(0.2133)
δ_2	0.9603	0.9603	0.9603	0.9603	0.9603	0.9603	0.9603	0.9603	0.9603
	(0.3869)	(0.3869)	(0.3869)	(0.3869)	(0.3869)	(0.3869)	(0.3869)	(0.3869)	(0.3869)
Intercept	−0.0002	−0.0003	0.0000	0.0000	0.0001	0.0002	0.0001	0.0000	0.0000
	(0.0001)	(0.0002)	(0.0000)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0005)	(0.0002)
R^2	0.1740	0.0242	0.0572	0.0951	0.1624	0.1363	0.0989	0.1748	−0.0060

Note: Standard errors are in parentheses.

Source: Authors' calculations based on Barten's synthetic model and using aggregated monthly average household expenditures and consumer price indexes (U.S. Department of Labor, Bureau of Labor Statistics, Consumer Expenditure Survey 2010; U.S. Department of Labor, Bureau of Labor Statistics, Consumer Price Index Database 2010).

Table A-12. First-Stage Estimates of Uncompensated Elasticities of Demand from Barten's Synthetic Demand System Using BLS Data, 1998–2009, Monthly

Elasticity of Demand For	With Respect to Price of: Cereals and Bakery	Meat	Eggs	Dairy	Fruits and Vegetables	Other Foods	Nonalcoholic Beverages	FAFH	Alcoholic Beverages	Nonfood	Expenditure on Goods
Cereals and bakery	−0.31	0.03	0.03	0.34	−0.16	0.27	−0.11	−0.37	0.08	0.22	−0.02
	(0.26)	(0.15)	(0.02)	(0.08)	(0.13)	(0.33)	(0.18)	(0.44)	(0.17)	(0.34)	(0.05)
Meat	0.02	−0.13	0.04	0.05	0.05	0.36	0.10	−0.20	−0.17	−0.13	0.02
	(0.09)	(0.22)	(0.02)	(0.07)	(0.12)	(0.14)	(0.08)	(0.39)	(0.19)	(0.48)	(0.07)
Eggs	0.35	0.81	−0.23	0.12	0.74	−0.07	0.62	−2.05	0.15	−0.31	−0.13
	(0.27)	(0.31)	(0.06)	(0.15)	(0.25)	(0.43)	(0.27)	(0.82)	(0.35)	(0.65)	(0.09)
Dairy	0.44	0.10	0.01	−0.02	−0.07	−0.40	−0.23	0.23	−0.15	−0.02	0.11
	(0.10)	(0.14)	(0.02)	(0.09)	(0.11)	(0.16)	(0.09)	(0.35)	(0.16)	(0.32)	(0.05)
Fruits and vegetables	−0.14	0.07	0.05	−0.05	−0.70	0.55	0.17	0.11	−0.18	0.05	0.06
	(0.11)	(0.16)	(0.02)	(0.07)	(0.18)	(0.17)	(0.10)	(0.40)	(0.19)	(0.39)	(0.06)
Other foods	0.17	0.37	0.00	−0.19	0.41	−1.49	0.01	1.00	−0.04	−0.32	0.08
	(0.21)	(0.15)	(0.02)	(0.08)	(0.13)	(0.37)	(0.17)	(0.47)	(0.17)	(0.33)	(0.04)
Nonalcoholic beverages	−0.18	0.26	0.08	−0.29	0.34	0.04	−1.00	−0.05	−0.27	1.04	0.03
	(0.28)	(0.21)	(0.04)	(0.12)	(0.19)	(0.43)	(0.39)	(0.65)	(0.24)	(0.45)	(0.06)
FAFH	−0.09	−0.08	−0.04	0.04	0.03	0.36	−0.01	−1.15	0.21	0.49	0.24
	(0.10)	(0.15)	(0.02)	(0.06)	(0.11)	(0.17)	(0.09)	(0.50)	(0.18)	(0.44)	(0.06)
Alcoholic beverages	0.10	−0.36	0.02	−0.14	−0.28	−0.09	−0.21	1.18	−0.92	0.75	−0.05
	(0.22)	(0.40)	(0.04)	(0.16)	(0.29)	(0.36)	(0.19)	(1.00)	(0.68)	(1.12)	(0.15)
Nonfood	−0.01	−0.03	0.00	−0.01	−0.02	−0.04	0.00	−0.02	0.00	−1.05	1.20
	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.04)	(0.02)	(0.06)	(0.01)

Note: Estimates of elasticities of demand were evaluated at the mean of the data. Standard errors are in parentheses.

Source: Authors' calculations based on Barten's synthetic model and using aggregated monthly average household expenditures and consumer price indexes (U.S. Department of Labor, Bureau of Labor Statistics, Consumer Expenditure Survey 2010; U.S. Department of Labor, Bureau of Labor Statistics, Consumer Price Index Database 2010).

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