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THE STRUCTURE OF U.S. FOOD DEMAND

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The Structure of U.S. Food Demand

Abstract

An econometric model of U.S. food consumption is presented. The model is a flexible, full rank two Gorman polar form, is fully consistent with economic theory, and accommodates tradeoffs between eating for pleasure and for health. It aggregates exactly across income, demographic variables, and variations in micro demand parameters. New methods are derived and implemented for testing separability of foods from all other goods, exogeneity of group expenditure in a separable demand model, *global quasi-concavity* of the implied preference function, and parameter stability and model specification. An F-test for nonlinear restrictions in nonlinear seemingly unrelated regression equations is derived that overcomes the overcompensation of the Laitinen-Meisner correction for excessive type I errors in the LM test. A GMM test for exogeneity of expenditure in separable demand models is developed. A set of tests for model specification and parameter stability using within sample residuals is derived to analyze the stability of both the first- and second-order moment conditions. The model is estimated with per capita U.S. consumption of 21 food items and 17 nutrients over the period 1918-1994, using the mean, variance, and skewness of the U.S. population's age distribution and the proportion of the population that is White, Black, and neither White nor Black as demographic variables. The empirical results: (a) reject food expenditure as an exogenous variable; (b) reject a stable model structure if World War II is included; (c) fail to reject the specification and parameter stability if World War II is excluded; (d) fail to reject Slutsky symmetry in either case; and (e) reject global quasi-concavity with World War II included but fail to reject this hypothesis at the 10 percent level of significance when this period is excluded from the sample.

Key Words: Food Demand, Separability, Exogeneity, Model Stability

The Structure of U.S. Food Demand

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.

There are many reasons why it is not altogether clear what impacts these policy changes will have on the economic well being, food consumption patterns, or nutritional intakes of U.S. consumers. One important reason is that we simply do not fully understand the joint influences of past policies on these matters, much less what will happen once the new policies begin to take effect. As an illustrative example, consider the joint economic impacts of the food stamp program and the U.S. dairy program. Food stamps provide direct in-kind subsidies for food consumption. The goal of the food stamp program is to increase the food consumption and nutritional status of the poor. The food stamp program acts essentially as an income transfer mechanism.[1] On the other hand, price discrimination in federal milk marketing orders increases the retail price of fresh milk and lowers the prices of manufactured dairy products (Heien; Ippolito and Masson).[2] This creates incentives to substitute away from fresh foods toward processed foods.

As a second example, target prices for feed corn increased prices received by farmers, thereby increasing the supply of corn. To clear these additional supplies from the market, prices paid by demanders of feed corn, chiefly hog and cattle feedlot operators, were lower than they otherwise would nave been.[3] The resulting decreases in input costs to the livestock sector had the effect of increasing supplies of livestock to slaughterhouses, thereby reducing the market prices paid for red meat by consumers. The resulting increase in red meat consumption may be contrary to sound nutrition or health policy. It is commonly argued by nutritionists and healthcare professionals that foods which contain animal fat, cholesterol, salt, sugar, and/or chemical additives are less healthy than foods which contain little of these factors and are high in fiber, vitamins, and minerals.

The upshot is that, by and large, many farm level policies have created consumer incentives that directly oppose those created by food subsidy programs. What, then, 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, very few unequivocal judgments can be reached. For example, while food aid recipients spend more on food, they probably eat less healthy foods due to price distortions. From a

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[1] That is, recipients currently do not have to pay for the food stamps received and nearly all recipients spend more on food than the value of food stamps. This implies that food stamp recipients are not at a "corner solution" on their budget constraint and the value of stamps received is equivalent to an income transfer of the same dollar amount.

[2] Many federal marketing orders and agreements for fruits, nuts, and vegetables also contain regulations that lead to higher prices for fresh products and lower prices for manufactured products (Jamison).

[3] However, nonrecourse loans administered by the Commodity Credit Corporation place a floor on the price received by farmers for barley, corn, wheat and other farm products.

purely nutritional perspective, it is unclear whether this group is better or worse off with the combination of farm and food programs. It is not even totally clear whether they are better off economically than might be the case with no government intervention in the farm and food sector. On the other hand, individuals who are neither farmers nor food aid recipients pay higher taxes to finance farm and food subsidies. This lowers disposable incomes, food expenditures, and economic welfare. In addition, under the scenarios described above, policy-induced price distortions create incentives to consume a less healthy mix of foods for members of this group. Little is actually known about the size of the net economic costs or impacts on nutrition and health of these programs, however.

As a first cut at answering 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, called strict aggregation.[4] - 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, empirically implemented, and tested econometrically. Explicit nested parameter restrictions that are necessary and sufficient for the global quasi-concavity of preferences are derived and implemented. A procedure based on the generalized methods of moments principle is derived for testing the exogeneity of group expenditure in a set of conditional demand equations.[5] A set of robust, within sample, multivariate diagnostic tests for model specification and parameter stability are derived and implemented. These diagnostic tests are particularly useful in situations such as the present one where there is a large number of parameters relative to the number of observations, so that Chow tests or tests based on sequential post-sample recursive residuals (Brown, Durbin, and Evans; Harvey 1990, 1993; Hendry) are infeasible. Finally, a simple F-statistic is developed for testing nonlinear parameter restrictions in nonlinear seemingly unrelated regression equations. This test statistic is shown to be asymptotically equivalent to the Wald, likelihood ratio, and Lagrange multiplier statistics, and to overcome at least partially the well-known finite sample problems of these classical tests.

The organization of the paper is as follows. The next section considers the theoretical and econometric issues associated with the modeling problem. Section three characterizes the econometric model and its properties. Section four discusses the data, empirical results, hypothesis tests, and model diagnostics. The final section summarizes and concludes.

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[4] Strict aggregation allows for different preferences across individuals in addition to those that arise from measurable factors such as demographics. This concept of aggregation is more general than, and consequently more limited in interpretation and application, than that of exact aggregation, i.e., aggregation across income and demographics to the market level. See Stoker (1993) for an excellent recent survey of exact aggregation. Under exact aggregation, preferences of micro units are recovered from macro level demand equations. In contrast, under strict aggregation, a set of sufficient statistics are obtained for micro preferences from the macro level data, while individual micro-level preference functions can not be completely recovered.

[5] Strict exogeneity is the property of statistical independence between a right-hand-side regressor and the error term in a regression equation (Engle, Hendry, and Richard). When the regressor and the error term are normally distributed, strict exogeneity is equivalent to zero correlation.

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 z denote an m-vector of nutrients important to the health status of the household, let x denote an n_x-vector of food items, and let 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 $z = Nx$. Also, let y denote an n_y-vector of all other goods, let s be a k-vector of demographic variables and other demand shifters, and write the consumer's utility function as $u(x, y, z, s)$. The objective of the consumer is to

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

where p_x is the vector of prices for x, p_y is the vector of prices for 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 $\{(x, z), y\}$,

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

Let p_x be the vector of market prices for foods, let m_x be total expenditure on food, and let the nutrient equations be $Nx = z$. Then separability lets us focus on the maximization of the food sector sub-utility function, $u_x(x,z)$, subject to the food expenditure budget constraint, $p_x'x = m_x$. 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 $p = [p_x'\ \ p_y']' \in \mathbb{R}_+^n$, 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 $E(x|p,m,s,N) \equiv h^x(p,m,s,N)$. Separability of (x, z) from y is equivalent to the demands for x having the structure

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

where

$$\mu_x(p,m,s,N) \equiv p_x' h^x(p,m,s,N) \equiv E(p_x'x \mid p,m,s,N) \tag{2.4}$$

is the conditional mean of expenditure on x given prices, income, and demographic variables (Gorman 1995a; Blackorby, Primont, and Russell).[6]

The remainder of this section is devoted to three issues with estimating (2.3) and (2.4) using aggregate time series data. First, I address the question of aggregation across individuals to coherent, theoretically consistent market level demand equations when income, demographics, and the micro-parameters of individual utility functions all vary across consumers. Second, I consider the empirical consequences of the fact that the conditional mean of food expenditure, $\mu_x(\cdot)$, is a latent variable, while observed food expenditure is endogenous (Attfield 1985, 1991; Blundell 1986, 1988; Deaton 1975, 1986; Edgerton; LaFrance 1991; Theil). Third, I develop a set of robust, multivariate, within sample diagnostic tests for model specification and parameter stability.

2.1 Strict Aggregation

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 $\boldsymbol{d} = (m, s')' \in \mathbb{R}^{k+1}$ 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 $\Omega \subset \mathbb{R}^{k+1} \times \mathbb{R}^r$ be the set of household characteristics and micro parameters, and consider each household type $\omega = (\boldsymbol{d}, \theta)$ as an element of the set Ω. 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

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

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

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

$$\max_{x,y}\left\{u(x,y,Nx,s) : x \geq 0,\ y \geq 0,\ p_x'x + p_y'y \leq m\right\}.$$

sating variation relative to $\psi(\cdot)$ by integrating out the income and demographic variables,[7]

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

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

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

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 $x(p,\cdot)$ linearly and any elements of 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,

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

By an application of Roy's identity, we have

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

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

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

Suppose that $\alpha(s) \equiv \alpha_0 + As$, all of the elements of A are uncorrelated with s, B is constant across indi-

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

viduals, E(γ) = 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 γ = 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.

2.2 Exogeneity of Group Expenditure

Consider the empirical subsystem of demand equations

$$x_t = h^x(p_t, m_t, s_t) + \varepsilon_t, \quad t = 1, \ldots, T, \tag{2.8}$$

where ε_t is a vector of stochastic error terms.[8] Assume that $\{\varepsilon_t\}$ is a multivariate martingale difference sequence, so that $E(\varepsilon_t) = 0 \;\forall\; t$. Assume further that $E(\varepsilon_t \varepsilon_t') = \Sigma_t$ is a finite, positive definite $n_x \times n_x$ matrix $\forall\; t$.[9] Given separability of x from y, let observed food expenditures be defined by $m_{xt} \equiv p_{xt}' x_t$. Then we have

$$m_{xt} = \mu_x(p_t, m_t, s_t) + \upsilon_t, \tag{2.9}$$

where $\upsilon_t \equiv p_{xt}' \varepsilon_t \sim (0, p_{xt}' \Sigma_t p_{xt})$. Standard practice is to estimate a complete system of conditional demand equations for foods as functions of food prices, food expenditures, and demographics,

$$x_t = \tilde{h}^x(p_{xt}, m_{xt}, s_t) + \tilde{\varepsilon}_t, \tag{2.10}$$

where

$$\tilde{\varepsilon}_t \equiv \varepsilon_t + \tilde{h}^x(p_{xt}, \mu_{xt}(p_t, m_t, s_t), s_t) - \tilde{h}^x(p_{xt}, m_{xt}, s_t) \tag{2.11}$$

is the vector of conditional demand residuals. In this context, the following lemma gives the necessary and sufficient conditions for mean zero error terms in the conditional demand and group expenditure equations.

Lemma 1. $E(\upsilon_t \mid p_t, m_t, s_t) = 0$ *and* $E(\tilde{\varepsilon}_t \mid p_t, m_t, s_t) = 0$ *if and only if*

$$\frac{\partial \tilde{h}^x(p_{xt}, m_{xt}, s_t)}{\partial m_{xt}} \equiv \beta(p_{xt}, s_t).$$

A logically consistent specification for the conditional demands and expenditure equation restricts the functional form of the conditional demand model in the same way that exact aggregation in income restricts the

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[8] I will continue to omit reference to the nutrient content matrix whenever it plays no role in the arguments.

[9] Foods comprise a proper subset of goods, so that the budget identity does not imply that Σ_t is singular.

functional form of the unconditional demands.[10] By lemma 1, the conditional and unconditional residuals must satisfy

$$\tilde{\varepsilon}_t \equiv \left[\mathrm{I} - \frac{\partial \tilde{h}\ (p_t, \mu_t, s_t)}{\partial m_t} p'_t \right] \varepsilon_t, \tag{2.12}$$

so that the correlation between group expenditure and the conditional residuals is determined by

$$E(\tilde{\varepsilon}_t \upsilon_t \,|\, p_t, m_t, s_t) = \left[\mathrm{I} - \frac{\partial \tilde{h}\ (p_t, \mu_t, s_t)}{\partial m_t} p'_t \right] \Sigma_t p_t. \tag{2.13}$$

This implies the following necessary and sufficient condition for zero correlation between expenditure and the conditional demand residuals.[11]

Lemma 2. *If* $\Sigma_t p_{xt} \neq 0$ *then* $E(\tilde{\varepsilon}_t \upsilon_t \,|\, p_t, m_t, s_t) = 0$ *if and only if*

$$\frac{\partial \tilde{h}^x (p_{xt}, \mu_{xt}, s_t)}{\partial m_{xt}} \equiv (p'_{xt} S_t p_{xt})^{-1} S_t p_{xt} = (p'_{xt} \Sigma_t p_{xt})^{-1} \Sigma_t p_{xt},$$

where

$$S_t = \frac{\partial h^x (p_t, m_t, s_t)}{\partial p'_{xt}} + \frac{\partial h^x (p_t, m_t, s_t)}{\partial m_t} h^x (p_t, m_t, s_t)'.$$

is the $n_x \times n_x$ *sub-matrix of Slutsky substitution terms.*

We can construct a generalized method of moments (Hansen) test of <u>strict exogeneity</u> of expenditure by noting that lemma 2 defines n_x moment conditions, so that

$$\varepsilon_t \varepsilon'_t p_{xt} = \varepsilon_t \upsilon_t = -\varphi_t S_t p_{xt} + u_t, \tag{2.14}$$

where $E(u_t \,|\, p_t, m_t, s_t) = 0 \ \forall\ t$, $E(u_t u'_t) = \Phi_t$, say, and $\{u_t\}$ is a multivariate martingale difference sequence, with $\varphi_t > 0$ defined by

$$\varphi_t \equiv \varphi(p_t, m_t, s_t) \equiv -(p'_{xt} \Sigma_t p_{xt})^{-1} (p'_{xt} S_t p_{xt}). \tag{2.15}$$

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[10] It is always possible to modify the stochastic specification to construct a model with budget shares on the left-hand-side and nonlinear functions of expenditure on the right-hand-side, although a result analogous to lemma 1 applies to these cases as well. A coherent statistical model restricts our attention to at most rank two demand systems linear in a single nonlinear function of expenditure (Edgerton). The nature of the available aggregate data on income (or expenditure) dictates the nature of the analogue to lemma 1 that must be applied. For example, the geometric mean for the distribution of expenditure requires a PIGLOG model, while a mean of order ρ, say, requires a PIGL specification. The income variable here is per capita disposable income and the expenditure variable is per capita food expenditure; so I focus on demand models that are linear in income and expenditure.

[11] The focus here is on strict exogeneity (see Engle, Hendry and Richard) since it has been shown that group expenditure is not weakly (hence, neither strongly nor super) exogenous (Edgerton; LaFrance 1991).

Define $z_t = \varepsilon_t \upsilon_t$, $w_{it} = \sum_{j=1}^{n} s_{ijt} p_{x_j t}$, $w_t = [w_{1t} \quad \cdots \quad w_{n_x t}]'$, and assume that Φ_t is uniformly bounded $\forall\, t$. If we estimate φ_t for each t by ordinary least squares (OLS),[12]

$$\hat{\varphi}_t = -(w_t' w_t)^{-1} w_t' z_t, \tag{2.16}$$

then the OLS residuals can be written as

$$\hat{u}_t = \left[I - w_t (w_t' w_t)^{-1} w_t' \right] u_t = \mathcal{M}_t u_t, \tag{2.17}$$

with $E(\hat{u}_t \hat{u}_t') = \mathcal{M}_t \Phi_t \mathcal{M}_t$. For each t, define the within period average residual by $\bar{\hat{u}}_{\cdot t} = \sum_{i=1}^{n_x} \hat{u}_{i,t} / n_x$ and the overall average residual by $\bar{\bar{u}} = \sum_{t=1}^{T} \bar{\hat{u}}_{\cdot t} / T$. If expenditure is strictly exogenous, then we will have the asymptotic result,[13]

$$\frac{T\bar{\bar{u}}}{\sqrt{\sum_{t=1}^{T} \left(\bar{\hat{u}}_{\cdot t} \right)^2}} \xrightarrow{D} N(0,1). \tag{2.18}$$

This test can be related to the Durbin-Wu-Hausman (DWH) test for endogenous expenditure (Durbin; Hausman 1978; Wu). A Lagrange multiplier version of the DWH test could be carried out by estimating (2.6) consistently, so that

$$m_{xt} = \hat{\mu}_x (p_{xt}, p_{yt}, m_t, s_t) + \hat{\upsilon}_t, \tag{2.19}$$

and then including $\hat{\upsilon}_t$ as well as m_{xt} in the conditional demand model,

$$x_t = \alpha(p_{xt}, s_t) + \beta(p_{xt}, s_t) m_{xt} + \gamma \hat{\upsilon}_t + e_{xt}, \tag{2.20}$$

and calculating an F-statistic for $\gamma = \mathbf{0}$. The DWH test would have power against a range of alternatives, including the restrictions on preference heterogeneity associated with strict aggregation. However, this version of the DWH test ignores $-\beta(p_{xt}, s_t)\upsilon_t$ in (2.10) and does not produce consistent parameter estimates

[12] In practice, neither z_t nor w_t are observed. However, consistent estimates can be obtained readily. Since this does not alter any of the asymptotic results, for notational brevity this is ignored in the discussion.

[13] The conditional variance of $\bar{\bar{u}}$, given $W = [w_1 \ldots w_T]'$, is $E(\bar{\bar{u}}^2) = \sum_{t=1}^{T} \iota_{n_x}' \mathbb{M}_t \Phi_t \mathbb{M}_t \iota_{n_x} / (n_x T)^2$, under the Martingale difference property of u_t. Since $\mathbb{M}_t$ is symmetric, idempotent, while $\hat{u}_t = \mathbb{M}_t u_t$, a robust and heteroskedasticity-consistent estimator (White) for the variance of $\bar{\bar{u}}$, is

$$\hat{\sigma}_{\bar{\bar{u}}}^2 = \sum_{t=1}^{T} \iota_{n_x}' \mathbb{M}_t \hat{u}_t \hat{u}_t' \mathbb{M}_t \iota_{n_x} / (n_x T)^2 = \sum_{t=1}^{T} \iota_{n_x}' \hat{u}_t \hat{u}_t' \iota_{n_x} / (n_x T)^2 = \sum_{t=1}^{T} \bar{\hat{u}}_{\cdot t}^2 / T^2 .$$

under the alternative hypothesis.[14] Moreover, $\gamma = \mathbf{0}$ does not imply $E(m_{xt}\tilde{\varepsilon}_{xt}) = 0$ either in (2.20) or in

$$x_t = \alpha(p_{xt}, s_t) + \beta(p_{xt}, s_t)\hat{\mu}_{xt} + \gamma\hat{\upsilon}_t + e^*_{xt}. \tag{2.21}$$

In contrast, the GMM alternative directly tests the necessary and sufficient condition that expenditure is uncorrelated with the conditional demand residuals, which in turn is a necessary condition for strict exogeneity (sufficient under joint normality).

2.3 Model Specification and Parameter Stability Tests

The sample period for the empirical application is 1919-1994. This period includes the Great Depression, World War II, the OPEC Oil Embargo, and Iran-Iraq War. *Ex post*, it stretches the imagination to suppose that the structure of U.S. food demand remained constant throughout this period. On the other hand, this is an interesting empirical question, especially given recent empirical work on structural change in the demand for food and individual food groups.

Recently, many diagnostic procedures for testing parameter stability and model specification errors have been developed. Few of these test procedures are specifically designed for large systems of nonlinear seemingly unrelated regression equations. In the present case, the data set provides about three degrees of freedom per structural parameter in the unrestricted model. This precludes the use of recursive-forecast residuals or Chow tests based on sample splits to analyze model stability. Nevertheless, it is highly desirable to have at least some idea of the degree to which the data are consistent with the model's specification, the restrictions implied by utility theory, and the hypothesis of constant parameters over time. Therefore, in this section I present a set of model specification and parameter stability tests that can be applied to within sample estimated residuals. These have power against a range of local alternative, including nonstationary parameters, model specification errors (e.g., nonlinearities in group expenditure, income, or demographics), or the restrictions on preference heterogeneity required for strict aggregation.

The main idea is quite simple. If the model is stationary and the errors are innovations, then consistent estimates of the model parameters can be found in a number of ways. Given consistent parameter estimates, the estimated errors converge in probability (and therefore in distribution) to the true errors, $\hat{\varepsilon}_t \xrightarrow{p} \varepsilon_t$. For each $i = 1, \ldots, n$, by the central limit theorem for stationary Martingale differences, we have

$$\frac{1}{\sqrt{T\sigma_{ii}}}\sum_{t=1}^{T}\varepsilon_{it} \xrightarrow{D} N(0,1), \tag{2.22}$$

where $\sigma_{ii} = E(\varepsilon_{it}^2)$ is the variance of the i^{th} residual. If we use a fixed proportion, say $z \in [0,1]$, of the sample to construct a partial sum of the true model errors, we have the asymptotic result that

$$\frac{1}{\sqrt{T\sigma_{ii}}}\sum_{t=1}^{[zT]}\varepsilon_{it} \xrightarrow{D} N(0,z), \tag{2.23}$$

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[14] In general, the structural part of the right-hand-side of (2.20) does not define the conditional mean of quantities demanded given (p_t, m_{xt}, s_t). For example, under the linear conditional mean hypothesis,

$$E(x_t \mid p_{xt}, m_{xt}, s_t) = \alpha(p_{xt}, s_t) + \beta(p_{xt}, s_t)m_{xt} + [(p'_{xt}\Sigma_t p_{xt})^{-1}\Sigma_t p_{xt} - \beta(p_{xt}, s_t)]\upsilon_t,$$

which has the form of (2.20) if and only if $(p'_{xt}\Sigma_t p_{xt})^{-1}\Sigma_t p_{xt} - \beta(p_{xt}, s_t) \equiv \gamma$, an n_x-vector of constants.

where the notation $[zT]$ indicates the largest integer that does not exceed zT. The variance in this case is z since we now are summing $[zT]$ independent terms each with variance equal to $1/T$. Combining these results by multiplying (2.22) by z and subtracting it from (2.23), we obtain

$$\text{(2.24)} \qquad \frac{1}{\sqrt{T\sigma_{ii}}}\sum_{t=1}^{[zT]}(\varepsilon_{it}-\bar{\varepsilon}_i)\xrightarrow{D} W(z)-zW(1)\equiv B(z),$$

where $W(z)$ is a standard Brownian motion on the unit interval, so that $W(z)\sim N(0,z)$. The random variable on the far right-hand-side of (2.24) is known as a standard Brownian bridge, or tied Brownian motion.

We use the estimated residuals and their estimated sample variances to generate sample analogues to the asymptotic Brownian bridges, which gives

$$\text{(2.25)} \qquad B_{iT}(z)\equiv\frac{1}{\sqrt{T\hat{\sigma}_{ii}}}\sum_{t=1}^{[zT]}(\hat{\varepsilon}_{it}-\bar{\hat{\varepsilon}}_i)\xrightarrow{D} B(z),$$

uniformly in $z\in[0,1]$, under the null hypothesis that the model is correctly specified and its parameters are stationary. We refer to tests based on this group of statistics as single equation mean stability tests since they are based on the first-order moment conditions $E(\varepsilon_{it})=0\ \forall\ i,t$.[15] If the data generating process for the ε_t also satisfies the linear conditional mean hypothesis (see Spanos), then a systemwide mean stability test also can be constructed using $B_T(z)\equiv\sum_{i,t}^{[znT]}(\hat{\xi}_{it}-\bar{\hat{\xi}})/\sqrt{nT}\xrightarrow{D} B(z)$, where $\hat{\xi}_t\equiv\hat{\Sigma}^{-1/2}\hat{\varepsilon}_t$ is the n_x-vector of estimated standardized error terms for the t^{th} observation and $\bar{\hat{\xi}}\equiv\sum_{i,t}^{nT}\hat{\xi}_{it}/nT$.

For all $z\in[0,1]$, $B(z)$ has a Gaussian distribution, with mean zero and standard deviation $\sqrt{z(1-z)}$ (Bhattacharya and Waymire). For a given z - i.e., to test for a break point at a known date - an asymptotic 95% confidence interval for $B_T(z)$ is $\pm 1.96\sqrt{z(1-z)}$. To test for an unknown structural break, the statistic

$$\text{(2.26)} \qquad Q_T=\sup_{z\in[0,1]}|B_T(z)|$$

has an asymptotic 5% critical value of 1.36 (Ploberger and Krämer).

Similar methods also can be applied to test for homoskedasticity. The focus here is on a systemwide test. Let Σ be factored into $\boldsymbol{LL'}$, where $\boldsymbol{L}$ is lower triangular and nonsingular. Define the random vector ξ_t by $\varepsilon_t=L\xi_t$. In addition to the previous assumptions on the stochastic error terms ε_t, we now also assume that $\sup_{i,t}E(\varepsilon_{it}^4)<\infty$. We estimate the within period average sum of squared standardized residuals by

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[15] Subtracting the residual sample means is innocuous when each equation includes a free intercept term. However, if the model does not include independent intercepts, the test statistics $\sqrt{(T/\hat{\sigma}_{ii})}\,\bar{\hat{\varepsilon}}_i\xrightarrow{D} N(0,1)$ also should be calculated in addition to the Brownian bridge tests. Homogeneity and the adding up condition in demand models generically lead to constant terms that are linked nonlinearly across equations. My empirical application has this property. Hence, both single equation sample mean tests and Brownian bridge stability tests are reported as part of the empirical results.

(2.27)
$$\hat{\upsilon}_t = \frac{1}{n}\hat{\xi}_t'\hat{\xi}_t = \frac{1}{n}\hat{\varepsilon}_t\hat{\Sigma}^{-1}\hat{\varepsilon}_t,$$

where $\hat{\varepsilon}_t$ is the vector of estimated residuals for period t and $\hat{\Sigma} = \sum_{t=1}^{T}\hat{\varepsilon}_t\hat{\varepsilon}_t'/T$ is the estimated error covariance matrix. The mean of the true υ_t is unity for each t and the martingale difference property of ε_t is inherited by $\upsilon_t - 1$, so that the asymptotic variance can be estimated consistently with

(2.28)
$$\hat{\sigma}_\upsilon^2 = \frac{1}{T}\sum_{t=1}^{T}(\hat{\upsilon}_t^2 - 1).$$

A systemwide variance stability test is obtained by calculating the sequence of centered and standardized partial sums of the $\hat{\upsilon}_t$, which gives

(2.29)
$$B_T(z) = \frac{1}{\sqrt{T}\hat{\sigma}_\upsilon}\cdot\sum_{t=1}^{[zT]}(\hat{\upsilon}_t - 1) \xrightarrow[T\to\infty]{D} B(z).$$

In this case, the limiting distribution on the right follows from the identity $\bar{\hat{\upsilon}} \equiv \sum_{t=1}^{T}\hat{\upsilon}_t / T \equiv 1$.

3. The Econometric 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 1981; LaFrance and Hanemann) and a small loss in generality results from aggregating non-food items to a Hicks composite commodity. Therefore, let y be a scalar representing nonfood expenditures, let $\pi(p_y)$ 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,

(3.1)
$$\begin{aligned} u(x,y,z,s) = {} & \tfrac{1}{2}(x-\alpha_1(s))'B_{xx}(x-\alpha_1(s)) + \tfrac{1}{2}\beta_{yy}(y-\alpha_2(s))^2 \\ & + \tfrac{1}{2}(z-\alpha_3(s))'B_{zz}(z-\alpha_3(s)) + (x-\alpha_1(s))'\beta_{xy}(y-\alpha_2(s)) \\ & + (x-\alpha_1(s))'B_{xz}(z-\alpha_3(s)) + (y-\alpha_2(s))\beta'_z(z-\alpha_2(s)), \end{aligned}$$

a second-order flexible functional form that generates demand functions that are linear in income. The utility function (3.1) is strictly aggregable if

(a) $\alpha_i(s) = \alpha_{i0} + A_i s,\ i = 1,2,3;$

(b) B_{xx}, β_{yy}, B_{zz}, β_{xy}, and β_{zy} are constant across individuals; and

(c) $E(A_i s) = E(A_i)E(s),\ i = 1,2,3.$

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

$$(3.2)\, h^x(p_x, \pi(p_y), m, s) = \alpha_x(s) + \left(\frac{m - \alpha_x(s)' p_x - \alpha_y(s)\pi(p_y)}{p_x' C_{xx} p_x + 2 p_x' \gamma_{xy} \pi(p_y) + \gamma_{yy} \pi(p_y)^2} \right) \cdot \left(C_{xx} p_x + \gamma_{xy} \pi(p_y) \right),$$

where

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

$$\begin{bmatrix} \alpha_x(s) \\ \alpha\ \ (s) \end{bmatrix} = \begin{bmatrix} C_{xx} & \gamma_x \\ \gamma'_x & \gamma \end{bmatrix} \begin{bmatrix} \mathcal{B}_{xx} + N' \mathcal{B}_{zx} & \beta_x\ + N \beta_z & \mathcal{B}_{xz} + N' \mathcal{B}_{zz} \\ \beta'_x & \beta & \beta'_z \end{bmatrix} \begin{bmatrix} \alpha_1(s) \\ \alpha_2(s) \\ \alpha_3(s) \end{bmatrix},$$

while the compensating variation for price changes from p_x^0 to p_x^1 is given by

$$(3.3) \qquad cv(p_x^0, p_x^1, m, s) = m - \alpha_x(s)' p_x^1 - \alpha_y(s)\pi(p_y)$$

$$- \left(m - \alpha_x(s)' p_x^1 - \alpha_y(s)\pi(p_y) \right) \cdot \sqrt{\frac{(p_x^1)' C_{xx} p_x^1 + 2(p_x^1)' \gamma_{xy} \pi(p_y) + \gamma_{yy} \pi(p_y)^2}{(p_x^0)' C_{xx} p_x^0 + 2(p_x^0)' \gamma_{xy} \pi(p_y) + \gamma_{yy} \pi(p_y)^2}}.$$

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

$$(3.4) \qquad e_x \equiv P_x x = P_x \alpha_x(s) + \left(\frac{m - \alpha_x(s)' p_x - \alpha_y(s)}{p_x' C_{xx} p_x + 2\gamma'_{xy} p_x + \gamma_{yy}} \right) P_x \left(C_{xx} p_x + \gamma_{xy} \right) + \varepsilon_x,$$

where m and p_x now have been deflated by $\pi(p_y)$ and $P_x \equiv \mathrm{diag}(p_{xi})$. 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 estimation procedure is nonlinear seemingly unrelated regression equations (SURE) with one iteration on the residual covariance matrix. This produces consistent, efficient, and asymptotically normal parameter estimates under standard conditions (Malinvaud; Rothenberg and Leenders), while avoiding spurious over-fitting of a subset of equations, which can result from iterative SURE methods.[16]

3.1 Parameter Restrictions and Test Procedures

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[16] The reason for this numerical result with iterative SURE in small samples with numerous shared parameters across equations can be understood best by writing the estimated covariance matrix, say $\hat{\Sigma}$, at a given iteration in factored form as $\hat{\Sigma} = Q \Delta Q'$, where $QQ' = Q'Q = I$, and $\Delta = \mathrm{diag}(\delta_i)$ is the diagonal matrix of eigen values. If one or more of the δ_i is "small" relative to all others, then since $\hat{\Sigma}^{-1}$ is held fixed during the next iteration on the structural parameters, the linear combination of the ε_i's associated with that eigen value will carry a "large" weight relative to all others in the sum of squares criterion. The associated linear combination of residuals approaches a perfect fit, which can lead to singularity in a finite sample.

The right-hand-side of (3.2) 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 the Gorman polar form representation for the indirect preference function and is 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 $\gamma_{xy} = 0$.

The $n_x \times n_x$ submatrix of Slutsky substitution terms for food items is

$$(3.5)\qquad S = \left(\frac{m-\alpha_x(s)'p_x-\alpha_y(s)\pi}{p_x'C_{xx}p_x+2p_x'\gamma_{xy}\pi_x+\pi^2}\right)\left[C_{xx}'-\left(\frac{(C_{xx}p_x+\gamma_{xy}\pi)(p_x'C_{xx}+\gamma_{xy}'\pi)}{p_x'C_{xx}p_x+2p_x'\gamma_{xy}\pi+\pi^2}\right)\right].$$

Hence, global symmetry is accommodated by $\frac{1}{2}n_x(n_x-1)$ linear parameter restrictions on C_{xx}.

Symmetry of S guarantees the existence of the direct and indirect preference functions, but 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 (x, y), in turn, implies that at least n_x eigen values of $-C$ must be negative (Lau). Hence, at least n_x of the eigen values of C must be positive for quasi-concavity. Given separability, the quadratic utility function in (3.1) is additively separable in x and y. Quasi-concavity then requires that preferences must be concave either in x or in y (Gorman 1995c).[17] Treating foods and total nonfood expenditure symmetrically implies that the eigen values of C_{xx} all must be non-negative. This is straightforward to implement. Let $C_{xx} = LL'$, where L is a lower triangular matrix, so that C_{xx} is positive semi-definite. These explicit, nonlinear parameter restrictions ensure that the (quasi-)utility function is <u>globally weakly integrable</u> (LaFrance and Hanemann).

The rank of L generally will be less than n_x unless the symmetry restricted, but not curvature restricted, estimate of C_{xx} is positive definite. In that case, the curvature restrictions are not binding. In the alternative case where L has a reduced rank of, say, n_x-g for $0 \le g \le n_x$, the matrix 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 C_{xx} that has rank n_x-g (see, e.g., Diewert and Wales), and is associated with $\frac{1}{2}g(g+1)$ restrictions for curvature in addition to the $\frac{1}{2}n_x(n_x-1)$ symmetry restrictions.

In this study there are 21 equations and 76 annual time series data points within the sample, for a total of 1596 observations. The unrestricted model has 615 parameters. There are 210 parameter restrictions associ-

[17] For strict quasi-concavity, this can be easily demonstrated as follows. Strict quasi-concavity requires

$$[dx' \quad dy]\begin{bmatrix} u_{xx} & 0 \\ 0' & u_{yy}\end{bmatrix}\begin{bmatrix} dx \\ dy\end{bmatrix} < 0 \;\; \forall \begin{bmatrix} dx \\ dy\end{bmatrix} \neq \begin{bmatrix} 0 \\ 0\end{bmatrix} \ni [dx' \quad dy]\begin{bmatrix} u_x \\ u_y\end{bmatrix} = 0.$$

Setting $dy = 0$ implies that $dx'u_{xx}dx < 0 \;\; \forall \;\; dx'u_x = 0$, so that the sectoral utility function for foods must be strictly quasi-concave. But if u_{xx} is indefinite (has a positive eigen value) and $u_{yy} > 0$, then the sign condition fails for joint quasi-concavity of u in (x, y).

ated with symmetry of C_{xx} and 238 restrictions associated with symmetry and positive definiteness of C_{xx}.[18] In large demand models, the classical Wald (W), likelihood ratio (LR), and Lagrange multiplier (LM) asymptotic χ^2 test statistics are well-known to be substantially biased towards rejecting a true null hypothesis too often (Laitinen; Meisner; Bera, Byron and Jarque). W is largest and most likely to reject a true null, while LM is smallest and therefore least likely to reject. Careful examination of the Monte Carlo results of Bera, Byron and Jarque also reveals that Laitinen and Meisner's simple, intuitively appealing degrees of freedom correction $(NT-K)/(G\cdot NT)$, combined with critical values from the $F(G, NT\text{-}K)$ distribution to under-corrects W and LR but over-corrects LM.

The approach I take to this is to construct an approximate F-test based on the Lagrange multiplier principle. Let a "^" denote unrestricted estimates, let a "~" denote restricted estimates, and let the variance-covariance matrix for ε_x be denoted by Σ. Given an estimate for Σ, say S, the least squares criterion for the SURE estimates is

$$s(S)=\sum_{t=1}^{T}\varepsilon'_{xt}S^{-1}\varepsilon_{xt}\,. \tag{3.6}$$

Denote the first round estimate of Σ obtained with the unrestricted specification by $\hat{\Sigma}$, the corresponding estimate of Σ obtained with the restricted model by $\tilde{\Sigma}$, the second round unrestricted sum of squares given $\hat{\Sigma}$ by $\hat{s}(\hat{\Sigma})$, the unrestricted sum of squares given $\tilde{\Sigma}$ by $\hat{s}(\tilde{\Sigma})$, and the restricted sum of squares given $\tilde{\Sigma}$ by $\tilde{s}(\tilde{\Sigma})$. The F-statistic is calculated as

$$F(G,NT-K)=\frac{\left(\tilde{s}(\tilde{\Sigma})-\hat{s}(\tilde{\Sigma})\right)/G}{\hat{s}(\hat{\Sigma})/(NT-K)}. \tag{3.7}$$

The numerator converges in distribution to a $\chi^2(G)/G$ random variable. It is calculated using the first round variance-covariance matrix obtained from the restricted model specification. This is consistent with the Lagrange multiplier principle and is well-known to have the smallest empirical size among W, LR, and LM. Under joint normality of the true residuals, the denominator of the F-test converges in distribution to a $\chi^2(NT-K)/(NT-K)$ random variable. It is calculated using the unrestricted model for both the first and second round estimates. But the F-test remains asymptotically valid even if the errors are not normally distributed. In that case, the denominator converges to one, while $F(G,NT-K)\xrightarrow[T\to\infty]{D}\chi^2(G)/G$. Finally, minimization implies that $\hat{s}(\hat{\Sigma})\le NT$, with equality if and only if the convergent iterative SURE estimates occur in the second round of the unrestricted estimation procedure. Note that this is a probability zero event. Hence, with probability one, this F-statistic's empirical size will be closer to the nominal size than a degrees of freedom corrected LM test that uses the F tables.

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[18] As noted above, the maximal number of independent parameters associated with a Choleski factorization LL' that is positive semidefinite with rank n_x-g for $0\le g\le n_x$ has the elements of the lower right triangle of L all equal to zero. This block has seven rows and columns in the quasi-concave model, which is the same number of negative eigen values that appear in the symmetry restricted model. This generates ½$g(g+1)$ = 28 parameter restrictions for the binding curvature constraints, in addition to the symmetry restrictions.

3.2 Data

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 as follows. Detailed disaggregated retail price estimates that are available for 1967 were used 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 and/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 also allow for habit formation by including lagged quantities as elements of 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.

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 N matrix makes the model parameters time-varying. In principle, a time-varying 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 N matrix. Second, the construction of the annual nutrient content matrices creates a simultaneity problem. That is, the elements of x are used to calculate the elements of 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 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 N, the longest available time period with consistent percentage contribution estimates for all 21 food items. These estimates are presented in Table 1.

4. Empirical Results

Table 2 presents model diagnostics for two samples: 1919-94, including World War II; and 1919-41 and 1947-94, which excludes World War II plus 1946 to account for the dynamic effects of habit formation. The rationale for this is explained by the model stability tests at the bottom of table 2 and depicted graphically in figures 1 through 3. The top panel of figure 1 shows the plots of the system tests for the first moment, while the bottom panel depicts the system tests for the second moment, both for the full period 1919-1994. While the unrestricted model does not show evidence of a structural break over the complete sample, the second-moment tests for both the symmetric and quasi-concave specifications strongly suggest that a break occurs in World War II. On the other hand, from table 2 we see that the F-test for Slutsky symmetry fails to reject this hypothesis even at the 20 percent level of significance. Given symmetry, there is strong evidence of a structural break during the second world war.

I therefore re-estimated the model with the years 1942-46 excluded from the sample. Figure 2 depicts the system specification error tests for this sample, in the same format as figure 1. For this sample period, the unrestricted version fails to reject the model specification at a 5 percent significance, 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 in the reduced sample is tempered by several factors. First, neither of the restricted specifications is rejected in favor of the unrestricted model for this sample. Second, neither restricted version shows evidence of mis-specification in the reduced sample. Third, the unrestricted model shows no evidence of mis-specification in the full sample. Finally, when 1942-1946 is excluded from the sample, none of the model versions show evidence of mis-specification in either the system or single equations mean stability tests for the reduced sample. A full set of plots for the latter tests is presented in figure 3.

Additional properties of the empirical results are presented in table 2. Neither restricted specification shows evidence of autocorrelation in the error terms, either in the full or reduced sample periods. This is unusual in that the imposition of parameter restrictions such as symmetry usually tends to introduce serial correlation among the error terms. There is little evidence of skewness in the residuals in either sample period. The two restricted models do not show evidence of thicker tails in the error terms than occurs in the unrestricted model.[19] However, all three versions of the model show evidence of leptokurtosis in both sample periods. Nevertheless, all of 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.

The results of testing for strict exogeneity of food expenditure strongly suggest that food expenditure is correlated with the conditional error terms. This conclusion is invariant to the level of restriction of the specification and the sample period. The common practice of including the price-weighted sum of quantities demanded on the right-hand-side of a system of conditional demands clearly is not legitimate for this data set. Tests of separability are reported for the unrestricted model in both sample periods.[20] Separability is marginally not rejected in the complete sample at the 5 percent significance level and marginally rejected at the same level when the war years are excluded. While this issue clearly warrants further consideration, and is the subject of ongoing research, separability of foods from nonfood items is maintained for the rest of the paper.

Table 3 reports the equation summary statistics for the fully restricted, globally quasi-concave and separable model specification for both sample periods. In this table, the average per capita expenditure levels for individual food items also are reported in constant 1967 dollars. For all commodities, eliminating the war years substantially reduces the equation standard error of the estimate, denoted by $\hat{\sigma}_i$ in the table. This is consistent with the war years representing a separate structure in the market for food. There were high price supports for dairy products to encourage sufficient milk production to supply the Allied Armed Forces, as well as rationing and other quantity controls for beef, pork and other foods. Hence, this result is consistent with pure common sense.

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[19] For example, the point estimate for the coefficient of excess kurtosis in the unrestricted model for the same sample period 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.

[20] Additional tests of symmetry and quasi-concavity were conducted without imposing separability, with results similar to those reported in table 2. Details of these results are available upon request.

Table 4 presents the estimated structural parameters associated with the constant 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.[21] 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.

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, are 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 several new test statistics and derives their asymptotic distributions. An approximate F-test for nonlinear restrictions in nonlinear seemingly unrelated regression equations is developed. The numerator of this statistic is based on the Lagrange multiplier principle. In linear models subject to linear restrictions, the Lagrange multiplier test has the smallest empirical size among the three classical test criteria. The denominator of the F-statistic uses the unrestricted first-round estimated error covariance matrix and the unrestricted second-round estimated residuals. By minimizing the second-round sum of squared residuals, this denominator term is strictly less than *NT-K* with probability one. Hence, in principle at least, this approximate F-test at least partially overcomes the tendency of the Laitinen-Meisner degrees of freedom correction to overcompensate for excessive type I errors in the LM test statistic. Additional research on the finite sample properties of this simple solution to hypothesis tests in nonlinear models is warranted.

A GMM test for the necessary and sufficient condition for strict exogeneity of group expenditure in a separable demand model also is presented. This test can be implemented readily with matrix language operations available in most statistical packages. In the empirical application using annual per capita U.S. food consumption data, the test results suggest that treating food expenditure as an exogenous variable may lead to seriously misleading empirical estimates and statistical inferences.

Finally, a set of asymptotic tests for specification errors and parameter stability are presented and imple-

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[21] 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.

mented. This battery of tests is based on within sample least squares residuals, which are known to better approximate the true residuals than, e.g., one-step ahead recursive residuals. These tests consider stability of both the first- and second-order moment conditions. As noted by Ploberger and Krämer, tests based on the latter should have more power against a range of local alternatives. In the empirical application, both the single equation and system tests reject the null hypothesis of a stable model structure when the World War II years 1942-1946 are included in the sample, but fail to reject the model's specification and parameter stability when these years are excluded from the sample period. Including the War years also has a significant and negative influence on the test results for the implications of economic theory.

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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$\lvert B_T(z)\rvert$	.39	.40	.66	.41	.42	.47
P-value	.998	.997	.78	.996	.995	.98
2nd Moment						
max$\lvert B_T(z)\rvert$	.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.

	Constant	Age Distribution			Ethnicity		Habit
		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.

	Constant	Age Distribution			Ethnicity		Habit
		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 &			Frozen	Other	Beef &		Other		
	Cream	Butter	Cheese	Dairy	Dairy	Veal	Pork	Meat	Fish	Poultry
Fresh Milk & Cream	.721 (.129)									
Butter	.00716 (.00646)	.00511 (.00103)								
Cheese	.00105 (.0101)	-.00102 (.00087)	.00447 (.00160)							
Frozen Dairy Products	-.0659 (.0391)	-.00235 (.00281)	-.00699 (.00469)	.142 (.0302)						
Other Dairy Products	-.119 (.0403)	-.00456 (.00290)	-.00697 (.00415)	.0125 (.0189)	.0704 (.0241)					
Beef & Veal	-.0279 (.0104)	.00250 (.00096)	-.00369 (.00135)	.00694 (.00402)	.0107 (.00371)	.0617 (.00564)				
Pork	.0100 (.0127)	-.00167 (.00140)	-.00499 (.00185)	.00742 (.00506)	.00764 (.00472)	-.0195 (.00312)	.0904 (.00834)			
Other Meat	.0305 (.0162)	-.00131 (.00110)	-.00071 (.00185)	-.0103 (.00700)	-.0137 (.00654)	-.0147 (.00237)	-.0106 (.00252)	.0376 (.00512)		
Fish	.0211 (.0086)	-.00271 (.00081)	.00418 (.00111)	-.00179 (.00428)	-.00536 (.00383)	-.00310 (.00124)	-.00680 (.00176)	-.00051 (.00176)	.00610 (.00139)	
Poultry	-.0664 (.0138)	.00033 (.00140)	.00258 (.00189)	-.0133 (.00542)	.00167 (.00567)	-.00550 (.00210)	-.00449 (.00310)	.00220 (.00267)	.00197 (.00172)	.0209 (.00347)
Fresh Citrus Fruit	.00608 (.0211)	-.00022 (.00251)	.00063 (.00255)	-.00152 (.00751)	-.00075 (.00698)	-.00152 (.00466)	-.00837 (.00605)	.00103 (.00328)	.00086 (.00207)	-.00972 (.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	.260									
	(.0210)	(.0586)									
Fresh Vegetables	-.0176	.0199	.0636								
	(.0108)	(.0288)	(.0211)								
Potatoes	.0276	.0485	-.0534	.372							
	(.0218)	(.0495)	(.0325)	(.0747)							
Processed Fruit	.0200	.0198	-.0166	.0132	.0419						
	(.00786)	(.0157)	(.00954)	(.0171)	(.00811)						
Processed Vegetables	-.0111	-.00378	.00816	-.0132	-.0288	.124					
	(.00945)	(.0241)	(.0169)	(.0232)	(.00900)	(.0270)					
Fats & Oils	.00411	.0181	-.00275	.00822	.00650	.00454	.0244				
	(.00570)	(.0125)	(.00835)	(.0126)	(.00390)	(.00864)	(.00565)				
Eggs	-.00071	.0225	.0105	-.0296	.00128	-.0208	-.00563	.0244			
	(.00477)	(.00898)	(.00689)	(.00952)	(.00302)	(.00654)	(.00304)	(.00397)			
Cereeal Products	-.0167	.161	-.00179	.00087	-.0218	.0419	.00410	.0206	.276		
	(.0186)	(.0502)	(.0332)	(.0501)	(.0169)	(.0377)	(.0166)	(.0147)	(.110)		
Sugar	-.0152	-.0543	-.00448	-.0521	-.0128	.0393	.00670	.00812	.0247	.119	
	(.0109)	(.0219)	(.0161)	(.0265)	(.00890)	(.0121)	(.00538)	(.00419)	(.0273)	(.0194)	
Coffee, Tea & Cocoa	.00534	-.00465	.00370	.00534	-.00076	-.00287	-.00087	-.00129	-.00416	.00048	.00415
	(.00189)	(.00363)	(.00194)	(.00350)	(.00141)	(.00133)	(.00084)	(.000637)	(.00281)	(.00179)	(.00051)

Figure 1. System Specification Tests, World War II Included.

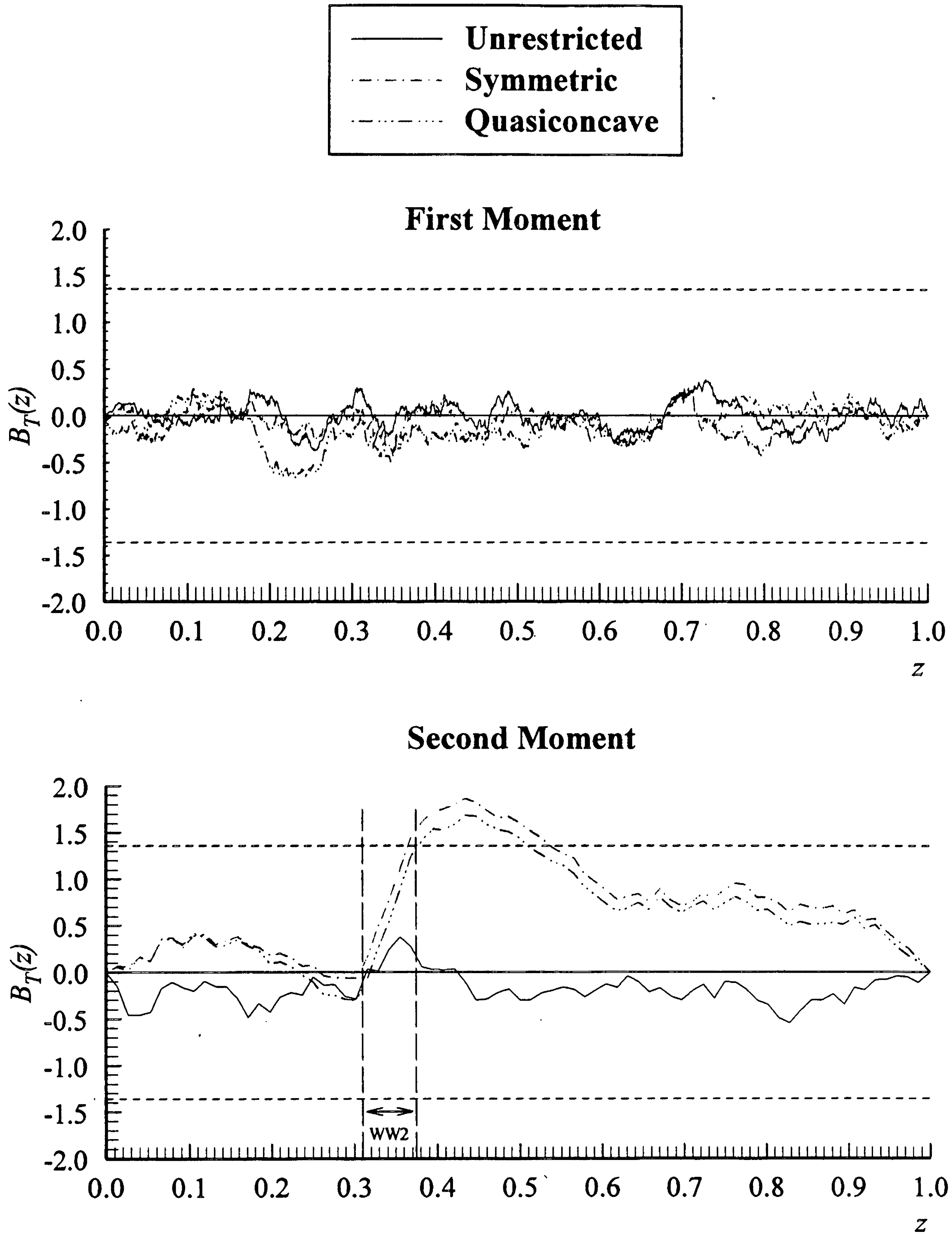


Figure 2. System Specification Tests, World War II Excluded.

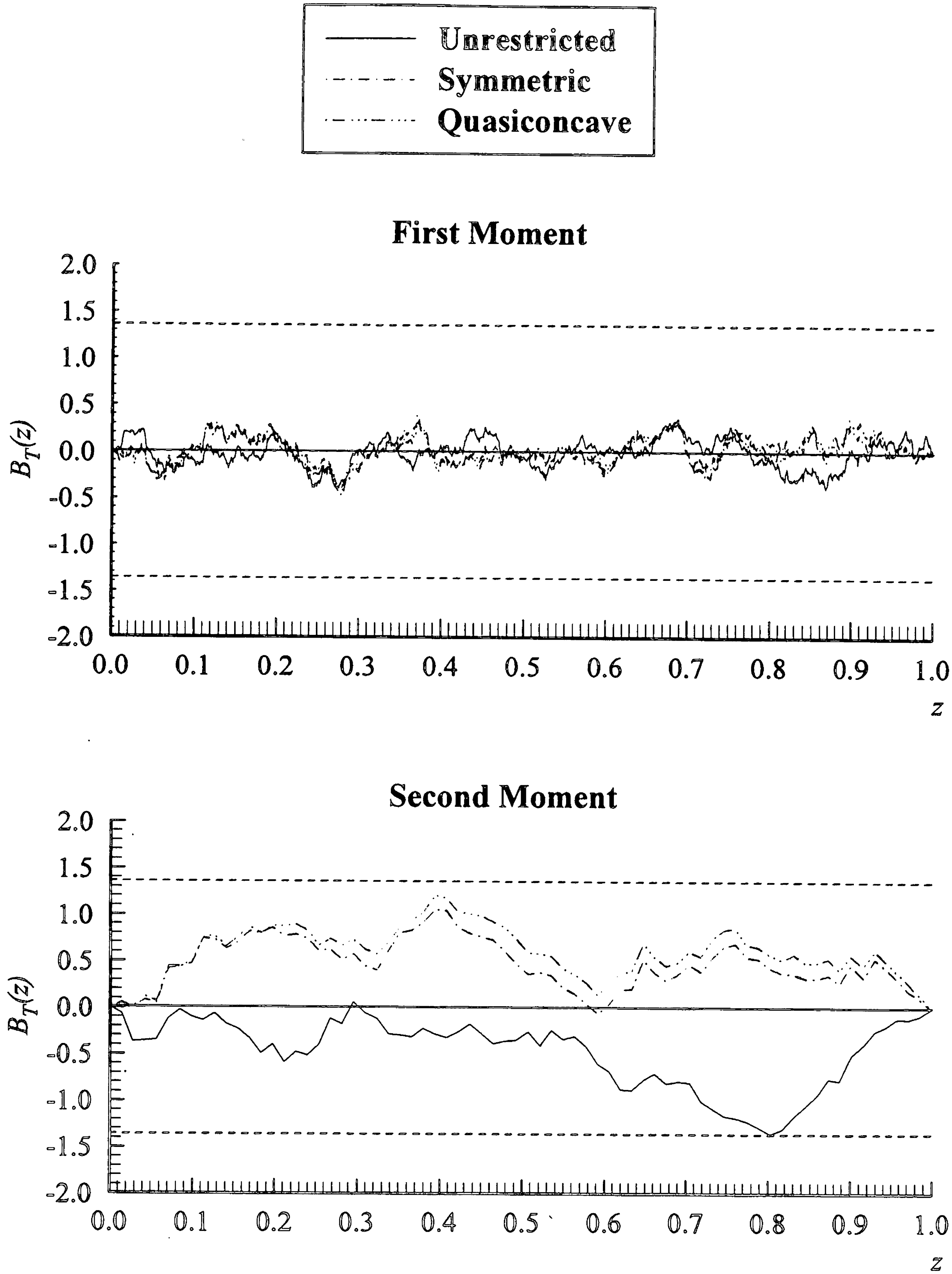


Figure 3. Single Equation Specification Tests.

World War II Excluded

Dairy Products

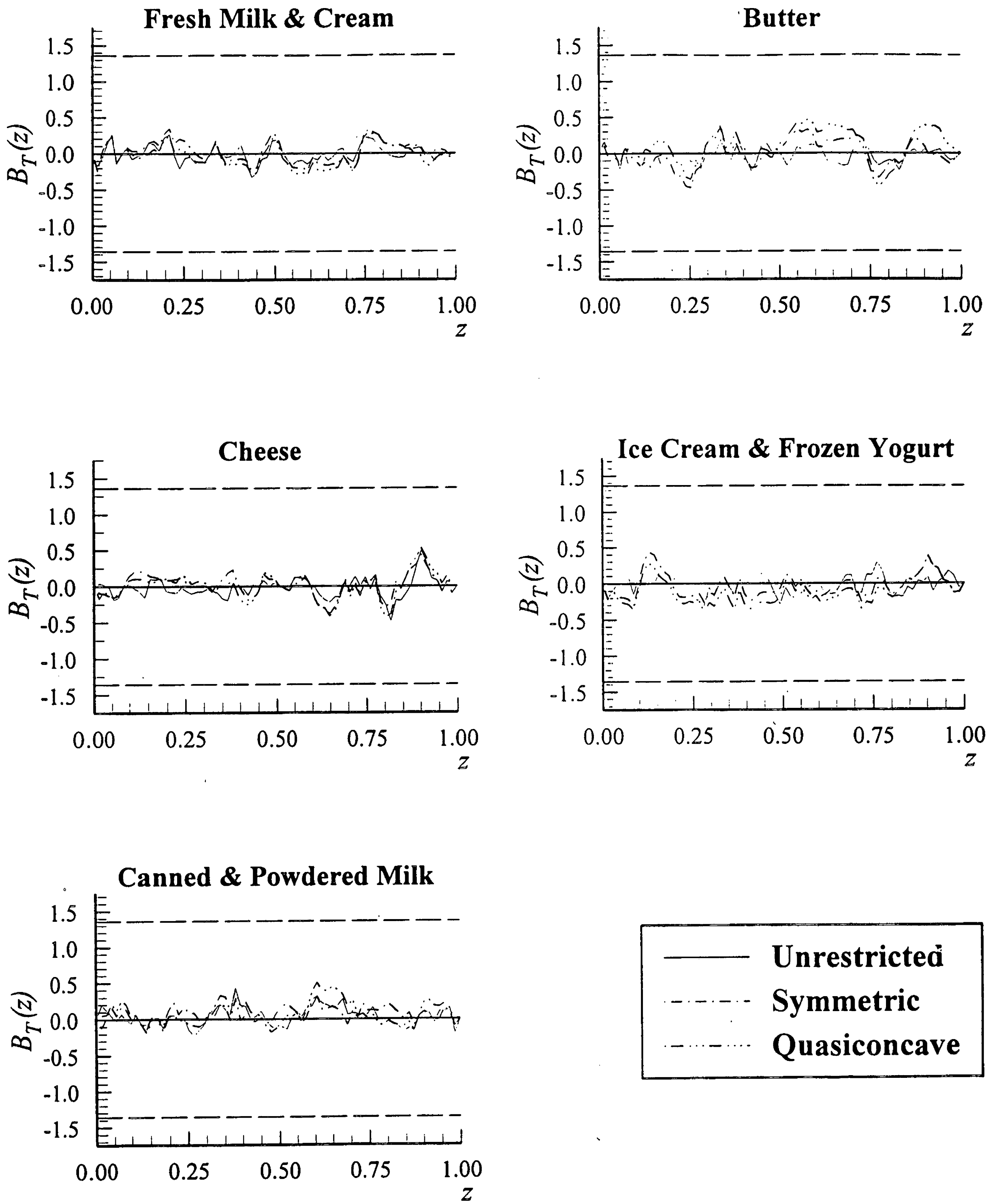
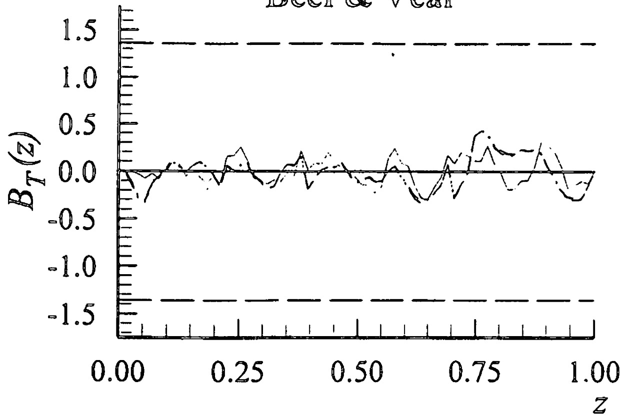


Figure 3. Single Equation Specification Tests, Continued.

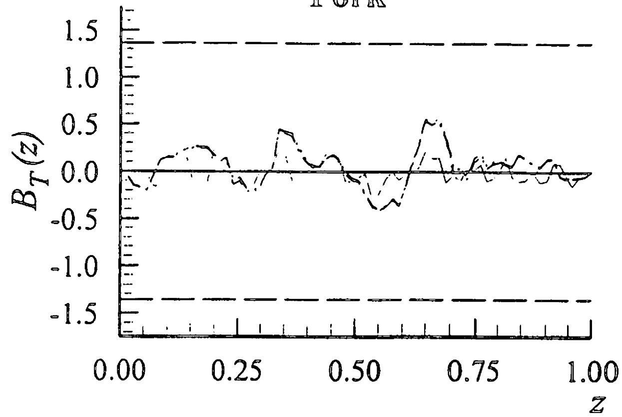
World War II Excluded

Meats, Fish & Poultry

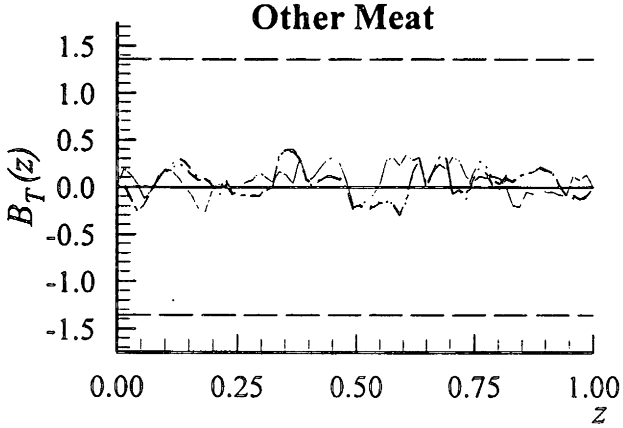
Beef & Veal



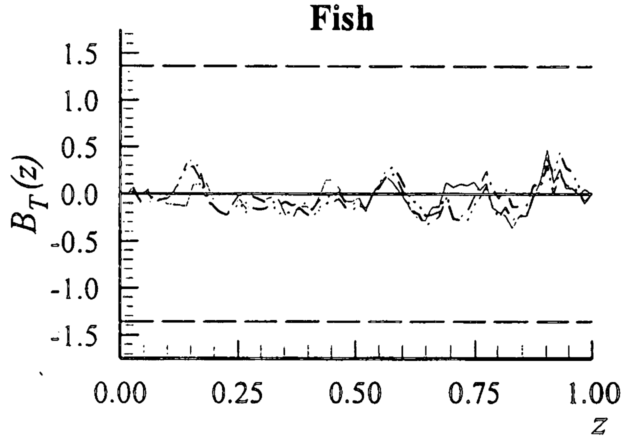
Pork



Other Meat



Fish



Poultry

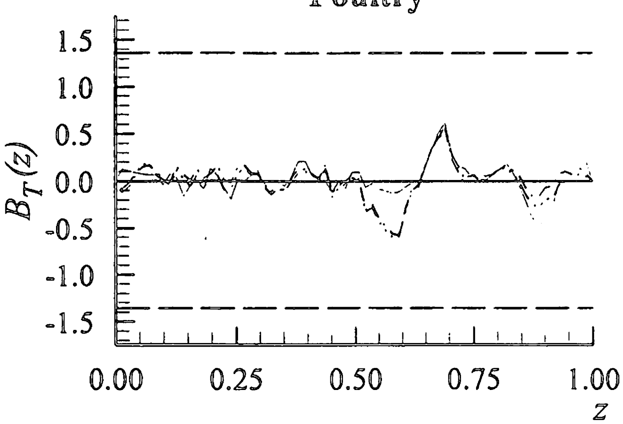


Figure 3. Single Equation Specification Tests, Continued.

World War II Excluded

Fruits & Vegetables

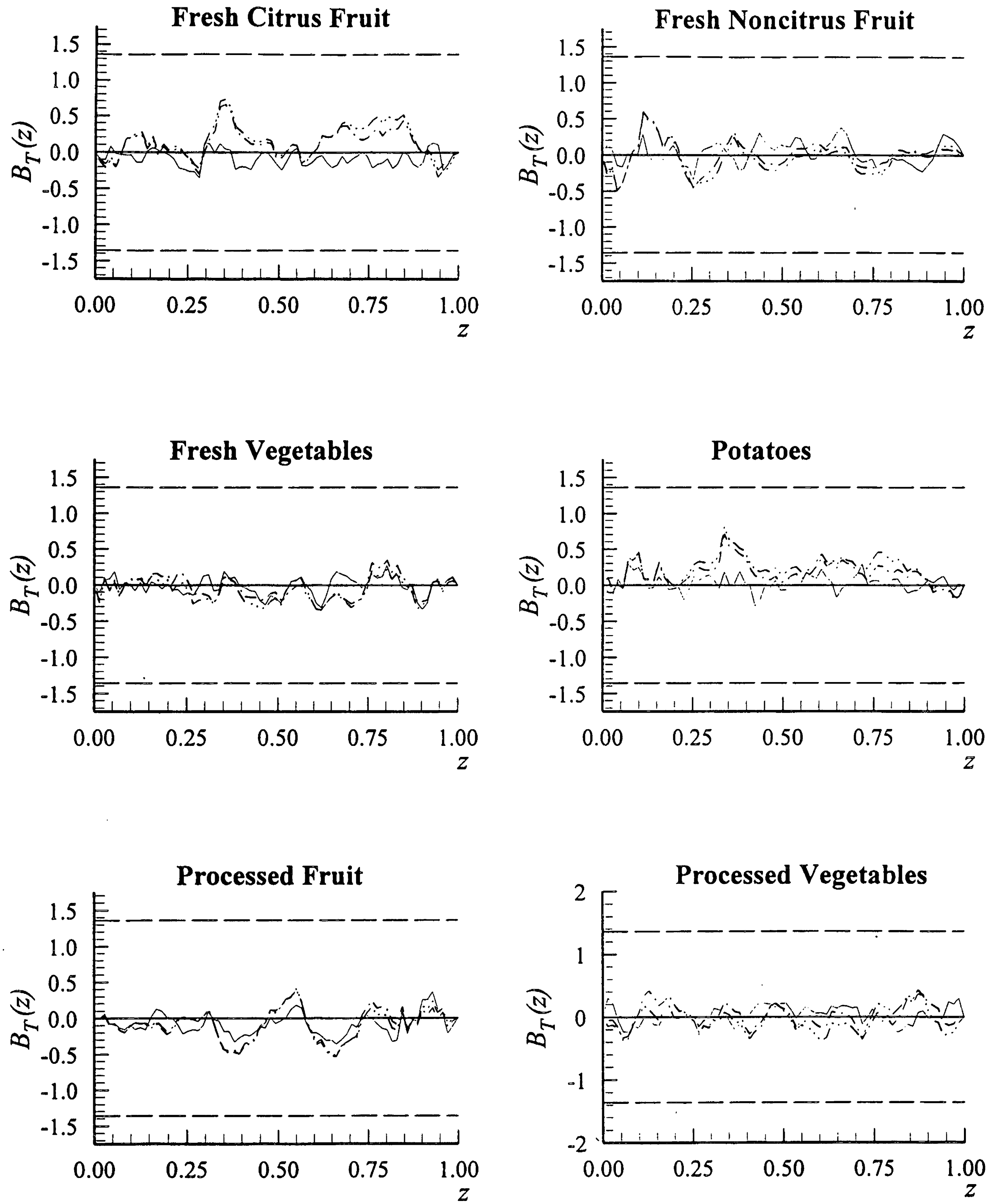


Figure 3. Single Equation Specification Tests, Continued.

World War II Excluded

Miscellaneous Foods