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AN ECONOMETRIC MODEL OF THE DEMAND FOR FOOD AND NUTRITION

by

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Abstract

A flexible, full rank two model of food consumption that is globally consistent with economic theory, aggregates across income, demographic variables, and variations in micro demand parameters, and accommodates tradeoffs between tastes and nutrition is derived. The econometric demand model is estimated with per capita U.S. consumption of 21 foods on the time period 1919-1994, excluding the World War II years 1942-1946. An approach for inferring the percentage of nutrients available from individual commodities in the U.S. food supply is derived and implemented empirically on the time period 1949-1995 for the nutrients energy, protein, total fat, carbohydrates, and cholesterol. The two sets of model results are combined to generate time paths for income and Hicksian compensated price elasticities of demand for individual foods and macronutrients.

Key Words: Aggregation, Demand, Food, Nutrition, Hicksian Compensated Price Elasticities

An Econometric Model of the Demand for Food and Nutrition

1. Introduction

Farm and food policy in the United States is undergoing a major transformation. Most, though not all, farm-level price and income support programs are being replaced by cash payments and a move toward an open market. At the same time, welfare, food stamps, Women, Infants and Children (WIC), Aid to Families with Dependent Children (AFDC), and school lunch programs are being reduced in scope at the federal level and replaced by block grants to states. It almost goes without saying that these changes will influence the prices paid for and quantities consumed of food items and nutrients, as well as incomes and food expenditures of U.S. consumers. Exactly how much and in which directions these effects will be realized, however, is much more of an open question. Many farm level policies have created consumer incentives that directly oppose those created by food subsidy programs. What can we say about the joint impact of domestic U.S. farm and food aid policies on food and nutrition consumption, health, and economic welfare of the U.S. population? At this juncture, probably not very much. As a stark example, while food stamp recipients spend more on food, they also probably eat less healthy foods due to price distortions. From a purely nutritional perspective, it is unclear whether this group is better or worse off with the combination of farm and food programs, or even whether they are economically better off than might be the case with no government intervention whatever in the farm and food sectors.

As a first cut at addressing these important and interesting questions, this paper presents a model of U.S. food and nutrition consumption. The model is estimated econometrically using annual time series data for per capita U.S. food consumption and nutritional intake over the period 1919-1994. The theoretical model exploits household production theory (Becker; Lancaster 1966, 1971; Lucas; Michael and Becker; and Muth) to link food and nutrition consumption and accommodates tradeoffs between nutrition and taste in food preferences. A general and plausible concept of aggregation across individuals' incomes, demographics, and micro-level preference parameters to market-level demand equations which are consistent with the theory of consumer choice is defined, implemented, and tested. Explicit nested parameter restrictions that are necessary and sufficient for global quasi-concavity of preferences are derived and implemented. The empirical model is subjected to a battery of diagnostic tests for model specification and parameter stability. An approach for inferring the percentage of nutrients available from individual commodities in the U.S. food supply also is derived and implemented empirically on the time period 1949-1995 for the nutrients energy, protein, total fat, carbohydrates, and cholesterol. Finally, the two sets of model results are combined to generate time paths for short- and long-run Hicksian compensated price elasticities of demand for these five nutrients.

The organization of the paper is as follows. The next section considers the theoretical issues associated with modeling food and nutrient demand. Section three characterizes the econometric food demand model and it's empirical properties, the data, empirical results, hypothesis tests, and model diagnostics. Section four presents an approach to inferring the nutritional content of aggregate food items and discusses the application of this method to U.S. annual time series data. Section five combines the empirical results of the preceding two sections to generate time paths for the per capita income and Hicksian compensated price elasticities of food and nutrient "demands." The final section summarizes and concludes.

2. Modeling Food Demand

It is reasonable to assume that food is eaten for two fundamental reasons — for its contribution to health due to nutritional intake and for its contribution to pleasure through flavor, odor, appearance, texture, and other qualities of the foods consumed. The relationship between nutrient intake and food consumption can be represented linearly. That is, "twice as much meat yields twice as much protein and twice as much fat, hence the technology must be homogeneous of degree one. Further, the amount of protein contained in an egg is not dependent of the amount of meat consumed, so the technology is additive" (Lucas, p. 167). This specification is independent of the household's welfare function for nutrients, and therefore does not relate to such findings from nutrition studies as (Dantzig; Hall; Foytik; Smith; and Stigler):

1. After certain levels of intake, additional quantities of nutrients yield decreasing (and sometimes eventually negative) returns to health.

2. The optimum quantity of any nutrient depends on the level of intake of the other nutrients.

3. Purely nutritional requirements appear to have at most a small effect on food expenditures.

Thus, let $\boldsymbol{z}$ denote an m-vector of nutrients important to the health status of the household, let $\boldsymbol{x}$ denote an n_x-vector of food items, and let $\boldsymbol{N}$ denote an $(m \times n_x)$ matrix of nutrient content per unit of food. Let the relationship between food consumed and nutrient availability be $\boldsymbol{z} = \boldsymbol{Nx}$. Also, let $\boldsymbol{y}$ denote an n_y-vector of all other goods, let $\boldsymbol{s}$ be a k-vector of demographic variables and other demand shifters, and write the consumer's utility function as $u(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{z}, \boldsymbol{s})$. The objective of the consumer is to

$$\text{(2.1)} \qquad \underset{\boldsymbol{x},\boldsymbol{y},\boldsymbol{z}}{\text{maximize}}\left\{u(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{z}, \boldsymbol{s}) : \boldsymbol{x} \geq \boldsymbol{0},\ \boldsymbol{y} \geq \boldsymbol{0},\ \boldsymbol{p}_x'\boldsymbol{x} + \boldsymbol{p}_y'\boldsymbol{y} \leq m,\ \boldsymbol{Nx} = \boldsymbol{z}\right\},$$

where $\boldsymbol{p}_x$ is the vector of prices for $\boldsymbol{x}$, $\boldsymbol{p}_y$ is the vector of prices for $\boldsymbol{y}$, and m is income.

There is empirical evidence that food is separable from non-food items in consumer preferences (see, e.g., deJanvry). This is equivalent to separability of the utility function in the partition $\{(\boldsymbol{x}, \boldsymbol{z}), \boldsymbol{y}\}$,

$$\text{(2.2)} \qquad u(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{z}) = \tilde{u}(u_x(\boldsymbol{x}, \boldsymbol{z}), \boldsymbol{y}).$$

Let $\boldsymbol{p}_x$ be the vector of market prices for foods, let m_x be total expenditure on food, and let the nutrient equations be $\boldsymbol{Nx} = \boldsymbol{z}$. Then separability lets us focus on the maximization of the food sector sub-utility function, $u_x(\boldsymbol{x}, \boldsymbol{z})$, subject to the food expenditure budget constraint, $\boldsymbol{p}_x'\boldsymbol{x} = m_x$. This substantially reduces the size of the parameter space. In this paper, I consider (2.2) to be the model structure of interest, but nest separability within the larger paradigm (2.1) following Epstein, Gorman (1995b), and LaFrance (1985).

Let $\boldsymbol{p} = [\boldsymbol{p}_x' \ \ \boldsymbol{p}_y']' \in \mathbb{R}_+^n$, where $n = n_x + n_y$, denote the vector of market prices for all goods and let the utility-maximizing conditional mean vector of quantities demanded given prices, income, demographics, and the nutrient content matrix be written as $E(\boldsymbol{x} | \boldsymbol{p}, m, \boldsymbol{s}, \boldsymbol{N}) \equiv \boldsymbol{h}^{\boldsymbol{x}}(\boldsymbol{p}, m, \boldsymbol{s}, \boldsymbol{N})$. Separability of $(\boldsymbol{x}, \boldsymbol{z})$ from $\boldsymbol{y}$ is equivalent to the demands for $\boldsymbol{x}$ having the structure

$$\text{(2.3)} \qquad \boldsymbol{h}^{\boldsymbol{x}}(\boldsymbol{p}, m, \boldsymbol{s}, \boldsymbol{N}) \equiv \tilde{\boldsymbol{h}}^{\boldsymbol{x}}(\boldsymbol{p}_{\boldsymbol{x}}, \mu_x(\boldsymbol{p}, m, \boldsymbol{s}, \boldsymbol{N}), \boldsymbol{s}, \boldsymbol{N}),$$

where

$$\text{(2.4)} \qquad \mu_x(\boldsymbol{p}, m, \boldsymbol{s}, \boldsymbol{N}) \equiv \boldsymbol{p}_x'\boldsymbol{h}^{\boldsymbol{x}}(\boldsymbol{p}, m, \boldsymbol{s}, \boldsymbol{N}) \equiv E\left(\boldsymbol{p}_x'\boldsymbol{x} | \boldsymbol{p}, m, \boldsymbol{s}, \boldsymbol{N}\right)$$

is the conditional mean of expenditure on $\boldsymbol{x}$ given prices, income, and demographic variables (Gorman 1995a; Blackorby, Primont, and Russell).[1]

There are many reasons to consider the effects of aggregation from micro units to market level data in demand analyses. First, the effects of any policy vary across individuals. Eligibility for the food stamp program is based on income, household size, and total assets, while non-recipients share the cost of the program through income taxes, which vary with income. Second, it is highly likely that preferences differ across individuals. Some of this variation may be predictable with observable demographics like ethnicity, gender, or age characteristics of household members (Pollak and Wales). But available empirical evidence from cross-section studies suggests that preference variation across individuals remains after measurable influences have been accounted for. Finally, the theory of consumer choice applies to individual decision-makers, not to aggregate behavior. Although the economic rationality of the representative consumer is an interesting empirical question, without aggregation across economic agents there is no reason to expect this property to hold. Nevertheless, tracing the economic consequences of farm and food policies on prices, quantities traded, and so forth requires market-level data and analyses.

Let $\boldsymbol{d} = (m, \mathbf{s}')' \in \mathbb{R}^{k+1}$ denote the vector of income and other measurable demographic characteristics that distinguish between household types, let $\theta \in \mathbb{R}^r$ be the vector of micro parameters that vary across households, let $\boldsymbol{\Omega} \subset \mathbb{R}^{k+1} \times \mathbb{R}^r$ be the set of household characteristics and micro parameters, and consider each household type $\omega = (\boldsymbol{d}, \theta)$ as an element of the set $\boldsymbol{\Omega}$. Write the conditional mean of quantities demanded for food items given prices, income, demographics, and micro-parameters as $\boldsymbol{x}(\boldsymbol{p}, \omega)$ and let the conditional mean for compensating variation for a change from $\boldsymbol{p}^0$ to $\boldsymbol{p}^1$ be $cv(\boldsymbol{p}^0, \boldsymbol{p}^1, \omega)$, which is defined by

$$u^0 \equiv v(\boldsymbol{p}^0, m, \boldsymbol{s}, \theta) \equiv v(\boldsymbol{p}^1, m - cv(\boldsymbol{p}^0, \boldsymbol{p}^1, \omega), \boldsymbol{s}, \theta), \tag{2.3}$$

where $v(\boldsymbol{p}, m, \boldsymbol{s}, \theta)$ is the indirect utility function, and $\boldsymbol{N}$ has been omitted from $v(\cdot)$ for notational convenience. Let $(\boldsymbol{\Omega}, \mathcal{F}, \psi)$ be a probability measure space, with $\psi : \boldsymbol{\Omega} \to \mathbb{R}_+$ a finite, countably additive measure on $\mathcal{F} \equiv \sigma(\boldsymbol{\Omega})$, the smallest sigma algebra for the Borel subsets of $\boldsymbol{\Omega}$, and $\psi(\boldsymbol{\Omega}) = 1$. Assume that ω, $cv(\boldsymbol{p}^0, \boldsymbol{p}^1, \omega)$, and $\boldsymbol{x}(\boldsymbol{p}, \omega)$ are ψ-integrable $\forall\ \boldsymbol{p}, \boldsymbol{p}^0, \boldsymbol{p}^1 \in \mathbb{R}^n_+$. Define the mean demands and compensating variation relative to $\psi(\cdot)$ by integrating out the income and demographic variables,[2]

$$E[cv(\boldsymbol{p}^0, \boldsymbol{p}^1, \omega)] = \int_{\boldsymbol{\Omega}} cv(\boldsymbol{p}^0, \boldsymbol{p}^1, \omega) d\psi(\omega), \tag{2.4a}$$

$$E[\boldsymbol{x}(\boldsymbol{p}, \omega)] = \int_{\boldsymbol{\Omega}} \boldsymbol{x}(\boldsymbol{p}, \omega) d\psi(\omega). \tag{2.4b}$$

Preferences are <u>strictly aggregable</u> with respect to $\boldsymbol{x}$ if, $\forall\ \boldsymbol{p}, \boldsymbol{p}^0, \boldsymbol{p}^1 \in \mathbb{R}^n_+$, $E[\boldsymbol{x}(\boldsymbol{p}, \omega)] = \boldsymbol{x}[\boldsymbol{p}, E(\omega)]$ and $E[cv(\boldsymbol{p}^1, \boldsymbol{p}^0, \omega)] = cv[\boldsymbol{p}^1, \boldsymbol{p}^0, E(\omega)]$.

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[1] To see this, simply substitute $\boldsymbol{Nx}$ for $\boldsymbol{z}$ in $u(\cdot)$ to obtain the neoclassical utility maximization problem

$$\max_{x,y} \left\{ u(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{Nx}, \boldsymbol{s}) : \boldsymbol{x} \geq \boldsymbol{0},\ \boldsymbol{y} \geq \boldsymbol{0},\ \boldsymbol{p}_x' \boldsymbol{x} + \boldsymbol{p}_y' \boldsymbol{y} \leq m \right\}.$$

[2] Equivalent variation, $ev(\boldsymbol{p}^0, \boldsymbol{p}^1, \omega)$, defined by $u^1 \equiv v(\boldsymbol{p}^1, m, \boldsymbol{s}, \theta) \equiv v(\boldsymbol{p}^0, m + ev(\boldsymbol{p}^1, \boldsymbol{p}^0, \omega), \boldsymbol{s}, \theta)$, is strictly aggregable if and only if compensating variation is.

Remark 1. Linearity of the nutrient equations, $z = Nx$, implies that nutrient demands are strictly aggregable if food demands are strictly aggregable.

Remark 2. Strict aggregation is stronger than exact aggregation across a single function of income (Gorman 1953, 1961; Muellbauer, 1975, 1976) or across income and demographic variables (Stoker 1993), since strict aggregation requires aggregation jointly across income, demographics, and individual-specific micro-parameters. Strict aggregation requires that all elements of ω individually enter $\boldsymbol{x}(\boldsymbol{p},\cdot)$ linearly and any elements of $\boldsymbol{d}$ and θ that interact must be uncorrelated.

Remark 3. One important characteristic of strict aggregation is that both quantities demanded and welfare measures must aggregate. A simple example illustrates the reason for this. Let the indirect utility function be a full rank three Quadratic Expenditure System (Howe, Pollack, and Wales; van Daal and Merkies) of the form,

$$v(\boldsymbol{p},m) = -\frac{\sqrt{\boldsymbol{p}'\boldsymbol{Bp}}}{(m-\alpha(\boldsymbol{s})'\boldsymbol{p})} + \frac{\gamma'\boldsymbol{p}}{\sqrt{\boldsymbol{p}'\boldsymbol{Bp}}}. \tag{2.5}$$

By an application of Roy's identity, we have

$$\boldsymbol{x}(\boldsymbol{p},\omega) = \alpha(\boldsymbol{s}) + \left(\frac{m-\alpha(\boldsymbol{s})'\boldsymbol{p}}{\boldsymbol{p}'\boldsymbol{Bp}}\right)\boldsymbol{Bp} + \left[\boldsymbol{I} - \frac{\boldsymbol{Bpp}'}{\boldsymbol{p}'\boldsymbol{Bp}}\right]\gamma\frac{\left(m-\alpha(\boldsymbol{s})'\boldsymbol{p}\right)^2}{\boldsymbol{p}'\boldsymbol{Bp}}, \tag{2.6}$$

while the compensating variation for the price change $\boldsymbol{p}^0 \to \boldsymbol{p}^1$ is

$$cv(\boldsymbol{p}^0,\boldsymbol{p}^1,\omega) = m - \alpha(\boldsymbol{s})'\boldsymbol{p}^1 - \left\{\frac{\sqrt{(\boldsymbol{p}^1)'\boldsymbol{Bp}^1/(\boldsymbol{p}^0)'\boldsymbol{Bp}^0}\times\left(m-\alpha(\boldsymbol{s})'\boldsymbol{p}^0\right)}{1+\left[\frac{\gamma'\boldsymbol{p}^0}{\sqrt{(\boldsymbol{p}^1)'\boldsymbol{Bp}^1\cdot(\boldsymbol{p}^0)'\boldsymbol{Bp}^0}} - \frac{\gamma'\boldsymbol{p}^1}{(\boldsymbol{p}^0)'\boldsymbol{Bp}^0}\right]\times\left(m-\alpha(\boldsymbol{s})'\boldsymbol{p}^0\right)}\right\}. \tag{2.7}$$

Suppose that $\alpha(\boldsymbol{s}) \equiv \alpha_0 + \boldsymbol{As}$, all of the elements of $\boldsymbol{A}$ are uncorrelated with $\boldsymbol{s}$, $\boldsymbol{B}$ is constant across individuals, $E(\gamma) = \boldsymbol{0}$, and γ is stochastically independent of all other micro-parameters and demographic variables. Then quantities demanded aggregate to a model that is linear in per capita income. But compensating variation aggregates if and only if $\gamma = \boldsymbol{0}$ with probability one. Otherwise**,** no finite expansion of the moments of γ will recover the representative consumer's compensating or equivalent variation exactly for this model.

In the empirical application, I use a simplified version of (2.1) based on the concept of weak integrability (LaFrance and Hanemann). Only part of the preference map is recovered from a proper subset of demands (Epstein; Hausman; LaFrance and Hanemann) and a small loss in generality results from aggregating nonfood items to a Hicks composite commodity. Therefore, let y be a scalar representing nonfood expenditures, let $\pi(\boldsymbol{p}_y)$ be a known, increasing, linearly homogeneous and concave price index for nonfood items, and assume that the (quasi-) utility function for foods, nutrients and nonfood expenditures is quadratic,

$$u(\boldsymbol{x},y,\boldsymbol{z},\boldsymbol{s}) = \tfrac{1}{2}(\boldsymbol{x}-\alpha_1(\boldsymbol{s}))'\boldsymbol{B}_{\boldsymbol{xx}}(\boldsymbol{x}-\alpha_1(\boldsymbol{s})) + \tfrac{1}{2}\beta_{yy}(y-\alpha_2(\boldsymbol{s}))^2 \tag{2.8}$$

$$+\tfrac{1}{2}(\boldsymbol{z}-\boldsymbol{\alpha}_3(\boldsymbol{s}))'\boldsymbol{B}_{zz}(\boldsymbol{z}-\boldsymbol{\alpha}_3(\boldsymbol{s}))+(\boldsymbol{x}-\boldsymbol{\alpha}_1(\boldsymbol{s}))'\boldsymbol{\beta}_{xy}(y-\alpha_2(\boldsymbol{s}))$$

$$+(\boldsymbol{x}-\boldsymbol{\alpha}_1(\boldsymbol{s}))'\boldsymbol{B}_{xz}(\boldsymbol{z}-\boldsymbol{\alpha}_3(\boldsymbol{s}))+(y-\alpha_2(\boldsymbol{s}))\boldsymbol{\beta}'_{yz}(\boldsymbol{z}-\boldsymbol{\alpha}_2(\boldsymbol{s})),$$

a second-order flexible functional form that generates demand functions that are linear in income. The utility function (2.8) is strictly aggregable if (and only if)

(a) $\boldsymbol{\alpha}_i(\boldsymbol{s})=\boldsymbol{\alpha}_{i0}+\boldsymbol{A}_i\boldsymbol{s},\ \ i=1,2,3;$

(b) $\boldsymbol{B}_{xx}$, β_{yy}, $\boldsymbol{B}_{zz}$, β_{xy}, and β_{zy} are constant across individuals; and

(c) $E(\boldsymbol{A}_i\boldsymbol{s})=E(\boldsymbol{A}_i)E(\boldsymbol{s}),\ i=1,2,3.$

This follows from substituting $\boldsymbol{Nx}$ for $\boldsymbol{z}$ in (3.1) and maximizing $u(\boldsymbol{x}, y, \boldsymbol{Nx}, \boldsymbol{s})$ with respect to $(\boldsymbol{x}, y)$ subject to the budget constraint, $\boldsymbol{p}'_x\boldsymbol{x}+\pi(\boldsymbol{p}_y)y\le m$, to obtain the unconditional demands for $\boldsymbol{x}$ as

$$\text{(2.9)}\qquad \boldsymbol{h}^x(\boldsymbol{p}_x,\pi(\boldsymbol{p}_y),m,\boldsymbol{s})=\boldsymbol{\alpha}_x(\boldsymbol{s})+\left(\frac{m-\boldsymbol{\alpha}_x(\boldsymbol{s})'\boldsymbol{p}_x-\alpha_y(\boldsymbol{s})\pi(\boldsymbol{p}_y)}{\boldsymbol{p}'_x\boldsymbol{C}_{xx}\boldsymbol{p}_x+2\boldsymbol{p}'_x\boldsymbol{\gamma}_{xy}\pi(\boldsymbol{p}_y)+\gamma_{yy}\pi(\boldsymbol{p}_y)^2}\right)\cdot\left(\boldsymbol{C}_{xx}\boldsymbol{p}_x+\boldsymbol{\gamma}_{xy}\pi(\boldsymbol{p}_y)\right),$$

where

$$\boldsymbol{C}=\begin{bmatrix}\boldsymbol{C}_{xx} & \boldsymbol{\gamma}_{xy}\\ \boldsymbol{\gamma}'_{xy} & \gamma_{yy}\end{bmatrix}=\begin{bmatrix}\boldsymbol{B}_{xx}+\boldsymbol{B}_{xz}\boldsymbol{N}+\boldsymbol{N}'\boldsymbol{B}_{zx}+\boldsymbol{N}'\boldsymbol{B}_{zz}\boldsymbol{N} & \boldsymbol{\beta}_{xy}+\boldsymbol{N}'\boldsymbol{\beta}_{zy}\\ \boldsymbol{\beta}'_{xy}+\boldsymbol{\beta}'_{zy}\boldsymbol{N} & \beta_{yy}\end{bmatrix}^{-1},$$

$$\begin{bmatrix}\boldsymbol{\alpha}_x(\boldsymbol{s})\\ \alpha_y(\boldsymbol{s})\end{bmatrix}=\begin{bmatrix}\boldsymbol{C}_{xx} & \boldsymbol{\gamma}_{xy}\\ \boldsymbol{\gamma}'_{xy} & \gamma_{yy}\end{bmatrix}\begin{bmatrix}\boldsymbol{B}_{xx}+\boldsymbol{N}'\boldsymbol{B}_{zx} & \boldsymbol{\beta}_{xy}+\boldsymbol{N}'\boldsymbol{\beta}_{zy} & \boldsymbol{B}_{xz}+\boldsymbol{N}'\boldsymbol{B}_{zz}\\ \boldsymbol{\beta}'_{xy} & \beta_{yy} & \boldsymbol{\beta}'_{zy}\end{bmatrix}\begin{bmatrix}\boldsymbol{\alpha}_1(\boldsymbol{s})\\ \alpha_2(\boldsymbol{s})\\ \boldsymbol{\alpha}_3(\boldsymbol{s})\end{bmatrix},$$

while the compensating variation for price changes from $\boldsymbol{p}_x^0$ to $\boldsymbol{p}_x^1$ is given by

$$\text{(2.10)}\qquad cv(\boldsymbol{p}_x^0,\boldsymbol{p}_x^1,m,\boldsymbol{s})=\boldsymbol{m}-\boldsymbol{\alpha}_x(\boldsymbol{s})'\boldsymbol{p}_x^1-\alpha_y(\boldsymbol{s})\pi(\boldsymbol{p}_y)$$

$$-\left(\boldsymbol{m}-\boldsymbol{\alpha}_x(\boldsymbol{s})'\boldsymbol{p}_x^1-\alpha_y(\boldsymbol{s})\pi(\boldsymbol{p}_y)\right)\cdot\sqrt{\frac{(\boldsymbol{p}_x^1)'\boldsymbol{C}_{xx}\boldsymbol{p}_x^1+2(\boldsymbol{p}_x^1)'\boldsymbol{\gamma}_{xy}\pi(\boldsymbol{p}_y)+\gamma_{yy}\pi(\boldsymbol{p}_y)^2}{(\boldsymbol{p}_x^0)'\boldsymbol{C}_{xx}\boldsymbol{p}_x^0+2(\boldsymbol{p}_x^0)'\boldsymbol{\gamma}_{xy}\pi(\boldsymbol{p}_y)+\gamma_{yy}\pi(\boldsymbol{p}_y)^2}}.$$

Due to the adding up condition, heteroskedasticity considerations suggest an empirical specification with expenditures deflated by $\pi(\boldsymbol{p}_y)$, rather than quantities demanded, as left-hand-side variables (Brown and Walker). Abusing notation slightly, then, the empirical model is

$$\text{(2.11)}\qquad \boldsymbol{e}_x\equiv\boldsymbol{P}_x\boldsymbol{x}=\boldsymbol{P}_x\boldsymbol{\alpha}_x(\mathbf{s})+\left(\frac{m-\boldsymbol{\alpha}_x(\mathbf{s})'\boldsymbol{p}_x-\alpha_y(\boldsymbol{s})}{\boldsymbol{p}'_x\boldsymbol{C}_{xx}\boldsymbol{p}_x+2\boldsymbol{\gamma}'_{xy}\boldsymbol{p}_x+\gamma_{yy}}\right)\boldsymbol{P}_x\left(\boldsymbol{C}_{xx}\boldsymbol{p}_x+\boldsymbol{\gamma}_{xy}\right)+\boldsymbol{\varepsilon}_x,$$

where m and $\boldsymbol{p_x}$ now have been deflated by $\pi(\boldsymbol{p_y})$ and $\boldsymbol{P}_x \equiv \mathrm{diag}(p_{xi})$. Adding up implies $\iota'\varepsilon_x + \varepsilon_y \equiv 0$, where ι is an n_x-vector of ones and ε_y is the residual for total expenditures on nonfood items.

The right-hand-side of (2.11) is zero degree homogeneous in C, so that a normalization is required for identification. A useful choice is $\gamma_{yy} = 1$, which tacitly replaces C with –C and fixes the lower diagonal element at unity. This generates convenient for deriving the parameter restrictions for global quasi-concavity. Separability of foods from nonfood expenditures, which in turn is necessary and sufficient for separability of foods from all other goods (LaFrance and Hanemann), is equivalent to the n_x restrictions $\boldsymbol{\gamma_{xy}} = 0$. The $n_x \times n_x$ submatrix of Slutsky substitution terms for food items is

$$\text{(2.12)} \qquad \boldsymbol{S} = \left(\frac{m - \boldsymbol{\alpha}_x(\mathbf{s})'\boldsymbol{p}_x - \alpha_y(\boldsymbol{s})\pi}{\boldsymbol{p}_x'\boldsymbol{C}_{xx}\boldsymbol{p}_x + 2\boldsymbol{p}_x'\boldsymbol{\gamma}_{xy}\pi_x + \pi^2} \right) \left[\boldsymbol{C}_{xx}' - \left(\frac{(\boldsymbol{C}_{xx}\boldsymbol{p}_x + \boldsymbol{\gamma}_{xy}\pi)(\boldsymbol{p}_x'\boldsymbol{C}_{xx} + \boldsymbol{\gamma}_{xy}'\pi)}{\boldsymbol{p}_x'\boldsymbol{C}_{xx}\boldsymbol{p}_x + 2\boldsymbol{p}_x'\boldsymbol{\gamma}_{xy}\pi + \pi^2} \right) \right].$$

Hence, symmetry is accommodated by ½$n_x(n_x$-1) linear parameter restrictions on $\boldsymbol{C}_{xx}$. While symmetry of $\boldsymbol{S}$ guarantees the existence of the direct and indirect preference functions, it does not ensure the proper curvature associated with utility maximization. The necessary and sufficient condition for consistency with utility theory is quasi-concavity. Quasi-concavity of the (quasi-)utility function in $(\boldsymbol{x}, y)$, in turn, implies that at least n_x eigen values of $-\boldsymbol{C}$ must be negative (Lau). Hence, at least n_x of the eigen values of $\boldsymbol{C}$ must be positive for quasi-concavity. Given separability, the quadratic utility function in (3.1) is additively separable in $\boldsymbol{x}$ and y. Quasi-concavity then requires that preferences must be concave either in $\boldsymbol{x}$ or in y (Gorman 1995c). Treating foods and nonfood expenditure symmetrically implies that the eigen values of $\boldsymbol{C_{xx}}$ all are non-negative. Letting $\boldsymbol{C}_{xx} = \boldsymbol{LL'}$, where $\boldsymbol{L}$ is a lower triangular matrix, so that $\boldsymbol{C}_{xx}$ is positive semi-definite, we therefore can ensure that the (quasi-)utility function is globally weakly integrable. The rank of $\boldsymbol{L}$ generally will be less than n_x unless the symmetry restricted (but not curvature restricted) estimate of $\boldsymbol{C_{xx}}$ is positive definite. In that case, the curvature restrictions are not binding. In the alternative case where $\boldsymbol{L}$ has a reduced rank of n_x-g for $0 \le g \le n_x$, the matrix $\boldsymbol{L}$ will have all entries on and below the last g diagonal elements equal to zero. This gives the greatest number of independent parameters associated with a symmetric, positive semi-definite matrix $\boldsymbol{C_{xx}}$ that has rank n_x-g (see, e.g., Diewert and Wales), and is associated with ½$g(g$+1) restrictions for curvature in addition to the ½$n_x(n_x$–1) symmetry restrictions.

3. Empirical Estimates for United States Food Demand

The data set consists of annual time series observations over the period 1918-1994. Per capita consumption of twenty-one food items and corresponding average retail prices for those items were constructed from several USDA and Bureau of Labor Statistics (BLS) sources. The quantity data are aggregates taken from the USDA series *Food Consumption, Prices and Expenditures*. Estimated retail prices corresponding to the quantity data were constructed for 1967 using detailed disaggregated retail price estimates along with the respective quantity observations to construct an average retail price per pound in 1967 for each food category (e.g., beef). For all other years, the fixed 1967 quantity weights, together with consumer price indices or average retail food prices for the individual food items were combined to construct a consistent retail price series for each commodity. The consumer price index (CPI) for all nonfood items is used for the price of nonfood expenditures.

The demographic factors included in the data are the first three moments (mean, variance, and skewness) of the empirical age distribution for the U.S. population and proportions of the U.S. population that are Black and neither White nor Black. The estimated age distribution is based on ten-year age intervals, plus categories for children less than five years old and adults that are sixty-five years old and older. The ethnic variables are linearly interpolated estimates of Bureau of Census figures reported on 10-year intervals. I allow for habit formation by including lagged quantities as elements of $\boldsymbol{s}$. This reduces the effective sample period to 1919-1994, with 1918 required for initial conditions, for a total of 76 annual time series observations. The income variable is per capita disposable personal income. My previous work with this data (LaFrance 1999a, 1999b) provided strong evidence that World War II represented a substantial structural break in the data set. Hence, I omit the years 1942-1946 to account for this.

With the assistance of the Human Nutrition Information Service (HNIS), annual estimates of the percentages of the total availability of seventeen nutrients from each of the twenty-one food categories were compiled for the period 1952-1983. These percentages were multiplied by the respective total supply of nutrients per capita and divided by the respective per capita consumption of each food item to obtain year-to-year estimates of the average nutrient content per pound of each food item - e.g., the number of grams of protein per pound of beef. These year-to-year nutrient content estimates present several issues. First, there are only slight annual changes in these data over the period 1952-1983. A non-constant $\boldsymbol{N}$ matrix makes the model parameters time-varying. In principle, a time-varying $\boldsymbol{N}$ matrix permits the separate identification and estimation of the preference parameters associated with nutrition and taste. However, this is not possible with a constant $\boldsymbol{N}$ matrix. Second, the construction of the annual nutrient content matrices creates a simultaneity problem. That is, the elements of $\boldsymbol{x}$ are used to calculate the elements of $\boldsymbol{N}$ each year, so that quantities demanded tacitly end up on both sides of the demand equations. Third, the percentage contribution estimates are reported with only two or three significant digits. This generates errors in variables, and exaggerates the changes in $\boldsymbol{N}$ over time. As a result, on the advice of the HNIS, the nutrient content matrix is assumed constant across years using the average of the 1952-1983 annual estimates for $\boldsymbol{N}$, the longest available time period with consistent percentage contribution estimates for all 21 food items as a starting point for our analysis of the nutritional content of food items developed and discussed in the next section. These average annual estimates are presented in Table 1.

Table 2 presents model diagnostics for the sample period 1919-41 and 1947-94, which excludes World War II plus 1946 to account for the dynamic effects of habit formation. Model stability tests appear at the bottom of table 2. The unrestricted version fails to reject the model specification at a 5 percent significance level, while the symmetric and globally quasi-concave versions fail to reject at the 10 percent level. In addition, symmetry is not rejected at a 5 percent level of significance level, while global quasi-concavity is not rejected at the 10 percent level. Moreover, the less definitive result regarding model specification and parameter stability for the unrestricted model is tempered by several factors. First, neither of the restricted specifications is rejected in favor of the unrestricted model. Second, neither restricted version shows evidence of misspecification. Third, none of the model versions show evidence of misspecification in any of a large battery of single equation stability tests (see LaFrance 1999a for details). In addition, neither restricted specification shows evidence of autocorrelation in the error terms. This is unusual in that the imposition of parameter restrictions such as symmetry usually tends to introduce serial correlation among the error terms. There also is little evidence of skewness in the residuals and the two restricted models show no evidence of thicker tails in the error terms than occurs in the unrestricted model,[3] although all three versions of the model show evidence of leptokurtosis. However, the estimation and inference methods employed here are robust to thick tails so long as the fourth moments of the underlying data generating process exist.

Table 3 reports the equation summary statistics for the fully restricted, globally quasi-concave model specification. In this table, the average per capita expenditure levels for individual food items also are reported in constant 1967 dollars. Table 4 presents the estimated structural parameters associated with the constant

[3] For example, the point estimate for the coefficient of excess kurtosis in the unrestricted model falls well within a 95 percent confidence interval of the corresponding estimate for the quasi-concave model. In other words, the parameter restrictions associated with symmetry and jointly with symmetry and quasi-concavity do not appear to create spurious outliers in the data.

terms, demographic variables, and lagged quantities consumed, with estimated asymptotic standard errors in parentheses below the respective parameter estimates. One notable feature in this table is that habit formation appears to be considerably weaker than previous studies of food demand suggest. This result is likely due to the inclusion of the variables associated with the age distribution and ethnic makeup of the U.S. population.[4] These variables have changed substantially, although rather smoothly and nonlinearly, over time. Hence, they likely represent nonlinear trends in food consumption that previously have been proxied by lagged quantities demanded. Finally, table 5 presents the estimated parameters associated with the negative of the inverse Hessian for the food sector's subutility function, with the associated asymptotic standard errors in parentheses below the estimated coefficients.

These empirical results and hypothesis tests suggest that this data set readily accommodate this model specification, even under the imposition of global symmetry and negative semidefiniteness of the associated submatrix of Slutsky substitution terms. While this result is surprising given the restrictive nature of strict aggregation, it does suggest that the model is a reasonable, coherent framework for studying the aggregate consumer effects of changes in farm and food policies in the United States. An additional interesting empirical result is that including a reasonable list of demographic variables in the aggregate demand equations eliminates virtually all evidence of serial correlation in the error terms and much of the empirical support for habit formation in food consumption.

4. Inferring the Nutrient Content of Food

A central focus of much research on farm and food policy on consumer choice and nutrition has been an effort to establish the economic links between food consumption choices and nutrition. Suppose that we have a stable, theoretically consistent reduced form model of the demand for foods that can be written in the form $E(\boldsymbol{x}|\,\boldsymbol{p}_x, m, \boldsymbol{s}) = \boldsymbol{h}^x(\boldsymbol{p}_x, m, \boldsymbol{s})$, such as is presented in the previous section. Given measurements on the nutrient content matrix transforming foods into nutrients, $\boldsymbol{z} = \boldsymbol{N}\boldsymbol{x}$, we can analyze policy effects on nutritional intakes using the demand model since

$$E(\boldsymbol{z}|\,\boldsymbol{p}_x, m, \boldsymbol{s}) = \boldsymbol{N}\boldsymbol{h}^x(\boldsymbol{p}_x, m, \boldsymbol{s}) \,. \tag{4.1}$$

For example, both the ordinary and compensated nutrient price elasticities of "demand" satisfy

$$\varepsilon^{z_i}_{p_k} = \sum_{j=1}^{n_x} w_{ij}\varepsilon^{x_j}_{p_k} \,, \tag{4.2}$$

where $\varepsilon^{z_i}_{p_k} \equiv (p_k/z_i)\cdot\partial z_i/\partial p_k$ is either the ordinary or compensated price elasticity of nutrient *i* with respect to price *k*, $\varepsilon^{x_j}_{p_k} \equiv (p_k/x_j)\cdot\partial x^j/\partial p_k$ is the associated ordinary or compensated price elasticity of food *j* with respect to price *k*, and $w_{ij} \equiv n_{ij}x_j/z_i$ is the share of nutrient *i* supplied by food *j*. Economically, therefore, inferring the nutrient shares is of more interest than the nutrient content values.

I have annual observations on the total disappearance of twenty-one foods from the U.S. food supply and the total availability of seventeen nutrients from those foods for the period 1909-1994. I also have a sample of estimates for the individual nutritional content of each of these food items for the period 1952-1983. However, the food quantity and nutrient availability data has been updated several times by the USDA since the sample of 32 observations was originally constructed. Hence, the nutrient content estimates obtained from the extraneous sample are not entirely consistent with the available data on total annual food

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[4] Stoker (1986) and Buse reach a similar conclusion about the empirical significance of habit formation when they include summary measures for the income distribution, rather than demographic variables, in their demand models.

and nutrient consumption. But it is reasonable to think that the shorter 32-year data set can be used to draw inferences about the joint behavior of the elements of the nutrient content matrix over time.

My initial point of departure is an ingenious approach to ill-posed inference problems known as *generalized maximum entropy* recently developed by Golan (1994), Golan, Judge, and Miller (1996), and Golan, Judge, and Perloff (1996). Although I ultimately pursue a somewhat different strategy, it is useful to briefly summarize this approach as it relates to the present problem to motivate the solution approach that I actually followed. Consider the problem of estimating the nutritional content of food items in a given year from aggregate per capita disappearance data and estimates of the total nutrients available in the food supply. Rewriting the linear relationship between food and nutrients as

(4.3) $$\boldsymbol{z}_t = \boldsymbol{N}_t \boldsymbol{x}_t, \quad t = 1, \cdots, T,$$

Suppose that we have an average estimate of the nutrient content matrix, say $\boldsymbol{N}^\circ$, obtained independently of the current inference problem. But we do not have data on the nutrient content matrices on a year-to-year basis. Let's focus on the case of a single nutrient to simplify the discussion and omit the time subscripts whenever this is not confusing. We seek a vector, $\boldsymbol{\eta} \geq \boldsymbol{0}$ satisfying $z = \boldsymbol{\eta}'\boldsymbol{x}$, given a prior estimate, $\boldsymbol{\eta}^\circ$, and observations on *z* and $\boldsymbol{x}$. We specify a compact interval of support for each η_i containing the prior estimate, $\eta_i^\circ \in [\underline{\eta}_i, \overline{\eta}_i],\ i = 1, \ldots, m$, divide each interval into *N* subintervals, each having the form

(4.4) $$\left[\left(\frac{N-n+1}{N}\right)\underline{\eta}_i + \left(\frac{n-1}{N}\right)\overline{\eta}_i, \left(\frac{N-n}{N}\right)\underline{\eta}_i + \left(\frac{n}{N}\right)\overline{\eta}_i\right], \ n = 1, \ldots, N,$$

and write the η_i's as weighted averages of the *N*+1 endpoints,

(4.5) $$\begin{aligned}\eta_i &= \underline{\eta}_i q_{i0} + \left[\left(\frac{N-1}{N}\right)\underline{\eta}_i + \left(\frac{1}{N}\right)\overline{\eta}_i\right] q_{i1} + \cdots + \left[\left(\frac{1}{N}\right)\underline{\eta}_i + \left(\frac{N-1}{N}\right)\overline{\eta}_i\right] q_{iN-1} + \overline{\eta}_i q_{iN} \\ &= \sum_{j=0}^{N} \left[\underline{\eta}_i + (j/K)\delta_i\right] q_{ij}, \ i = 1, \cdots, m,\end{aligned}$$

where $\delta_i \equiv \overline{\eta}_i - \underline{\eta}_i\ \forall i$, $q_{ij} \geq 0\ \forall\ i,j$ and $\sum_{j=0}^{N} q_{ij} = 1$. The GME choice for $\boldsymbol{\eta}$ solves

(4.6) $$\max - \sum_{i=1}^{n_x} \sum_{j=0}^{N} q_{ij} \log(q_{ij}) \ \text{ subject to}$$

$$q_{ij} \geq 0 \ \forall\ i, j,$$

$$\sum_{j=0}^{N} q_{ij} = 1 \ \forall\ i,$$

$$\sum_{i=1}^{n_x} \sum_{j=0}^{N} \left[\underline{\eta}_i + (j/K)\delta_i\right] q_{ij} x_i = z.$$

This is a straightforward constrained optimization problem with a strictly concave objective function and linear constraints, and a unique solution is guaranteed to exist. Moreover, the logarithmic transformation strictly bounds the solution away from zero, so the non-negativity constraints are slack at the optimal solution. The GME solution can be written in the form

(4.7) $$q_{ij} = q_{i0} \exp\{-\lambda \delta_i x_i (j/K)\}, \ \forall\ j = 0, \ldots, K, \ \forall\ i = 1, \ldots, n_x,$$

with the normalizing condition

(4.8)
$$q_{i0} = 1 \Big/ \sum_{j=0}^{K} \exp\left\{-\lambda\delta_i x_i \left(j/K\right)\right\},$$

which ensures that the probabilities add up to one for each i. Finally, the optimal posterior choices for the η_i's are the means of the posterior discrete probability distributions,

(4.9)
$$\eta_i = \underline{\eta}_i + \delta_i \sum_{j=0}^{K} \left(\frac{j}{K}\right) \frac{\exp\left\{-\lambda\delta_i x_i \left(j/K\right)\right\}}{\sum_{k=0}^{K} \exp\left\{-\lambda\delta_i x_i \left(k/K\right)\right\}}, \ \forall\ i = 1, \ldots, n_x,$$

while the Lagrange multiplier for the mean constraint is defined by

(4.10)
$$\sum_{i=1}^{n_x} x_i \left[\underline{\eta}_i + \delta_i \sum_{j=0}^{K} \left(\frac{j}{K}\right) \frac{\exp\left\{-\lambda\delta_i x_i \left(j/K\right)\right\}}{\sum_{k=0}^{K} \exp\left\{-\lambda\delta_i x_i \left(k/K\right)\right\}}\right] = z.$$

This always produces a well-defined, unique answer to even highly ill posed inference problems, including the present one.

However, the GME algorithm raises some issues, at least for this application. First, what is a reasonable choice for the compact support for the nutrient content coefficients? This is treated as a subjective judgement in the typical GME solution, rather than truly arising from prior information. In the present case, however, we know with probability one that any given food item can not account for less than zero nor more than 100 percent of a given nutrient's total availability. Most of us (at least the non-nutritionists among us, including myself) probably know precious little more than this about the percent of total fat that is contributed by beef, say. This gives us a natural choice for the support for the elements of $\boldsymbol{\eta}$. But it is easy to show that the GME criterion applied to this support for each η_i implies that we simply choose equal nutrient shares for each food item in each nutrient – clearly a ridiculous inference.

Second, simply viewing the time series plots for any of the nutrient content or nutrient share estimates over the 32-year period 1952-1983 clearly demonstrates that the nutrient content of most foods has not remained constant over time. This is especially true for the nutrient content shares, which is illustrated clearly in figures 1-5 for the four macronutrients plus cholesterol. Using the 32-year sample average matrix $\boldsymbol{N}^\circ$ as the center of the support for the uniform (i.e., equally likely) prior in the GME solution tacitly assumes that the nutrient content matrix is time invariant. It seems problematic to employ the Bayesian method, at least in part because this is logically superior to classical statistics, but to start the Bayesian inference process with a set of prior beliefs that known to be false at the outset! Clearly, an alternative approach is required if we want to be logically consistent and not jump to silly conclusions.

The important motivating aspect of the GME solution that provides the motivation for the estimation procedure I adopt can be obtained by simply combining equations (4.7) and (4.8),

(4.11)
$$q_{ij} = \frac{\exp\left\{-\lambda\delta_i x_i \left(j/K\right)\right\}}{\sum_{k=0}^{K} \exp\left\{-\lambda\delta_i x_i \left(k/K\right)\right\}}, \ \forall\ j = 0, \ldots, K,\ \forall\ i = 1, \ldots, n_x.$$

This has precisely the form of a multinomial logit distribution (Golan, Judge, and Perloff) with time-varying weights due to the fact that the food quantities, x_i, vary over time. Therefore, consider estimating the nutrient content shares as multinomial logit probabilities with exponential coefficients as simple, smooth functions of time. We wish to obtain time paths for the fitted shares that are in some sense "close" to the observed share estimates obtained from the HNIS with in the sample period 1952-1983. This amounts to specifying the nutrient content shares in the form

$$(4.12) \qquad w_{ij}(t) = \frac{e^{\beta_{ij}(t)}}{\sum_{k=1}^{n_x} e^{\beta_{ik}(t)}} + v_{ij}(t),\ \forall\ i = 1,\ldots,m,\ \forall\ j = 1,\ldots,n_x,\ \forall\ t = 1952,\ldots,1983,$$

where the $\beta_{ij}(t)$ are polynomials in t, say, and the error terms, $v_{ij}(t)$, are assumed to have zero means and finite variances. This solution procedure maintains the flavor of the GME solution, while allowing for a time-varying nutrient content matrix – or more accurately, a time-varying nutrient content share matrix – and guarantees that the nutrient content shares are non-negative and sum to one for each nutrient in the data set and each year.

For each of the four macronutrients energy, protein, total fat, and carbohydrates plus total cholesterol, equation (4.12) is estimated over the sample period 1952-1983 using iterative nonlinear seemingly unrelated regressions estimation methods with each $\beta_{ij}(t)$ specified as a second-order polynomial in t. Iterative seemingly unrelated regressions methods are employed to obtain estimates that are invariant to the equation that is omitted due to the adding up condition (i.e., the observed and predicted nutrient content shares sum to one). The normalizing condition $\beta_{i1}(t) \equiv 1$ is imposed for identification, similar to the normalizing condition in equation (4.8) above. Any nutrient content shares that are constant (including zero shares) within the sample period is forecast to remain constant throughout the "forecast" period 1949-1995. In addition, the forecasted carbohydrate shares of pork and other red meat are fixed at 0.100% for the entire sample period and forecast period. The reason for this latter restriction is the fact that these two data series appear to have one and two, respectively very large (in percentage terms) outliers primarily due to rounding (see figure 4). The very small percentages of carbohydrates contributed by these foods, combined with the multinomial logit specification, leads to extraordinarily large weights on the exceptionally small values of these three observations, dominating the empirical estimates and producing implausible results. At very low levels, the nutrient content shares are reported as either 0.10%, 0.05%, or less than 0.05%, with the latter interpreted to be the midpoint value of 0.025%. It therefore seems quite clear that the relatively large percentage changes in these three observations are due to rounding of the data. Consequently these three data points are essentially thrown out of the data set, and the model is estimated as if the carbohydrate shares of pork and other red meat remain constant throughout the sample and forecast periods.

Figures 1 through 5 graphically illustrate the results of this estimation and forecasting process for energy, protein, total fat, carbohydrates, and total cholesterol, respectively. In each of the figures, the upper left panel depicts the observed and predicted time paths of the nutrient content shares of dairy products, the upper right panel contains the time paths for meats, fish and poultry, the lower left panel contains those for fruits and vegetables (except potatoes and sweetpotatoes), and the lower right panel depicts the time paths for other foods. The category "miscellany" includes coffee, tea and cocoa as well as fortifications and additives that are not allocated to any of the other specific food items or groups. The plots with solid lines and solid circles represent the observed data, while the plots with dashed lines represent the forecast values. With the exceptions of beef, pork and processed vegetables, particularly during the years 1973-1976 for these three food aggregates, the forecasting method appears to fit the data surprisingly well. Clearly there has been substantial movement in the shares of nutrients supplied by many foods over the past fifty years. This is not surprising. It merely reflects the combination of the changing mix of foods produced and consumed in the U.S. market, as well as the fact that the typical slaughter hog in 1949 bears only a slight resemblance to today's counterpart.

5. The Elasticities of "Demand" for Nutrition

In this section, we will combine the empirical results of the previous two sections to generate a series of time paths for short- and long run income and Hicksian compensated price elasticities of demand for the five nutrients energy, protein, total fat, carbohydrates, and total cholesterol. From equation (2.9), given separability and our normalization for $\boldsymbol{C}$, the vector of income elasticities for the food items is defined by

$$(5.1) \qquad \varepsilon_m^x = m\boldsymbol{X}^{-1}\left(\frac{\boldsymbol{C_{xx}p_x}}{\boldsymbol{p_x'C_{xx}p_x}+1}\right),$$

where $\boldsymbol{X} = \text{diag}(x_i)$. Since the $m \times n_x$ matrix of nutrient content shares satisfies $\boldsymbol{W} = \boldsymbol{Z}^1\boldsymbol{NX}$, the $m\times 1$ vector of income elasticities of the nutrient "demands" is equal to

$$\varepsilon_m^z = \boldsymbol{W}m\boldsymbol{X}^{-1}\left(\frac{\boldsymbol{C_{xx}p_x}}{\boldsymbol{p}_x'\boldsymbol{C_{xx}p_x}+1}\right) = m\boldsymbol{Z}^{-1}\boldsymbol{N}\left(\frac{\boldsymbol{C_{xx}p_x}}{\boldsymbol{p}_x'\boldsymbol{C_{xx}p_x}+1}\right). \tag{5.2}$$

Figure 6 illustrates the time paths of the income elasticities of the twenty-one food items, while figure 7 shows the time paths of the income elasticities for the five nutrients for the period 1949 - 1994. Among the food items, the only good with substantially negative income elasticity is butter, while all of the macronutrients are "normal" goods, with total fat generally displaying the highest income response.

Similar to the income elasticities of demand, we can combine the Slutsky substitution submatrix for food items from equation (2.12) under separability and symmetry,

$$\boldsymbol{S} = \left(\frac{m - \alpha_x(\mathbf{s})'\boldsymbol{p}_x - \alpha_y(\boldsymbol{s})}{\boldsymbol{p}_x'\boldsymbol{C}_{xx}\boldsymbol{p}_x+1}\right)\times\left[\boldsymbol{C}_{xx} - \left(\frac{\boldsymbol{C}_{xx}\boldsymbol{p}_x\boldsymbol{p}_x'\boldsymbol{C}_{xx}}{\boldsymbol{p}_x'\boldsymbol{C}_{xx}\boldsymbol{p}_x+1}\right)\right], \tag{5.3}$$

with the nutrient content share estimates to obtain the Hicksian compensated price elasticities for foods and nutrients as

$$\varepsilon_{\boldsymbol{p}_x'}^{\boldsymbol{x}} = \boldsymbol{X}^{-1}\boldsymbol{SP_x} = \left(\frac{m - \alpha_x(\mathbf{s})'\boldsymbol{p}_x - \alpha_y(\boldsymbol{s})}{\boldsymbol{p}_x'\boldsymbol{C}_{xx}\boldsymbol{p}_x+1}\right)\times \boldsymbol{X}^{-1}\left[\boldsymbol{C}_{xx} - \left(\frac{\boldsymbol{C}_{xx}\boldsymbol{p}_x\boldsymbol{p}_x'\boldsymbol{C}_{xx}}{\boldsymbol{p}_x'\boldsymbol{C}_{xx}\boldsymbol{p}_x+1}\right)\right]\boldsymbol{P_x}, \tag{5.4}$$

and

$$\varepsilon_{\boldsymbol{p}_x'}^{z} = \boldsymbol{W}\varepsilon_{\boldsymbol{p}_x'}^{\boldsymbol{x}} = \boldsymbol{WX}^{-1}\boldsymbol{SP_x} = \left(\frac{m - \alpha_x(\mathbf{s})'\boldsymbol{p}_x - \alpha_y(\boldsymbol{s})}{\boldsymbol{p}_x'\boldsymbol{C}_{xx}\boldsymbol{p}_x+1}\right)\times \boldsymbol{Z}^{-1}\boldsymbol{N}\left[\boldsymbol{C}_{xx} - \left(\frac{\boldsymbol{C}_{xx}\boldsymbol{p}_x\boldsymbol{p}_x'\boldsymbol{C}_{xx}}{\boldsymbol{p}_x'\boldsymbol{C}_{xx}\boldsymbol{p}_x+1}\right)\right]\boldsymbol{P_x}. \tag{5.5}$$

However, in the interests of space, the time paths of these large matrices are not included here.

6. Conclusions

This paper presents results on an econometric model of per capita food consumption and nutritional intake for the United States. The model is fully consistent with economic theory. It motivates food consumption for nutrition and taste and accommodates trade-offs between eating for pleasure and for health. The empirical model is consistent with strict aggregation across income, demographic factors, and varying micro-parameters. Explicit parameter solutions for the global imposition of the necessary and sufficient conditions for weak integrability, including global curvature restrictions, have been derived and implemented. The empirical application estimates a system of demands for twenty-one food items using annual U.S. per capita time series data for 1918-1994. Results of the hypothesis tests of the restrictions required for economic theory suggest that this data set and empirical model readily accommodate economic theory. This result is somewhat surprising given the restrictive nature of strict aggregation. Nevertheless, it suggests that the empirical model is a reasonable, coherent framework for studying aggregate consumer effects of changes in farm and food policies in the United States. An additional interesting empirical result is that including a reasonable list of demographic variables in the aggregate demand equations eliminates virtually all evidence of serial correlation in the error terms, and most of the empirical support for habit formation in food consumption.

The paper also presents an approach to inferring the year-to-year nutritional content of aggregate food items using prior information obtained from an extraneous sample. The procedure maintains the flavor of the generalized maximum entropy method for ill-posed inference problems, while overcoming some difficulties associated with this approach for the problem at hand. The main characteristics of the inference procedure are: (1) a polynomial expansion in a time trend for the exponential terms of a multinomial logit model for the nutrient content shares of individual food items; and (2) iterative nonlinear seemingly unrelated regression equations to obtain empirical results that are invariant to the parameter normalization and omitted food quantity. With only a few exceptions, this forecasting procedure works remarkably well on the data set for this study.

Finally, the empirical results from the two separate estimation approaches have been combined to generate price and income elasticities of demand for foods and nutrients that are consistent with the economic theory of consumer choice. These elasticity estimates offer a solid theoretical and empirical basis for the analysis of the economic impacts of changes in U.S. food and nutrition policy.

Some of the many issues not addressed in this paper include: (1) the effects of the distribution of income on aggregate demand behavior; (2) the impacts of the choice of functional form, especially the use of a quasi-homothetic demand model, rather than an alternative aggregable specification; (3) myopic versus rational habit formation, and perhaps even whether or not aggregate U.S. food consumption exhibits evidence of habits at all when demographics and the distribution of income have been taken into account properly; and (4) the life cycle theory of consumption choice and the importance (or lack thereof) of intertemporal optimization and expectations formation processes for future prices, incomes, and other relevant economic phenomena on observable food consumption choices. Reluctantly, however, I must leave all of these questions for the future.

References

Attfield, C. L. F. “Homogeneity and Endogeneity in Systems of Demand Equations.” *Journal of Econometrics* 27 (1985): 197-209.

___________.“Estimation and Testing When Explanatory Variables Are Endogenous.” *Journal of Econometrics* 48 (1991): 395-408.

Bhattacharya, R. N. and E. C. Waymire. *Stochastic Processes with Applications.* New York: John Wiley and Sons, 1990.

Becker, G. S. “A Theory of the Allocation of Time.” *The Economic Journal* 75 (1965): 493-517.

Bera, A. K., R. P. Byron, and C. M. Jarque. “Further Evidence on Asymptotic Tests for Homogeneity and Symmetry in Large Demand Models.” *Economics Letters* 8 (1981): 101-105.

Blackorby, C., D. Donaldson, and D. Maloney. “Consumer's Surplus and Welfare Change in a Simple Dynamic Model.” *Review of Economic Studies* 51 (1984): 171-176.

Blackorby, C., D. Primont and R.R. Russell. *Duality, Separability and Functional Structure: Theory and Economic Applications*, New York: North-Holland, 1978.

Blundell, R. “Econometric Approaches to the Specification of Life-Cycle Labour Supply and Commodity Demand Behavior.” *Econometric Reviews* 5(1986): 89-146.

___________. “Consumer Behavior: Theory and Empirical Evidence - A Survey” *The Economic Journal* 98 (1988): 16-65.

Brown, R. L., J. Durbin, and J. M. Evans. “Techniques for Testing the Constancy of Regression Relationships Over Time.” *Journal of the Royal Statistical Society*, Series B, 37 (1975): 149-92.

Brown, B. W. and M. B. Walker. “The Random Utility Hypothesis and Inference in Demand Systems.” *Econometrica* 57 (1989): 815-829.

Buse, A “Aggregation, Distribution and Dynamics in the Linear and Quadratic Expenditure Systems.” *Review of Economics and Statistics* 74 (1992): 45-53.

Csiszár, I. "Why Least Squares and Maximum Entropy? An Axiomatic Approach to Inference for Linear Inverse Problems." *The Annals of Statistics* 19 (1991): 2032-2066.

Dantzig, G. B. *Linear Programming and Extensions*, Princeton, N.J.: Princeton University Press, 1963.

Deaton, A. *Models and Projections of Demand in Post War Britain* London: Chapman and Hall, 1975.

___________.“Demand Analysis.” In *Handbook of Econometrics*, Vol. III, eds. Z. Griliches and M. Intriligator. New York: North-Holland, 1986:1767-1839.

deJanvry, A. “Measurement of Demand Parameters Under Separability.” Ph.D. dissertation, Department of Agricultural and Economics, University of California-Berkeley, 1966.

Diewert, W. E. and T. J. Wales. "Flexible Functional Forms and Global Curvature Conditions.” *Econometrica* 55 (1987): 43-68.

Durbin, J. “Errors in Variables.” *Review of the International Statistical Institute* 22 (1954): 23-32.

Edgerton, D. L. “On the Estimation of Separable Demand Models.” *Journal of Agricultural and Resource Economics* 18 (1993): 141-146.

Engle, R. F., D. F. Hendry, and J.F. Richard. “Exogeneity.” *Econometrica* 51 (1983): 277-304.

Epstein, L. “Integrability of Incomplete Systems of Demand Functions.” *Review of Economic Studies* 49 (1982): 411-425.

Foytik, J. “Very Low Cost Nutritious Diet Plans Designed by Linear Programming.” *Journal of Nutrition Education* 13 (1981): 63-66.

Gokhale, D. V. and S. Kullback. *The Information in Contingency Tables,* New York: Marcel Dekker, 1978.

Golan, A. "A Multivariable Stochastic Theory of Size Distribution of Firms with Empirical Evidence." *Advances in Econometrics* 10 (1994): 1-46.

Golan, A., G. Judge, and D. Miller *Maximum Entropy Econometrics: Robust Estimation with Limited Data,* New York: John Wiley and Sons, 1996.

Golan, A., G. Judge, and J. Perloff "A Maximum Entropy Approach to Recovering Information from Multinomial Response Data." *Journal of the American Statistical Association* 91 (1996): 841-853.

Gorman, W. M. “Community Preference Fields.” *Econometrica* 21 (1953): 63-80.

___________. “On a Class of Preference Fields.” *Metroeconomica* 13 (1961): 53-56.

___________. “Two-Stage Budgeting.” Unpublished typescript, University of North Carolina, 1970. Reprinted as Chapter 2 in C. Blackorby and T. Shorrocks, eds. *Separability and Aggregation: Collected Works of W. M. Gorman*, Oxford: Clarendon Press, 1995a.

___________. “Consumer Budgets and Price Indices.” Unpublished typescript, 1965. Reprinted as Chapter 5 in C. Blackorby and T. Shorrocks, eds. *Separability and Aggregation: Collected Works of W. M. Gorman*, Oxford: Clarendon Press, 1995b.

___________. “The Concavity of Additive Utility Functions.” Unpublished typescript, University of North Carolina, October 1970. Reprinted as Chapter 9 in C. Blackorby and T. Shorrocks, eds. *Separability and Aggregation: Collected Works of W. M. Gorman*, Oxford: Clarendon Press, 1995c.

Hall, C. “Activity Analysis Applied to Menu Planning.” M.S. Thesis, Iowa State University, Ames, IA, 1977.

Hansen, L. P. “Large Sample Properties of Generalized Methods of Moments Estimators.” *Econometrica* 50 (1982): 1029-1054.

Harvey, A. C. *The Econometric Analysis of Time Series*, Cambridge, Massachusetts: The MIT Press, 1990.

___________. *Time Series Models*, Second Edition, Cambridge, Massachusetts: The MIT Press, 1993.

Hausman, J. “Specification Tests in Econometrics.” *Econometrica* 46 (1978): 1251-1272.

___________. “Exact Consumer’s Surplus and Deadweight Loss.” *American Economic Review* 71 (1981): 662-676.

Heien, D. “The Cost of U.S. Dairy Price Support Programs: 1949-74.” *Review of Economics and Statistics* 59 (1977): 1-8.

Hendry, D. F. *Dynamic Econometrics* Oxford: Oxford University Press, 1995.

Howe, H., R. A. Pollak, and T. J. Wales. “Theory and Time Series Estimation of the Quadratic Expenditure System.” *Econometrica* 47 (1979): 1231-1247.

Ippolito, R. A. and R. T. Masson. “The Social cost of Government Regulation of Milk.” *Journal of Law and Economics* 21 (1978): 33-65.

Jamison, J. A. *Marketing Orders and Public Policy for the Fruit and Vegetable Industries*, Stanford: Food Research Institute, 1971.

___________. “Linear Demand Functions in Theory and Practice.” *Journal of Economic Theory* 37 (1985): 147-166.

___________. “When is Expenditure 'Exogenous' in Separable Demand Models?” *Western Journal of Agricultural Economics* 16 (1991):49-62.

Jaynes, E. "Information Theory and Statistical Mechanics." *Physics Review* 106 (1957a): 620-30.

_______. "Information Theory and Statistical Mechanics II." *Physics Review* 108 (1957b): 171-90.

_______. 'Prior Information and Ambiguity in Inverse Problems." in D. McLaughlin, ed., *Inverse Problems,* Providence RI: American Mathematical Society, 1984: 151-166.

Kullback, J. *Information Theory and Statistics,* New York: John Wiley and Sons, 1959.

Kullback, J. and R. Leibler. "On Information and Sufficiency." *Annals of Mathematical Statistics* 4 (1951): 99-111.

LaFrance, J. T. "U.S. Food and Nutrient Demand and the Effects of Agricultural Policies.” Working paper # 864, Department of Agricultural and Resource Economics, University of California, Berkeley, 1999a. USDA/ERS commissioned paper, *1999 FAMC Consortium*.

_______. "The Structure of U.S. Food Demand." Working paper # 862, Department of Agricultural and Resource Economics, University of California, Berkeley, 1999b: currently in review at the *Journal of Econometrics*.

_______. “Inferring the Nutrient Content of Food with Prior Information.” *American Journal of Agricultural Economics* 81 (1999c): in press.

LaFrance, J. T. and W. M. Hanemann. “The Dual Structure of Incomplete Demand Systems.” *American Journal of Agricultural Economics* 71 (1989):262-274.

Laitinen, K. “Why Is Demand Homogeneity So Often Rejected?” *Economics Letters* 1 (1978): 187-191.

Lancaster, K. J. “A New Approach to Consumer Theory.” *Journal of Political Economy* 74 (1966): 132-157.

___________. *Consumer Demand: A New Approach*, New York: Columbia University Press, 1971.

Lau, L. J. "Testing and Imposing Monotonicity, Convexity and Quasi-convexity Constraints." Appendix A.4 in *Production Economics: A Dual Approach to Theory and Applications*, M. Fuss and D. McFadden (eds.), Amsterdam: North-Holland Publishing Co., 1978: 409-455.

Lucas, R. E. "Hedonic Price Functions." *Economic Inquiry* 13 (1975):157-178.

Malinvaud, E. *Statistical Methods of Economics*, Second edition, Amsterdam: North-Holland, 1980.

Meisner, J. F. "The Sad Fate of the Slutsky Symmetry Test for Large Systems." *Economics Letters* 2 (1979): 231-233.

Michael, R. T. and G. S. Becker. "On the New Theory of Consumer Behavior." *Swedish Journal of Economics* 75 (1973): 378-396.

Muellbauer, J. "Aggregation, Income Distribution and Consumer Demand." *Review of Economic Studies* 42 (1975): 525-543.

___________. "Community Preferences and the Representative Consumer." *Econometrica* 44 (1976): 979-999.

Muth, R. F. "Household Production and Consumer Demand Functions." *Econometrica* 34 (1966): 699-708.

Ploberger, W. and W. Krämer. "The CUSUM Test with OLS Residuals." *Econometrica* 60 (1992): 271-286.

Pollak, R. A. and T. J. Wales. "Demographic Variables in Demand Analysis." *Econometrica* 49 (1981):1533-1551.

Rothenberg, T. J. and C. T. Leenders. "Efficient Estimation of Simultaneous Equation Systems." *Econometrica* 32 (1964):57-76.

Shannon, C. "A Mathematical theory of Communication." *Bell System Technical Journal* 27 (1948): 379-423.

Smith, V. C. "Linear Programming Models for the Determination of Palatable Human Diets." *Journal of Farm Economics* 41 (1959): 272-283.

Spanos, A. "On Normality and the Linear Regression Model," *Econometric Reviews* 14 (1995): 195-203.

Stigler, G. J. "The Cost of Subsistence." *Journal of Farm Economics* 27 (1945):303-314.

Stoker, T. M. "Simple Tests of Distributional Effects on Macroeconomic Equations." *Journal of Political Economy* 94 (1986): 763-795.

Stoker, T. M. "Empirical Approaches to the Problem of Aggregation over Individuals." *Journal of Economic Literature* 31 (1993): 1827-1874.

Theil, H. *Theory and Measurement of Consumer Demand*, Volume II, Amsterdam: North-Holland, 1976.

Tobias, J. and A. Zellner. "Further Results on the Bayesian Method of Moments Analysis of the Multiple Regression Model." H.G.B. Alexander Research Foundation, University of Chicago, 1997. Presented at the Econometric Society meeting, June 1997.

Van Daal, J. and A. H. Q. M. Merkies. "A Note on the Quadratic Expenditure Model." *Econometrica* 57 (1989): 1439-1443.

White, H. "A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity." *Econometrica* 48 (1980): 817-38.

Wu, D. "Alternative Tests of Independence Between Stochastic Regressors and Disturbances." *Econometrica* 41 (1973): 733-749.

Zellner, A. "The Bayesian Method of Moments (BMOM): Theory and Applications." In T. Fomby and R. Hill, eds., *Advances in Econometrics* 12 (1997): 85-105.

Zellner, A., J. Tobias, and K. Ryu. "Bayesian Method of Moments (BMOM) Analysis of Parametric and Semiparametric Regression Models." Alexander Research Foundation, University of Chicago, 1997

Table 1. Nutrient Content of U.S. Foods.

	Calories kilo-cals / lb.	Protein grams / lb.	Fat grams / lb.	Carbos grams / lb.	Calcium mil grm / lb.	Phosph mil grm / lb.	Iron mil grm / lb.	Magnes mil grm / lb.	A ret / lb.	Thiamin mil grm / lb.	Riboflav mil grm / lb.	Niacin mil grm / lb.	B_6 mil grm / lb.	B_{12} mil grm / lb.	C mil grm / lb.	Zinc mil grm / lb.	Choles mil grm / lb.
Milk	280.2	14.92	14.92	22.20	522.6	426.6	0.26	60.9	100.2	0.179	0.753	0.38	0.195	1.72	4.4	1.79	55.9
Butter	3259.4	4.44	369.15	6.10	110.5	110.3	1.03	9.7	2529.7	0.034	0.162	0.37	0.031	0.60	0.0	0.24	930.0
Cheese	1348.0	102.86	98.69	9.65	2311.3	1765.3	2.27	95.7	589.2	0.117	1.395	0.54	0.355	4.25	0.0	10.66	294.4
Ice Cream	450.9	15.20	33.72	21.25	511.5	408.0	0.22	47.4	222.3	0.187	0.671	0.31	0.155	1.85	2.9	1.76	80.7
Canned & Dry Milk	899.1	63.11	19.01	119.88	2306.0	2013.0	1.36	262.3	144.2	1.535	3.634	2.07	0.769	6.13	14.0	7.08	84.0
Beef & Veal	1053.3	75.72	80.79	0.00	43.1	700.6	11.27	73.5	27.0	0.351	0.695	18.17	1.378	6.24	0.0	14.05	232.6
Pork	1972.6	59.47	189.12	2.49	42.3	674.4	8.54	72.1	0.0	2.919	0.720	14.81	1.260	5.05	0.0	6.34	264.1
Other Red Meat	840.8	93.78	47.34	8.78	120.4	966.8	13.10	82.9	6757.2	0.892	4.530	30.12	1.828	90.36	31.7	16.34	808.2
Fish	863.3	112.74	39.40	3.02	310.7	1307.4	6.92	164.0	121.7	0.331	0.685	30.68	1.839	27.72	3.5	12.69	363.2
Poultry	648.8	61.48	42.52	0.88	37.5	520.1	4.52	63.3	465.0	0.237	0.745	19.11	1.199	4.51	7.4	5.52	272.4
Fresh Citrus Fruit	108.9	1.84	0.47	27.08	53.8	44.1	0.82	31.2	75.7	0.194	0.064	0.71	0.179	0.00	112.2	0.38	0.0
Other Fresh Fruit	251.5	2.89	1.81	64.16	39.3	74.4	2.03	62.3	459.8	0.171	0.181	1.93	0.751	0.00	42.6	0.49	0.0
Fresh Vegetables	177.3	8.53	1.20	38.94	155.2	212.5	3.50	111.5	1344.1	0.390	0.339	3.06	0.680	0.00	121.0	1.30	0.0
Potatoes	331.8	8.25	0.66	73.45	34.7	196.4	2.41	83.1	328.7	0.385	0.138	5.44	0.835	0.00	62.6	1.54	0.0
Processed Fruit	227.7	8.42	0.99	52.63	89.7	170.3	4.84	74.7	956.2	0.325	0.243	3.92	0.556	0.00	64.4	1.48	0.0
Proc. Vegetables	713.4	34.31	29.60	90.93	210.8	620.0	9.98	257.4	825.3	0.891	0.435	11.11	0.998	0.00	54.6	4.20	0.0
Fats & Oils	3834.0	0.94	429.36	0.78	0.0	0.0	0.00	0.0	543.9	0.000	0.000	0.00	0.000	0.00	0.0	0.13	101.4
Eggs	634.4	49.57	44.38	3.67	211.4	760.6	7.97	42.5	631.3	0.401	1.298	0.33	0.475	7.30	0.0	4.69	1964.1
Cereal	1705.3	47.09	5.57	361.73	81.1	495.8	12.45	151.4	14.3	1.987	1.083	14.95	0.471	0.04	1.9	3.96	0.0
Sugar	1684.0	0.08	0.00	441.08	9.7	3.8	0.58	3.2	0.0	0.003	0.010	0.03	0.004	0.00	0.1	0.06	0.0
Coffee, Tea & Cocoa	497.4	10.31	9.67	29.25	101.6	383.5	6.58	307.1	68.74	0.03	0.28	3.84	0.0	0.00	0.0	0.10	0.0

Table 2. System Model Diagnostics.

	With World War II			Without World War II		
	UNR	SYM	Q-C	UNR	SYM	Q-C
s(S)	1515.9	1361.9	1321.8	1415.7	1228.1	1249.3
ρ	-.124	-.044	-.0055	-.135	-.039	-.027
σ_ρ	.026	.027	.028	.027	.029	.029
t_ρ	4.78	1.61	0.20	5.02	1.35	0.94
η_3	.070	.0083	.011	.147	.045	.066
σ_{η_3}	.061	.061	.061	.063	.063	.063
t_{η_3}	1.14	0.14	0.18	2.31	0.71	1.05
η_4	.200	.658	.631	.451	.675	.628
σ_{η_4}	.123	.123	.123	.127	.127	.127
t_{η_4}	1.63	5.37	5.13	3.55	5.32	4.94
J-B $\chi^2(2)$	3.94	28.84	26.35	17.96	28.80	25.51
P-value	0.14	5.5×10^{-7}	1.9×10^{-6}	1.3×10^{-4}	5.6×10^{-7}	2.9×10^{-6}
Expenditure Exogeneity Tests						
$\bar{\hat{u}}$	1.696	3.398	3.506	1.624	5.150	5.061
$\sigma_{\bar{\hat{u}}}$	.340	1.016	1.001	.343	1.364	1.332
$t_{\bar{\hat{u}}}$	4.986	3.344	3.503	4.739	3.776	3.800
P-value	3.1×10^{-6}	4.1×10^{-4}	2.3×10^{-4}	1.1×10^{-5}	8.0×10^{-5}	7.2×10^{-5}
F-Tests						
Separability	1.55			1.57		
P-value	.05			.05		
Theory		1.09	1.84		1.18	1.12
P-value		.20	9.7×10^{-11}		.06	.12
Systemwide Stability Tests						
1st Moment						
$\max\|B_T(z)\|$	.39	.40	.66	.41	.42	.47
P-value	.998	.997	.78	.996	.995	.98
2nd Moment						
$\max\|B_T(z)\|$	.55	1.87	1.69	1.36	1.22	1.06
P-value	.92	.002	.007	.05	.10	.22

UNR, SYM, and Q-C are unrestricted, symmetric, and quasi-concave, respectively; s(S) is the second round error sum of squares; ρ is the first order autocorrelation coefficient; η_3 is the coefficient of skewness; η_4 is the coefficient of excess kurtosis; and J-B $\chi^2(2)$ is the Jarque-Bera test for normality.

Table 3. Single Equation Model Diagnostics, Globally Quasi-Concave Specification.

	With World War II			Without World War II		
	R^2	$\sqrt{T}\,\bar{\hat{\varepsilon}}_i / \hat{\sigma}_i$	$\max_{0 \le z \le 1} \lvert B_{iT}(z) \rvert$	R^2	$\sqrt{T}\,\bar{\hat{\varepsilon}}_i / \hat{\sigma}_i$	$\max_{0 \le z \le 1} \lvert B_{iT}(z) \rvert$
Fresh Milk & Cream	.9953	.325	.616	.9973	.122	.326
Butter	.9914	-.171	.649	.9965	-.164	.463
Cheese	.9952	-.060	.907	.9983	-.026	.529
Frozen Dairy Products	.9580	-.470	.619	.9877	-.190	.402
Other Dairy Products	.9139	-.027	.509	.9867	.073	.507
Beef & Veal	.9885	-.342	1.47	.9951	-.058	.438
Pork	.9521	-.116	1.09	.9747	.043	.561
Other Meat	.9567	-.0011	.646	.9590	.032	.380
Fish	.9883	-.307	.922	.9949	.148	.447
Poultry	.9746	.042	.634	.9893	.171	.607
Fresh Citrus Fruit	.8259	.316	1.15	.6717	.301	.728
Fresh Noncitrus Fruit	.9039	-.420	1.22	.9487	-.297	.560
Fresh Vegetables	.9868	.0091	.566	.9882	-.137	.346
Potatoes	.9368	.410	1.15	.9648	.240	.807
Processed Fruit	.9824	-.070	.816	.9882	-.020	.518
Processed Vegetables	.9716	-.100	.636	.9891	-.124	.426
Fats & Oils	.9605	-.387	.530	.9737	-.124	.394
Eggs	.9951	-.351	.600	.9989	-.240	.473
Cereal Products	.9666	1.7×10^{-4}	.494	.9889	-.082	.413
Sugar	.9780	-.275	.782	.9878	-.243	.478
Coffee, Tea, & Cocoa	.9694	-.470	1.02	.9803	-.242	.493

Table 4. Demographics and Habits, Quasi-Concave Specification with World War II Excluded.

		Age Distribution			Ethnicity		Habit
	Constant	Average	Variance	Skewness	Black	Others	x_{t-1}
Fresh Milk & Cream	374.1 (79.38)	-2.277 (2.419)	3.334 (0.673)	-.7492 (.7256)	-20.42 (13.43)	-3.503 (9.101)	.3680 (.0577)
Butter	4.975 (13.61)	.0268 (.2576)	-.2941 (.0917)	-.0263 (.0785)	1.222 (1.922)	-2.2417 (1.160)	.7394 (.0840)
Cheese	-16.21 (11.65)	.6015 (.3331)	-.1178 (.0798)	.0795 (.0846)	.2766 (1.883)	3.090 (1.322)	.5023 (.1090)
Frozen Dairy Products	-39.11 (27.78)	.0238 (.7482)	.8168 (.2791)	.0291 (.1956)	1.036 (4.214)	.7565 (2.674)	.3924 (.1204)
Other Dairy Products	34.47 (24.15)	-.2323 (.7751)	1.097 (.2870)	-.4906 (.1816)	-3.843 (4.511)	.8026 (2.492)	.3123 (.1345)
Beef & Veal	-377.7 (29.42)	1.801 (.8655)	1.859 (.2144)	-.0224 (.2424)	31.75 (5.089)	-21.30 (3.395)	.0206 (.0471)
Pork	151.0 (27.13)	.9419 (.8654)	.9444 (.2288)	.1261 (.2402)	-16.34 (4.947)	5.227 (3.285)	.0758 (.0396)
Other Meat	27.33 (13.13)	.1009 (.4196)	-.0149 (.1134)	.0907 (.1117)	-1.812 (2.419)	-.0203 (1.563)	.0727 (.1251)
Fish	42.94 (12.23)	.2894 (.3341)	-.1963 (.0812)	.1513 (.0904)	-4.272 (1.988)	5.653 (1.348)	.2578 (.0856)
Poultry	31.00 (20.66)	.0496 (.5240)	.2493 (.1646)	.0662 (.1441)	-3.797 (3.321)	12.92 (2.863)	.5027 (.0753)
Fresh Citrus Fruit	69.05 (40.34)	6.657 (1.444)	-.3189 (.3063)	.1289 (.3339)	-22.90 (7.486)	6.247 (4.749)	-.0509 (.0933)
Fresh Non-Citrus Fruit	1060.5 (97.33)	-4.393 (2.474)	-4.086 (.6862)	.5838 (.6709)	-67.74 (15.08)	59.81 (10.52)	-.4825 (.0756)
Fresh Vegetables	221.1 (50.57)	7.054 (1.554)	.3274 (.3485)	1.508 (.3852)	-45.84 (8.965)	34.11 (5.937)	.1745 (.0929)
Potatoes	575.1 (99.17)	-9.599 (2.806)	-2.288 (.6742)	.0084 (.7207)	-5.856 (15.78)	18.17 (9.994)	-.0283 (.0943)

Numbers in parentheses are asymptotic standard errors.

Table 4, continued.

		Age Distribution			Ethnicity		Habit
	Constant	Average	Variance	Skewness	Black	Others	x_{t-1}
Processed Fruit	-210.4 (41.89)	3.128 (1.062)	1.248 (.2697)	.2809 (.2948)	7.200 (6.499)	2.189 (4.287)	.2783 (.0753)
Processed Vegetables	41.94 (44.17)	7.004 (1.455)	-.3176 (.3406)	1.803 (.3598)	-28.89 (7.324)	20.99 (4.813)	.3156 (.0677)
Fats & Oils	22.08 (23.39)	3.297 (.7035)	-.2674 (.1852)	.9019 (.1940)	-12.80 (4.065)	15.66 (2.999)	.2192 (.0790)
Eggs	54.11 (16.58)	-.7929 (.4156)	.3898 (.1562)	-.1679 (.1098)	-2.399 (2.652)	-.4565 (1.757)	.7207 (.0631)
Cereal Products	1074.9 (125.8)	-9.290 (2.631)	-4.503 (.7121)	.1861 (.6382)	-47.94 (13.74)	51.32 (9.412)	.2835 (.0881)
Sugar	186.8 (53.46)	6.610 (1.738)	-2.381 (.3701)	1.791 (.4986)	-26.13 (10.19)	24.17 (6.890)	.0388 (.0589)
Coffee, Tea & Cocoa	22.33 (9.056)	.7490 (.3007)	.2174 (.0716)	-.0055 (.0781)	-4.127 (1.662)	1.595 (1.109)	.2142 (.0600)
Nonfood Expenditure	-4017.5 (1238.0)	317.5 (38.21)	14.67 (11.42)	88.94 (9.828)	-907.7 (185.4)	1273.5 (139.8)	--- ---

Numbers in parentheses are asymptotic standard errors.

Table 5. Negative Inverse Hessian of the Food Sector's Subutility Function, Quasi-Concave Specification with World War II Excluded.

	Milk & Cream	Butter	Cheese	Frozen Dairy	Other Dairy	Beef & Veal	Pork	Other Meat	Fish	Poultry
Fresh Milk & Cream	.721									
	(.129)									
Butter	.00716	.00511								
	(.00646)	(.00103)								
Cheese	.00105	-.00102	.00447							
	(.0101)	(.00087)	(.00160)							
Frozen Dairy Products	-.0659	-.00235	-.00699	.142						
	(.0391)	(.00281)	(.00469)	(.0302)						
Other Dairy Products	-.119	-.00456	-.00697	.0125	.0704					
	(.0403)	(.00290)	(.00415)	(.0189)	(.0241)					
Beef & Veal	-.0279	.00250	-.00369	.00694	.0107	.0617				
	(.0104)	(.00096)	(.00135)	(.00402)	(.00371)	(.00564)				
Pork	.0100	-.00167	-.00499	.00742	.00764	-.0195	.0904			
	(.0127)	(.00140)	(.00185)	(.00506)	(.00472)	(.00312)	(.00834)			
Other Meat	.0305	-.00131	-.00071	-.0103	-.0137	-.0147	-.0106	.0376		
	(.0162)	(.00110)	(.00185)	(.00700)	(.00654)	(.00237)	(.00252)	(.00512)		
Fish	.0211	-.00271	.00418	-.00179	-.00536	-.00310	-.00680	-.00051	.00610	
	(.0086)	(.00081)	(.00111)	(.00428)	(.00383)	(.00124)	(.00176)	(.00176)	(.00139)	
Poultry	-.0664	.00033	.00258	-.0133	.00167	-.00550	-.00449	.00220	.00197	.0209
	(.0138)	(.00140)	(.00189)	(.00542)	(.00567)	(.00210)	(.00310)	(.00267)	(.00172)	(.00347)
Fresh Citrus Fruit	.00608	-.00022	.00063	-.00152	-.00075	-.00152	-.00837	.00103	.00086	-.00972
	(.0211)	(.00251)	(.00255)	(.00751)	(.00698)	(.00466)	(.00605)	(.00328)	(.00207)	(.00556)

Table 5, Continued.

	Milk & Cream	Butter	Cheese	Frozen Dairy	Other Dairy	Beef & Veal	Pork	Other Meat	Fish	Poultry
Fresh Non-Citrus Fruit	-.0934 (.0502)	-.0113 (.00492)	.00422 (.00692)	-.0704 (.0241)	.0192 (.0192)	-.0197 (.00988)	-.0248 (.0131)	-.0230 (.00968)	.00820 (.00651)	.0207 (.00951)
Fresh Vegetables	.0445 (.0367)	-.0109 (.00340)	.00033 (.00436)	.0256 (.0163)	.0155 (.0153)	-.00150 (.00576)	.0127 (.00783)	-.00893 (.00796)	.00771 (.00407)	-.00440 (.00653)
Potatoes	-.0212 (.0487)	.00887 (.00533)	-.00313 (.00704)	-.0178 (.0162)	.0130 (.0169)	-.00574 (.00945)	-.00284 (.0125)	.00138 (.00794)	-.00754 (.00647)	-.0110 (.0119)
Processed Fruit	-.00756 (.0160)	-.00406 (.00163)	.00048 (.00223)	-.0196 (.00701)	-.00406 (.00612)	.00118 (.00344)	.00687 (.00436)	-.00545 (.00277)	-.00045 (.00202)	-.00567 (.00335)
Processed Vegetables	.0130 (.0406)	.00394 (.00300)	.00169 (.00464)	.0445 (.0187)	-.00252 (.0176)	-.0236 (.00507)	-.0217 (.00650)	.0117 (.00748)	.0101 (.00415)	.0209 (.00641)
Fats & Oils	.0177 (.0171)	-.00329 (.00156)	.00930 (.00212)	-.0209 (.00894)	-.0177 (.00735)	-.0145 (.00283)	-.0109 (.00378)	.00763 (.00330)	.00867 (.00204)	.00758 (.00302)
Eggs	.0290 (.0146)	.00056 (.00129)	-.00172 (.00188)	-.00687 (.00598)	.00433 (.00611)	-.00116 (.00175)	.00478 (.00278)	-.00685 (.00270)	-.00321 (.00164)	-.00959 (.00260)
Cereal Products	-.256 (.0991)	.00083 (.00663)	-.00320 (.00918)	.0245 (.0404)	.0221 (.0360)	-.0293 (.0108)	-.0226 (.0135)	.00462 (.0172)	-.00690 (.00838)	.0363 (.0134)
Sugar	-.0334 (.0270)	.00740 (.00266)	.00339 (.00352)	.00452 (.00777)	.0186 (.00819)	-.0179 (.00542)	-.00985 (.00662)	.00534 (.00479)	-.00156 (.00347)	.0153 (.00534)
Coffee, Tea Cocoa	-.00406 (.00288)	-.00024 (.00035)	-.00075 (.00039)	.00231 (.00112)	.00185 (.00102)	.00016 (.00074)	.00179 (.00092)	.00031 (.00048)	-.00051 (.00035)	.00022 (.00095)

Table 5, Continued.

	Fresh Citrus Fruits	Fresh Noncitrus Fruits	Fresh Vegetables	Potatoes	Processsed Fruit	Processed Vegetables	Fats & Oils	Eggs	Flour & Cereals	Sugar	Coffee, Tea & Cocoa
Fresh Citrus Fruit	.0448 (.0106)										
Fresh Non-Citrus Fruit	.00325 (.0210)	.260 (.0586)									
Fresh Vegetables	-.0176 (.0108)	.0199 (.0288)	.0636 (.0211)								
Potatoes	.0276 (.0218)	.0485 (.0495)	-.0534 (.0325)	.372 (.0747)							
Processed Fruit	.0200 (.00786)	.0198 (.0157)	-.0166 (.00954)	.0132 (.0171)	.0419 (.00811)						
Processed Vegetables	-.0111 (.00945)	-.00378 (.0241)	.00816 (.0169)	-.0132 (.0232)	-.0288 (.00900)	.124 (.0270)					
Fats & Oils	.00411 (.00570)	.0181 (.0125)	-.00275 (.00835)	.00822 (.0126)	.00650 (.00390)	.00454 (.00864)	.0244 (.00565)				
Eggs	-.00071 (.00477)	.0225 (.00898)	.0105 (.00689)	-.0296 (.00952)	.00128 (.00302)	-.0208 (.00654)	-.00563 (.00304)	.0244 (.00397)			
Cereal Products	-.0167 (.0186)	.161 (.0502)	-.00179 (.0332)	.00087 (.0501)	-.0218 (.0169)	.0419 (.0377)	.00410 (.0166)	.0206 (.0147)	.276 (.110)		
Sugar	-.0152 (.0109)	-.0543 (.0219)	-.00448 (.0161)	-.0521 (.0265)	-.0128 (.00890)	.0393 (.0121)	.00670 (.00538)	.00812 (.00419)	.0247 (.0273)	.119 (.0194)	
Coffee, Tea & Cocoa	.00534 (.00189)	-.00465 (.00363)	.00370 (.00194)	.00534 (.00350)	-.00076 (.00141)	-.00287 (.00133)	-.00087 (.00084)	-.00129 (.000637)	-.00416 (.00281)	.00048 (.00179)	.00415 (.00051)

Figure 1. Percent of Energy Supplied by Foods, 1949-1995

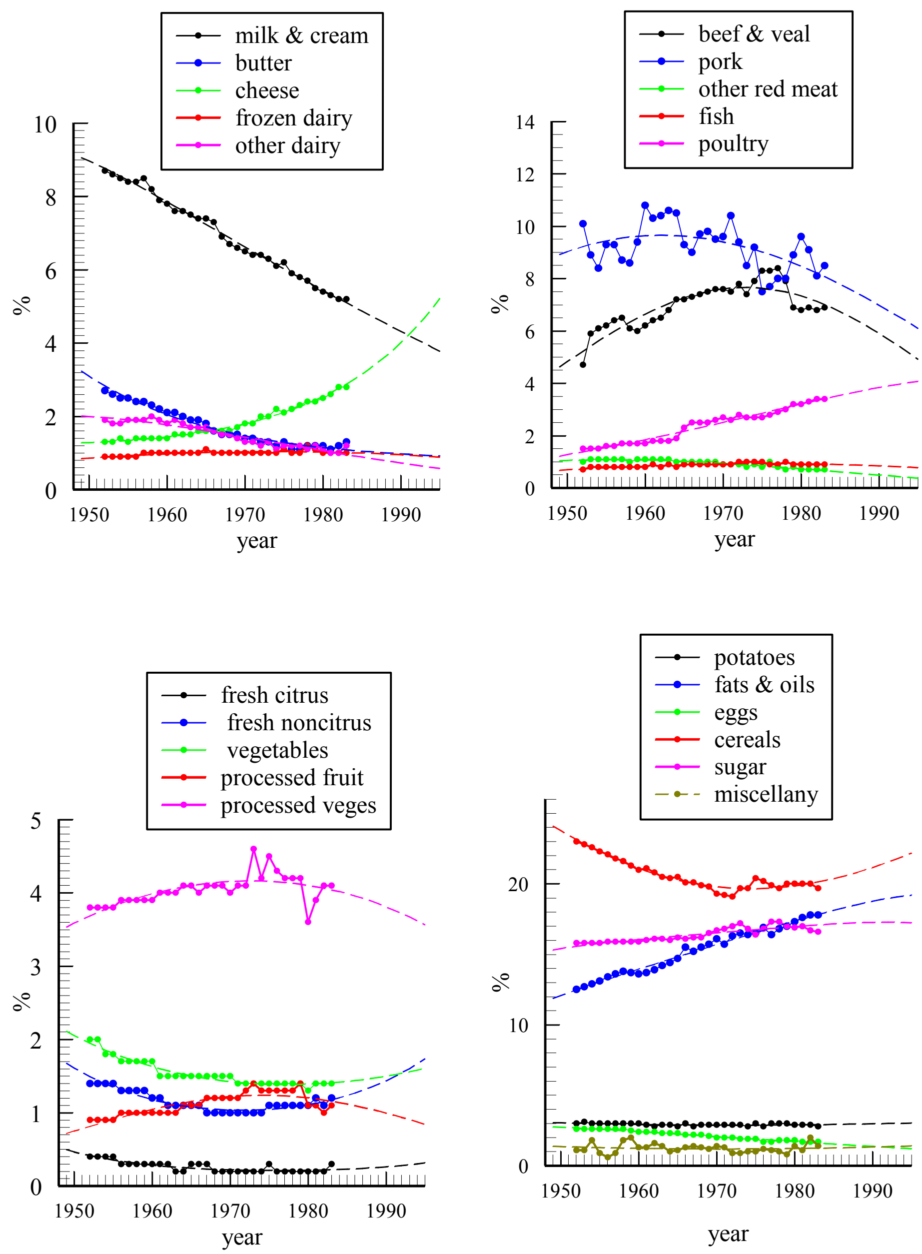

Figure 2. Percent of Protein Supplied by Foods, 1949-1995

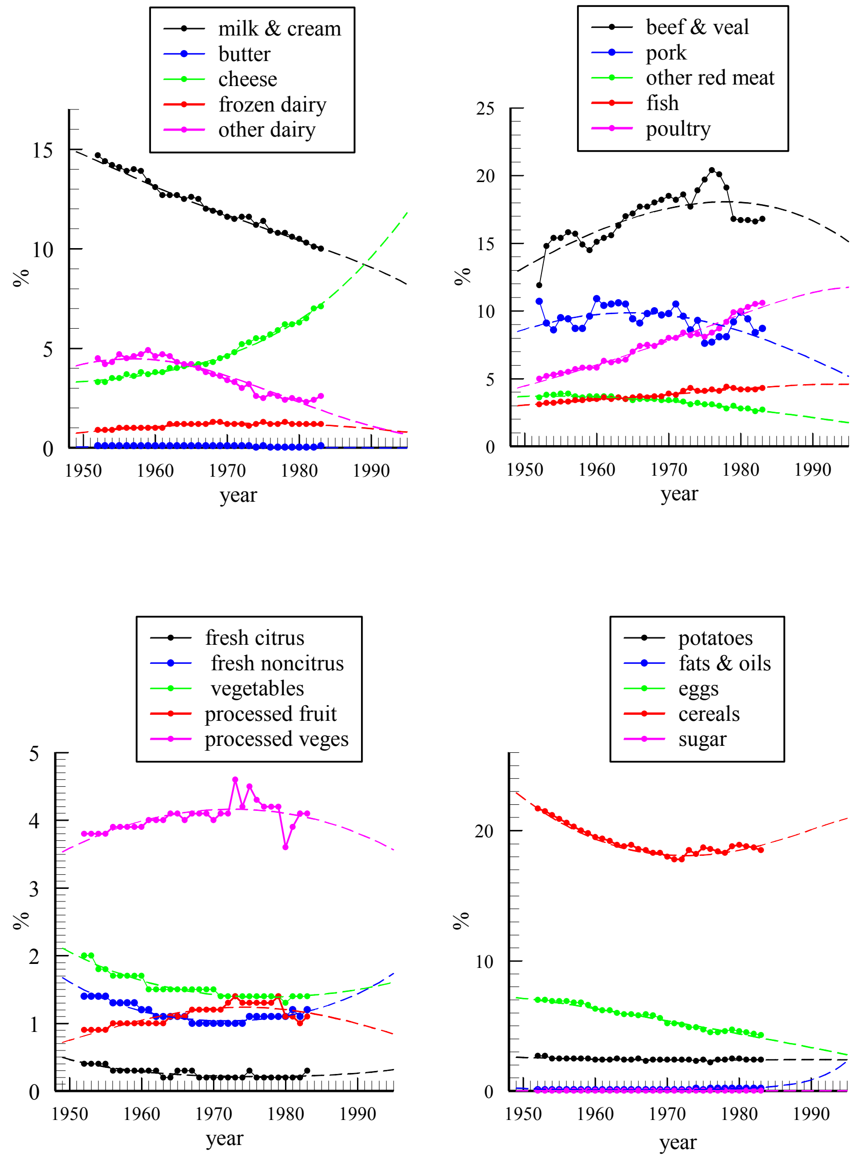

Figure 3. Percent of Fat Supplied by Foods, 1949-1995

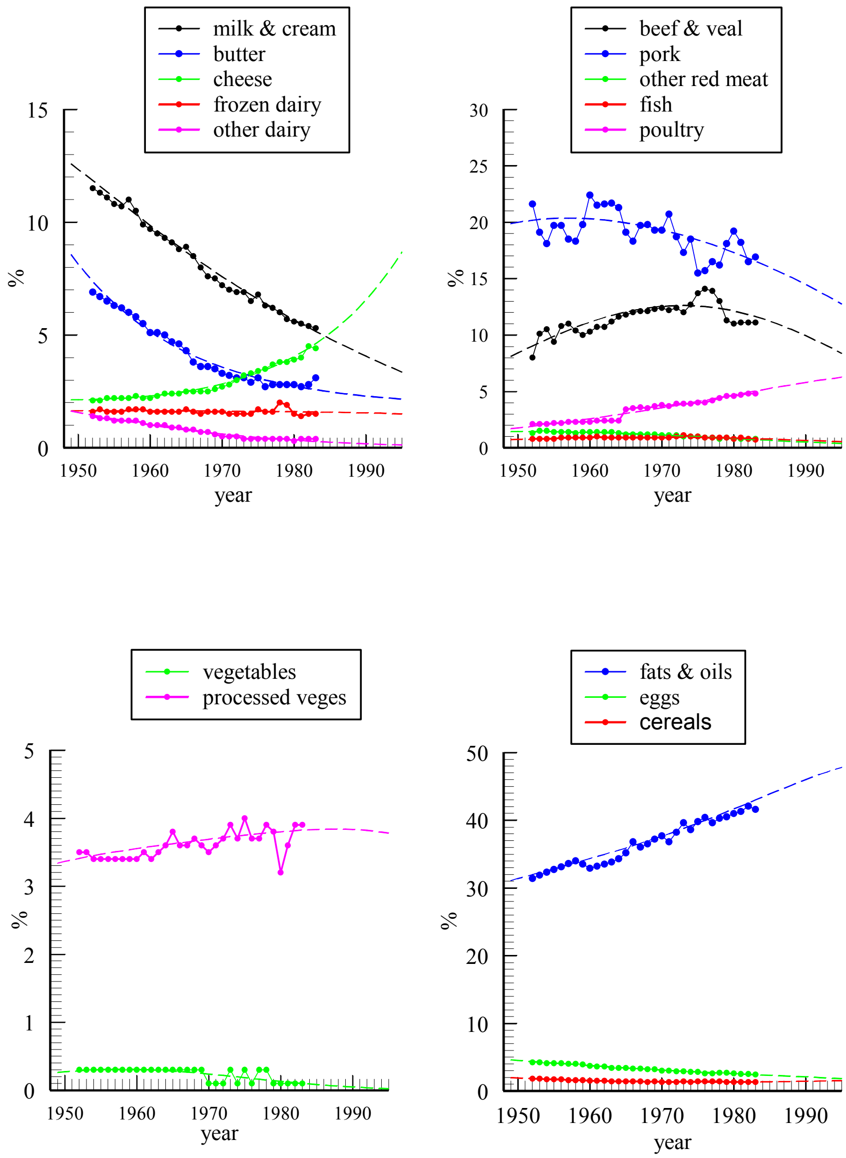

Figure 4. Percent of Carbohydrates Supplied by Foods, 1949-1995

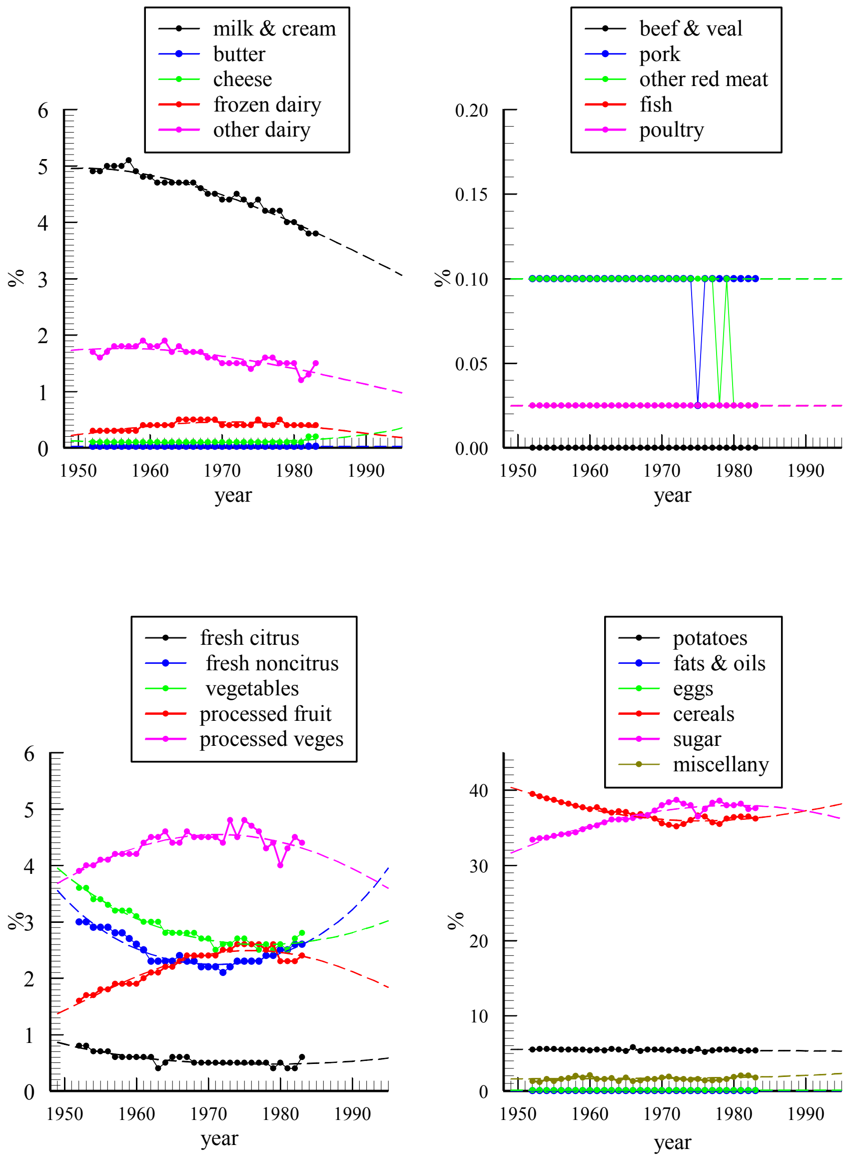

Figure 5. Percent of Cholesterol Supplied by Foods, 1949-1995

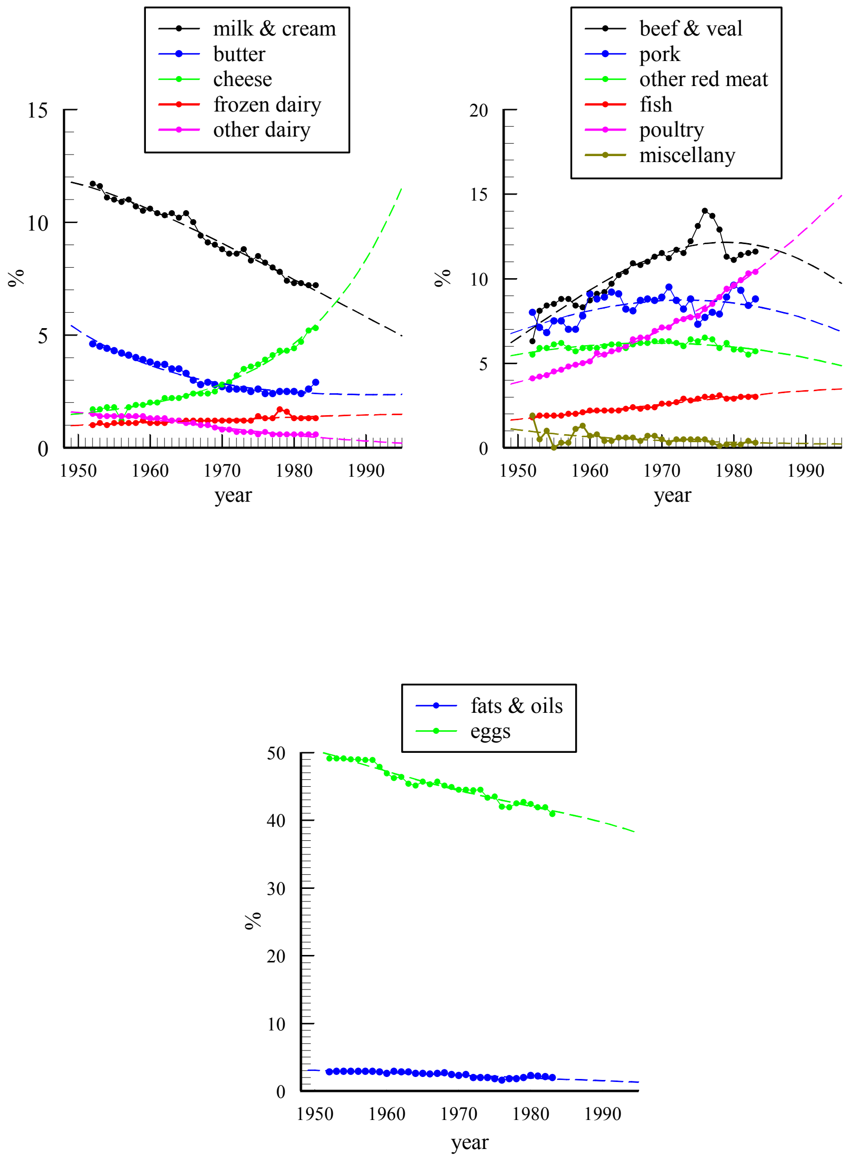

Figure 6. Income Elasticities of Demand for Foods, 1949-1995

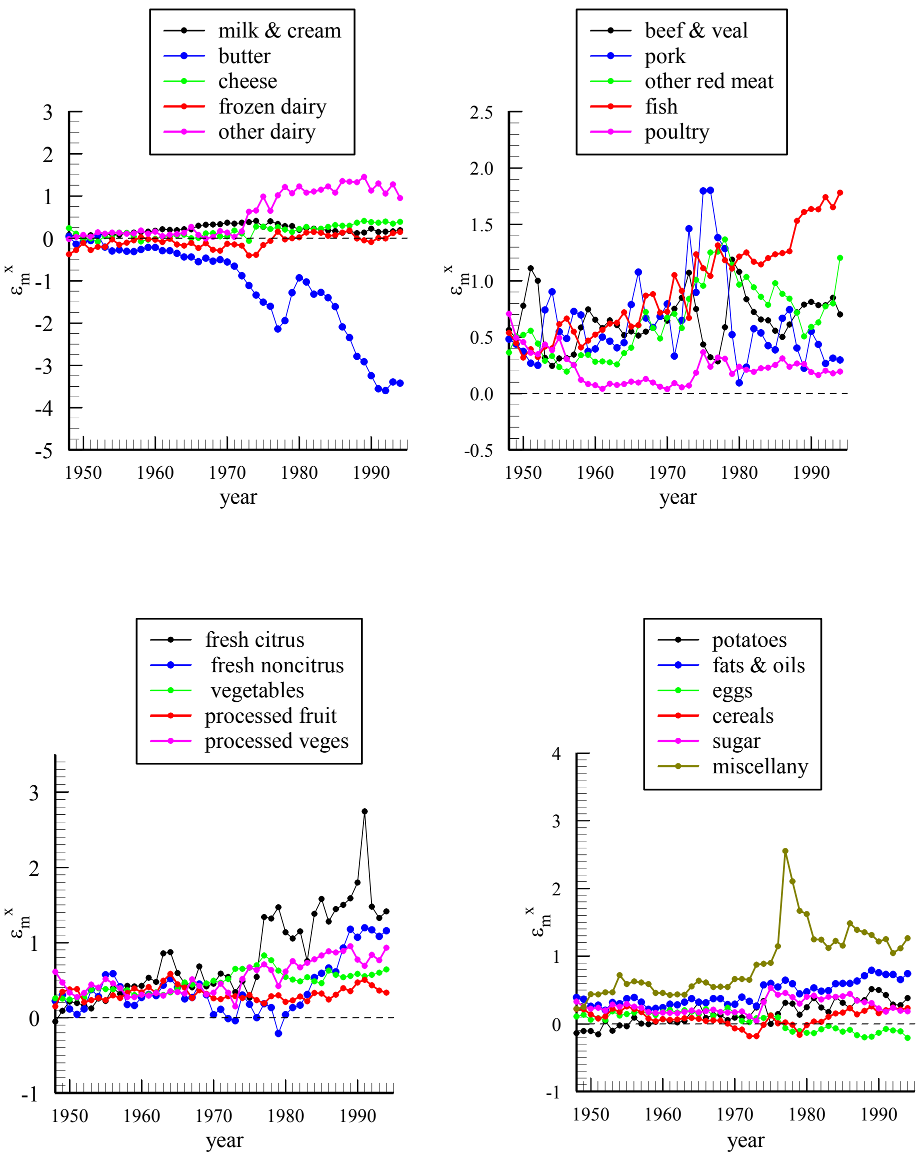

Figure 7. Income Elasticities of Nutrient "Demands", 1949-1994.