UNITED STATES DEMAND FOR FOOD AND NUTRITION IN THE TWENTIETH CENTURY

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The relationships between diet and health are once again the center of debate over farm and food policy. Targeted food aid programs—Food Stamps, Aid to Families with Dependent Children, and the Women, Infants, and Children Program—can create incentives for food purchases and consumption that are not consistent with those created by programs to support farm prices and incomes—marketing orders, target prices and deficiency payments, the sugar program, and farm price supports. The result could be that food aid recipients spend more on food but are presented with incentives to eat unhealthy diets due to policy induced price distortions. Understanding the economic forces behind food and nutrient consumption is, therefore, an important research topic.

This article discusses a new method to analyze the demand for food and nutrients, and consumer welfare. The foundation for this method is an extension of Gorman's class of aggregable demand models to incomplete systems (LaFrance et al. 2000, 2002; LaFrance, Beatty, and Pope 2004, 2005; LaFrance 2004). This extension allows us to derive and implement coherent, flexible models of demand, to estimate these models consistently with aggregate data, and to draw inferences on the distributional impacts of policies that effect food demand on food and nutrient consumption and consumer welfare across income, ethnicity, and age groups in the population.[1] We currently have several policy studies underway using this model.

A New Model of Food Demand

This section presents our empirical model of food consumption. The essential properties of this model are as follows: (1) it nests a large class of functional forms for income and prices within a flexible demand system; (2) by incorporating the income distribution into the modeling framework, it permits consistent estimation with aggregate time series data; (3) by combining demand estimates with data on the nutrient content of foods, it permits us to make inferences on the nutritional impacts of changes in food consumption; and (4) it permits coherent inferences on the economic welfare effects of farm and food policies.

Most demand analyses use existing models taken off the shelf—for example, the almost ideal demand system (AIDS), translog, generalized Leontief, linear expenditure system, or Rotterdam model. Our approach is to generalize many functional forms and model specifications in a single unifying framework and let the data choose the form that best fits the data through estimation and inference.

One result of this strategy that may be surprising is that the most commonly used functional form for prices and income—natural logarithms—is strongly rejected in our dataset. In fact, the log–log form—such as the AIDS, translog, and in log-differences, the Rotterdam model—is statistically the worst choice among the entire class of specifications we consider. While this result may seem surprising, it makes good economic sense for the income terms in any system of demands. LaFrance, Beatty, and Pope (2005; hereafter LBP) show that the logarithmic functional form for income is irregular and tends to produce expenditure functions that are not concave.

We begin with a small amount of notation and a few definitions. Let $\boldsymbol{\rho} \in \mathbb{R}^{n_q}_{++}$ be an

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[1] A detailed discussion of the theoretical foundation, econometric issues associated with estimating this model with aggregate U.S. time series data, and a comprehensive set of empirical results can be found in LaFrance (2005).

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n_q-vector of nominal market prices for food items, which we denote by $\boldsymbol{q} \in \mathbb{R}^{n_q}_{++}$. Let $\tilde{\boldsymbol{\rho}} \in \mathbb{R}^{n_{\tilde{q}}}_{++}$ be an $n_{\tilde{q}}$-vector of nominal market prices for all other goods, which we denote by $\tilde{\boldsymbol{q}} \in \mathbb{R}^{n_{\tilde{q}}}_{++}$. Denote nominal personal disposable income by $M \in \mathbb{R}_{++}$. Let $\boldsymbol{s} \in \mathbb{R}^K$ denote a K-vector of demographic variables that influence the demand for food items, and include lagged quantities demanded as elements of the vector $\boldsymbol{s}$ to account for the possibility of naïve habit formation.[2] LBP show that normalizing prices and income by a linearly homogeneous function of other prices is flexible and does not introduce any ad hoc conditions on the demands for the goods that are not included as part of an arbitrary subsystem of demand equations. Therefore, define the linearly homogeneous, concave function of other prices by $\pi(\tilde{\boldsymbol{\rho}})$ and denote normalized prices and income by $\boldsymbol{p} \equiv \boldsymbol{\rho}/\pi(\tilde{\boldsymbol{\rho}})$, $\tilde{\boldsymbol{p}} \equiv \tilde{\boldsymbol{\rho}}/\pi(\tilde{\boldsymbol{\rho}})$, and $m \equiv M/\pi(\tilde{\boldsymbol{\rho}})$.

The first step is to define an n_q-vector of translated Box-Cox functions of normalized prices, $x_i(p_i) = 1 + (p_i^\lambda - 1)/\lambda, i = 1, \ldots, n_q$, and a translated Box-Cox function for normalized income, $y(m) = 1 + (m^\kappa - 1)/\kappa$. Note that if $\lambda = 1, x_i(p_i) = p_i \,\forall i$, while $\lim_{\lambda\to 0} x_i(p_i) = 1 + \ln p_i \,\forall i$. Similarly, if $\kappa = 1, y(m) = m$, while $\lim_{\kappa\to 0} y(m) = 1 + \ln m$. LBP show that the transformation y allows us to nest the class of price independent generalized linear (PIGL) and price independent generalized logarithmic (PIGLOG) functional forms for the income terms (Muellbauer 1975, 1976) within a unified model. Similarly, the transformations $\boldsymbol{x}$ nest a large class of functional forms for prices.

The second step is to define the functions,

$$(1) \qquad \varphi(\boldsymbol{p}) = \boldsymbol{x}(\boldsymbol{p})^\top \boldsymbol{B}\boldsymbol{x}(\boldsymbol{p}) + 2\boldsymbol{\gamma}^\top \boldsymbol{x}(\boldsymbol{p}) + 1$$

$$(2) \qquad \theta(\boldsymbol{p}, \boldsymbol{s}) = \alpha_0 + \boldsymbol{\alpha}^\top \boldsymbol{s} + (\boldsymbol{a} + \boldsymbol{A}\boldsymbol{s})^\top \boldsymbol{x}(\boldsymbol{p})$$

where α_0 is a scalar parameter, $\boldsymbol{\alpha}$ is a $\boldsymbol{K}$-vector of parameters, $\boldsymbol{a}$ is an n_q-vector of parameters, $\boldsymbol{A}$ is an $n_q \times K$ matrix of parameters, $\boldsymbol{B}$ is an $n_q \times n_q$ symmetric matrix, and $\boldsymbol{\gamma}$ is an n_q-vector of parameters. We then define the class of indirect utility functions that underpins the empirical model,

$$(3) \quad v(\boldsymbol{p}, \tilde{\boldsymbol{p}}, \boldsymbol{s}, \boldsymbol{m}) = \psi\left\{\frac{y - \theta(\boldsymbol{p}, \boldsymbol{s})}{\sqrt{\varphi(\boldsymbol{p})}}, \tilde{\boldsymbol{p}}, \boldsymbol{s}\right\}.$$

This class of preferences extends the Gorman polar form (Gorman 1961) for indirect preferences arising from quadratic utility to incomplete PIGL/PIGLOG systems.

Now define the matrices $\boldsymbol{P} = \mathrm{diag}[p_i]$, $\boldsymbol{Q} = \mathrm{diag}[q_i]$ and $\boldsymbol{W} = \mathrm{diag}[p_i q_i/m]$, and apply Roy's identity to equation (3), to obtain the demands for food with expenditures on the left-hand side as

$$(4) \quad \boldsymbol{P}\boldsymbol{q} = m^{1-\kappa}\boldsymbol{P}^\lambda\Bigg[\boldsymbol{a} + \boldsymbol{A}\boldsymbol{s} + \left(\frac{y(m) - \alpha_0 - \boldsymbol{\alpha}^\top \boldsymbol{s} - (\boldsymbol{a} + \boldsymbol{A}\boldsymbol{s})^\top \boldsymbol{x}(\boldsymbol{p})}{\boldsymbol{x}(\boldsymbol{p})^\top \boldsymbol{B}\boldsymbol{x}(\boldsymbol{p}) + 2\gamma^\top \boldsymbol{x}(\boldsymbol{p}) + 1}\right) \times (\boldsymbol{B}\boldsymbol{x}(\boldsymbol{p}) + \boldsymbol{\gamma})\Bigg] + \boldsymbol{u}$$

where the vector of stochastic error terms $\boldsymbol{u}$ are assumed to satisfy $E(\boldsymbol{u} \mid \boldsymbol{p}, \tilde{\boldsymbol{p}}, \boldsymbol{s}, \boldsymbol{m}) = \boldsymbol{0}$, $E(\boldsymbol{u}\boldsymbol{u}^\top \mid \boldsymbol{p}, \tilde{\boldsymbol{p}}, \boldsymbol{s}, m) = \Sigma$, a symmetric, positive definite, constant matrix, and $\boldsymbol{u}$ is independently and identically distributed across time series observations.

Unscrambling the income terms on the right-hand side of equation (4), it is easy to see that this model is a member of Gorman's class of Engel curves (Gorman 1981) with two income terms, m and $m^{1-\kappa}$ when $\kappa \neq 0$, and m and $m \ln m$ when $\kappa = 0$. Thus, we obtain all possible PIGL and PIGLOG models as special cases that depend on the estimated value of the parameter κ. Because we also estimate the parameter λ, this model can range from quadratic utility—a special case of demand models that are linear in income—through extended forms of translog and generalized Leontief functional forms for indirect preferences, illustrating in important strength of this modeling framework. Monotonicity, homogeneity, adding up, and curvature are maintained during estimation to ensure that the estimated demand equations are economically meaningful.[3]

Price and Income Elasticities of Foods and Nutrients

The n_q-vector of income elasticities for foods can be written as

[2] The empirical results show little evidence of habits, with point estimates on the lagged quantities small and mostly insignificant. We also do not find any evidence of serial correlation in the error terms. The demographic variables and entire distribution of income probably capture these effects that are commonly found in time series demand models.

[3] Each restriction is testable, in principle, and LaFrance (2005) contains results of a battery of diagnostic results for these restrictions, parameter stability, model specification, and independence and stationarity of the error terms.

$$\varepsilon_m^q = \boldsymbol{Q}^{-1}\frac{\partial \boldsymbol{q}}{\partial m}m = (1-\kappa)\boldsymbol{\iota} + \boldsymbol{W}^{-1}\boldsymbol{P}^{\lambda} \times \left(\frac{\boldsymbol{Bx}(\boldsymbol{p})+\boldsymbol{\gamma}}{\boldsymbol{x}(\boldsymbol{p})^{\mathsf{T}}\boldsymbol{Bx}(\boldsymbol{p})+2\boldsymbol{\gamma}^{\mathsf{T}}\boldsymbol{x}(\boldsymbol{p})+1}\right) \tag{5}$$

where $\boldsymbol{\iota}$ is an n_q-vector with one in each element. Similarly, the matrix of price elasticities of demand for food items can be written as

$$\begin{aligned}\varepsilon_p^q &= \boldsymbol{Q}^{-1}\frac{\partial \boldsymbol{q}}{\partial \boldsymbol{p}^{\mathsf{T}}}\boldsymbol{P} = (\lambda-1)\boldsymbol{I} + m^{-\kappa}\boldsymbol{W}^{-1}\boldsymbol{P}^{\lambda}\\ &\times\left\{-\left[\frac{\boldsymbol{Bx}(\boldsymbol{p})+\boldsymbol{\gamma}}{\boldsymbol{x}(\boldsymbol{p})^{\mathsf{T}}\boldsymbol{Bx}(\boldsymbol{p})+2\boldsymbol{\gamma}^{\mathsf{T}}\boldsymbol{x}(\boldsymbol{p})+1}\right](\boldsymbol{a}+\boldsymbol{As})^{\mathsf{T}}\right.\\ &+\left(\frac{y(m)-\alpha_0-\boldsymbol{\alpha}^{\mathsf{T}}\boldsymbol{s}-(\boldsymbol{a}+\boldsymbol{As})^{\mathsf{T}}\boldsymbol{x}(\boldsymbol{p})}{\mathbf{x}(\boldsymbol{p})^{T}\boldsymbol{Bx}(\boldsymbol{p})+2\boldsymbol{\gamma}^{\mathsf{T}}\boldsymbol{x}(\boldsymbol{p})+1}\right)\\ &\left.\times\left[\boldsymbol{B}-2\left(\frac{(\boldsymbol{Bx}+\boldsymbol{\gamma})(\boldsymbol{Bx}+\boldsymbol{\gamma})^{\mathsf{T}}}{\boldsymbol{x}(\boldsymbol{p})^{\mathsf{T}}\boldsymbol{Bx}(\boldsymbol{p})+2\boldsymbol{\gamma}^{\mathsf{T}}\boldsymbol{x}(\boldsymbol{p})+1}\right)\right]\boldsymbol{P}^{\lambda}\right\}\end{aligned} \tag{6}$$

where $\boldsymbol{I}$ is an $n_q \times n_q$ identity matrix. Note the significant roles that the parameters κ and λ play in determining these elasticities. In particular, if $\kappa = \lambda = 1$ the leading terms in equations (5) and (6) vanish, while if $\kappa = \lambda = 0$ then they are $\boldsymbol{\iota}$ and $-\boldsymbol{I}$, respectively. This is one indication of the importance of extending demand models as we do here. Stated simply, the functional form matters.

We next combine these elasticity estimates with data on the nutrient content of foods to obtain price and income elasticities for nutrients. We model nutrient demand as a linear function of food quantities. Let $\boldsymbol{z}$ denote the vector of nutrients contained in foods and let $\boldsymbol{N}$ denote the matrix of nutrient content per unit of food, so that the *ij*th entry represents the amount of nutrient *i* per unit of food *j*.

We have $\boldsymbol{z} = \boldsymbol{Nq}$ as the basic relationship between food consumption and nutrients. Then the nutrient price elasticities of demand can be written as a weighted average of own- and cross-price food elasticities, $\varepsilon_{p_k}^{z_i} = \sum_{j=1}^{n_q} s_{ij}\varepsilon_{p_k}^{q_j}$, $i = 1, \ldots, n_z$, where $\varepsilon_{p_k}^{z_i}$ is the price elasticity of demand for nutrient i with respect to price k, $\varepsilon_{p_k}^{q_j}$ is the price elasticity of demand for food j with respect to price k, and s_{ij} is the proportion of nutrient i contributed by food item j. Similarly, the nutrient income elasticities of demand satisfy $\varepsilon_m^{z_i} = \sum_{j=1}^{n_q} s_{ij}\varepsilon_m^{q_j}$, $i = 1, \ldots, n_z$, where $\varepsilon_m^{z_i}$ is the income elasticity of demand for nutrient i and $\varepsilon_m^{q_j}$ is the income elasticity of demand for food j.

Data and Variable Definitions

We apply this framework to annual per capita U.S. demand for food and nutrients 1919–2000, excluding 1942–1946 to account for World War II.[4] The food quantity data are observations on annual per capita consumption (in pounds per person per year) of twenty-one food items in four general categories: (1) *dairy products*—fresh milk and cream, butter, cheese, ice cream and frozen yogurt, and canned and powdered milk; (2) *meats, poultry, and fish*—beef and veal, pork, other red meat, poultry, and fish and shellfish; (3) *fruits and vegetables*—fresh citrus fruit, other fresh fruit, fresh vegetables excluding potatoes, potatoes, processed fruit, and processed vegetables; and (4) *miscellaneous foods*—eggs, fats and oils excluding butter, cereal grains and bakery products, sugar and caloric sweeteners, and coffee, tea, and cocoa.

Annual time series data on average annual retail U.S. prices of each of the above twenty-one foods also were compiled and constructed from a host of United States Department of Agriculture and Bureau of Labor Statistics sources. Each price is measured in dollars per pound to be consistent with the quantity data as well as the economic theory implied by the underlying modeling framework. The consumer price index for all items except food is used to deflate all prices, expenditures, and income.

Demographic variables are widely accepted to exert important influences on the demand for food and other goods. To reflect this stylized fact, we compiled annual estimates of the age distribution of the U.S. population—proportions of the population that are <5, 5–14, 15–25, 24–34, 35–44, 45–54, 55–64, and ≥ 65 years old. We combine three age groups into the single category 25–54 to reflect working-age adults and normalize on this group.[5] We also compiled annual estimates of the ethnic distribution of the U.S. population—proportions of the population that are white, black, or neither white nor black, and normalize on the white segment of the population in the empirical model. We allow for naïve habit formation by including lagged quantities in the set of variables that can shift consumer preferences.

[4] The complete dataset is available at http://are.berkeley.edu/~lafrance.

[5] Since these proportions sum to unity, one must be omitted from the empirical model.

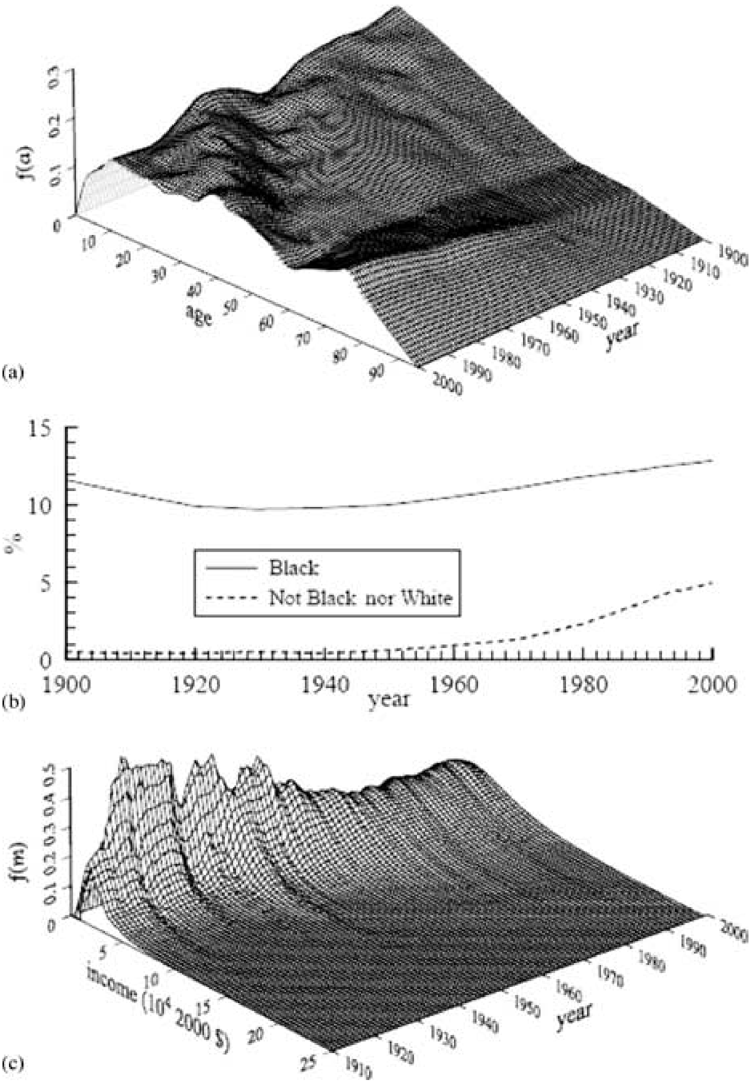

Figure 1. Twentieth century changes in U.S. demographics. (a) Age distribution. (b) Ethnicity. (c) Income distribution

The empirical model is an incomplete system of Gorman Engel curves that is nonlinear in income. This class of demand models generates theoretically consistent, exactly aggregable systems of demand equations for which only a small number of summary statistics for the distribution of income are required to estimate the model's parameters consistently using aggregate data. In particular, in our empirical application to per capita U.S. food consumption, we require annual cross-sectional estimates of the raw moments for m and $m^{1-\kappa}$ when $\kappa \neq 0$ and for m and $m \ln m$ when $\kappa = 0$.

The U.S. Bureau of the Census publishes annual quintile ranges, intra-quintile means, the top five-percentile lower bound for income, and the mean income within the top five-percentile range for all U.S. families. We incorporate this in our demand model by constructing annual estimates of a lognormal distribution for the incomes of U.S. households. We rescale this distribution by a linear change of variables so that the mean of the lognormal distribution is equal to annual per capita disposable personal income.[6] Figure 1 presents

[6] We have considered alternative forms for the U.S. income distribution, including a truncated three-parameter lognormal (LaFrance et al. 2000), piecewise uniform and piecewise exponential (LaFrance et al. 2002), and generalizations of up to eight moments (Wu). These alternative specifications for the income distribution produce very similar empirical results.

the distributions of this set of demographic variables over the twentieth century, clearly illustrating that the population has changed dramatically in these dimensions over our sample period.

We also estimate the impacts of changes in food consumption on the demand for nutrients. To accomplish this, we first need estimates of the nutrient content of the twenty-one foods. Shirley Gerrior and Lisa Bente of the Center for Nutrition Promotion and Policy generously provided us with annual estimates of total per capita consumption for seventeen nutrients—energy; protein; total fat; carbohydrates; total cholesterol; vitamins A, B_6, B_{12}, C, niacin, riboflavin, and thiamin; and minerals calcium, iron, magnesium, phosphorous, and zinc—as well as estimates of the percentages of these nutrients supplied by each of the twenty-one foods in each year for the period 1909–2000. Combining these with the empirical demand model, permits us to obtain a complete set of annual time series estimates of price and income elasticities for both the twenty-one food items and the seventeen nutrients.

Summary of Empirical Results

The empirical model is estimated by non-linear seemingly unrelated regressions (NLSUR) with a single iteration on the error covariance matrix. The most interesting parameters are those associated with the Box-Cox transformations of prices and income. The point estimates are $\hat{\kappa} = .8962\,(.0194)$ and $\hat{\lambda} = 1.003\,(.0181)$, respectively, with robust Huber–White standard errors in parentheses after the parameter estimates, for the globally restricted model satisfying the monotonicity, symmetry, and curvature conditions of economic theory (homogeneity and adding up is automatically satisfied). These estimates and their very small standard errors suggest that the log–log functional form—which is associated with $\kappa = \lambda = 0$—is not well suited to this dataset. An expansive set of empirical results implies that this conclusion also holds in an unrestricted and symmetry restricted model, as well as a model restricted so that foods are weakly separable from other goods (LaFrance 2005).

Figure 2 illustrates the results of a grid search over κ and λ in the second round of the NLSUR estimation procedure. Figure 2a depicts the results of a two-dimensional search in increments of 0.01 for both parameters over $(\kappa, \lambda) \in [0.00, 1.10] \times [0.00, 1.25]$. This figure illustrates that the global minimum of the generalized error sum of squares is near (1,1), while (0,0) is the globally worst choice for (κ, λ). In addition, the parameters α_0 and α are very difficult to estimate for low values of λ for each fixed value of κ.

Figure 2b depicts the results of a one-dimensional search over κ, letting λ adjust optimally with the other parameters. This plot clearly shows that $\kappa = 0$ is the worst possible choice for this parameter. Figure 2c then

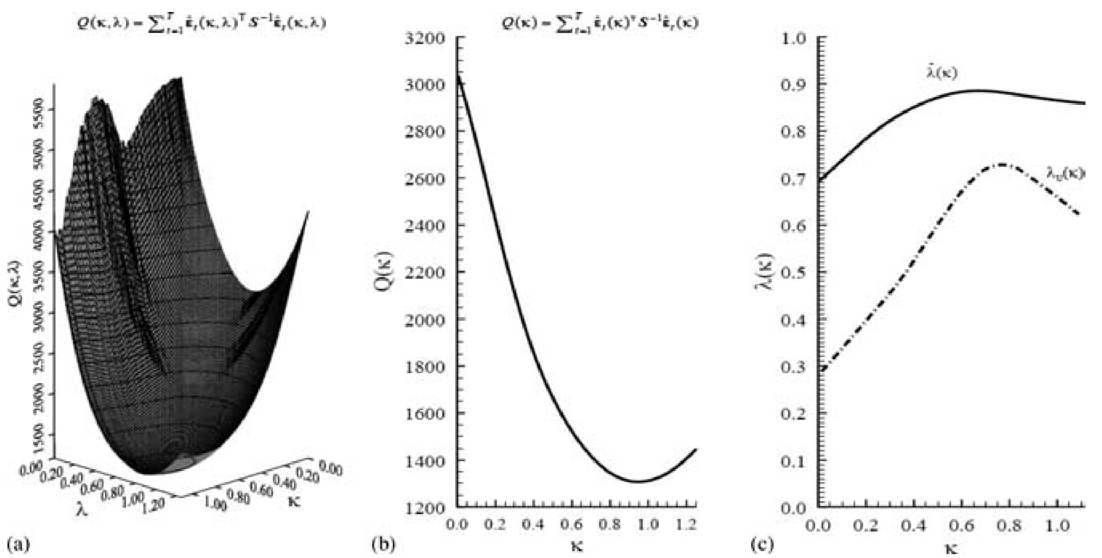

Figure 2. Grid search over κ and λ in the second round of NLSUR. (a) Search over κ and λ. (b) Search over κ only. (c) λ conditional on κ

Table 1. Equation Summary Statistics

Food Item	Sample Mean	Standard Error	R^2	Durbin–Watson
Fresh milk and cream	34.24	8.512	0.9974	1.699
Butter	7.693	5.340	0.9975	2.220
Cheese	12.72	7.892	0.9979	1.690
Frozen dairy products	4.218	1.183	0.9872	1.710
Canned and powdered milk	3.178	0.9835	0.9877	2.289
Beef and veal	67.44	24.23	0.9950	1.798
Pork	34.52	7.111	0.9767	1.281
Other red meat	9.659	2.410	0.9669	1.717
Fish and shellfish	8.581	3.868	0.9920	1.621
Poultry	16.46	4.935	0.9927	1.864
Fresh citrus fruit	4.637	0.7396	0.7172	1.587
Fresh non-citrus fruit	11.76	4.111	0.9533	1.603
Fresh vegetables	17.25	5.147	0.9937	2.379
Potatoes	8.318	1.737	0.9710	2.113
Processed fruit	24.55	11.84	0.9881	2.091
Processed vegetables	11.29	2.658	0.9862	1.655
Fats and oils except butter	13.55	2.148	0.9708	1.641
Eggs	14.97	7.645	0.9990	1.860
Cereal and bakery products	20.23	3.445	0.9909	1.524
Sugar and sweeteners	26.65	6.360	0.9897	2.363
Coffee, tea, and cocoa	12.26	3.461	0.9805	1.760

Note: R^2 is the squared correlation between observed and predicted dependent variables.

shows that the relationship between the conditionally optimal choice for λ as a function of κ (the solid curve denoted by $\hat{\lambda}(\kappa)$ in the figure) is relatively flat and quite far from zero for each value of κ. The conditional values for λ where the model becomes numerically unstable (the dash–dot curve denoted by $\lambda_U(\kappa)$ in the figure) are substantially below the conditionally optimal values and considerably above zero for each value of κ. The conclusion we draw is that for any fixed value of κ, zero is the worst possible choice for the parameter λ.

Table 1 presents a small set of equation summary statistics for the fully restricted empirical model. Interested readers are referred to LaFrance (2005) and the expanded version of this article for more details. We only have space here to summarize a few properties of the model. All foods except butter are either income normal or essentially independent of income over the great majority of the sample period. Butter is increasingly income inferior through the last half of the century. Some foods, most notably other red meat, fish and shellfish, all fresh fruits and vegetables, and coffee, tea and cocoa display marked increases in the income elasticity over this period. Only other red meat has an elastic own-price response, while only poultry displays a significant trend in its own-price elasticity, which decreases from near unity to near zero over the period 1947–2000. All other own-price elasticities of demand for foods are negative, in general substantially less than one in absolute value, and do not display noticeable trends over this time period. A battery of diagnostic tests for model specification, parameter stability, the restrictions associated with economic theory, and the independence and stationarity of the joint distribution of the error terms across time series observations indicates that this model is entirely consistent with economic theory and congruent with this dataset. These results are unusual for time series models of demand, and are very likely due to the flexibility of the model with respect to the functional form for income prices, including of the distribution of income and socioeconomic variables as explanatory variables, and the lack of ad hoc restrictions such as weak separability of food from other goods.

All seventeen nutrients increase with income throughout the sample period. This primary force in the observed changes in nutrient consumption during the last century is illustrated in figure 3. On the other hand, nutrient responses to changes in food prices are universally very small. This result is not surprising and is likely to be due to the availability of a wide range of substitute foods from which equivalent total nutrients can be obtained. It suggests,

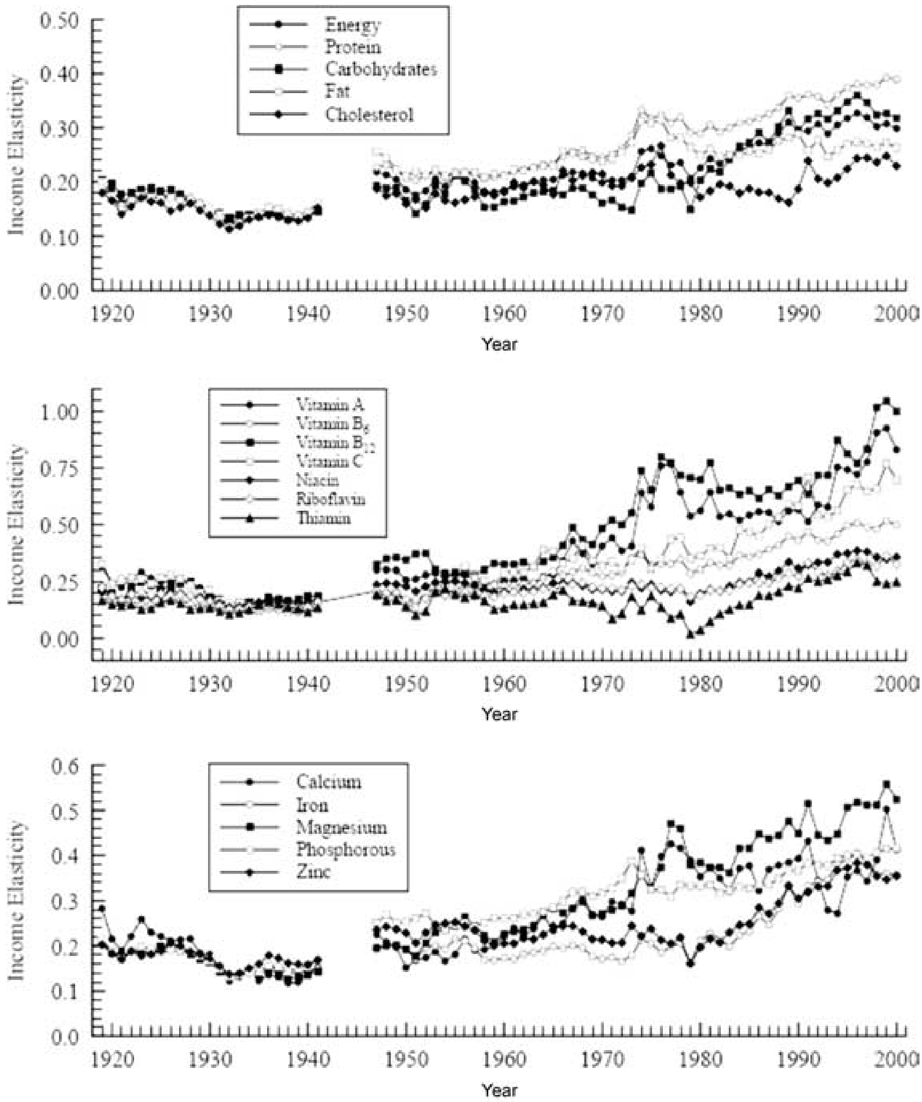

Figure 3. Income elasticities of demand for nutrients

however, that taxing some foods because they contain relatively high concentrations of fat, cholesterol, or sugar, for example, may not substantially modify nutrient intakes.

Conclusions

This article briefly summarizes the main structure and some empirical results of a new method to estimate and measure the primary economic forces that influence the demand for food and nutrients. This model is based on an incomplete demand system that extends Gorman's class of exactly aggregable demand models and that nests the functional forms that income and prices take in the model's specification. The empirical results suggest that this extension has real economic content and the most commonly used functional forms for both prices and income are strongly rejected for the time series dataset that we employ. The empirical model generates a complete time series of annual estimates of food and nutrient price and income elasticities for the period 1919–2000, excluding World War II. These estimates, as well as the structural model and modeling approach, should be useful to applied researchers interested in the demand for agricultural products.

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