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Short-Run Demand Relationships in the U.S. Fats and Oils Complex

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Fats and oils play a prominent role in U.S. dietary patterns. Recent concerns over the negative health consequences associated with fats and oils have led many to suspect structural change in demand conditions. Our analysis considers short run (monthly) demand relationships for edible fats and oils. In that monthly quantities of fats and oils are likely to be relatively fixed, an inverse almost ideal demand system specification is used. A smooth transition function is used to model a switching inverse almost ideal demand system that assesses short-run demand conditions for edible fats and oils in the United States. The results suggest that short-run demand conditions for fats and oils experienced a gradual structural shift that began in the late 1980s or early 1990s and persisted into the mid-1990s. Although this shift generally made price flexibilities more elastic, differences in scale flexibilities across regimes were modest in most cases. The results suggest that decreases in marginal valuations for most fats and oils in response to consumption increases are rather small. Scale flexibilities are relatively close to −1, suggesting near homothetic preferences for fats and oils.

Key Words: fats and oils, inverse demand system, structural change

JEL Classifications: Q0, D1

Fats and oils play an important role in the diet of the typical American consumer. Park and Yetley estimated that direct consumption of fats and oils accounts for 33% of the total dietary fat in U.S. food sources. Consumption of fats and oils has been linked to increased risks of coronary disease and certain types of cancer. In spite of increased public concerns over the consequences of a diet rich in fats and oils, U.S. per capita consumption of fats and oils has risen significantly over the past 20 years. For example, total annual consumption of fats and oils increased from 57.4 pounds per person in 1981 to 65.6 pounds per person in 1997 (Putnam and Allshouse). Although overall consumption of fats and oils has been increasing, there have been significant shifts among individual commodities within the fats and oils complex. For example, consumption of animal fats, such as butter, lard, and beef tallow, has fallen in recent years. At the same time, consumption of vegetable fats and oils has increased significantly, at least through the early 1990s. Recent trends in annual per capita consumption of selected fats and oils are illustrated in Figure 1. In that this diagram illustrates annual consumption, seasonal aspects of consumption are not revealed, although such seasonality is discussed below.

Existing research on the demand for fats

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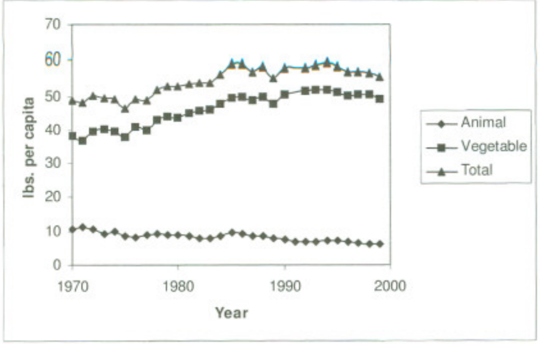

Figure 1. Consumption of Fats and Oils: 1970–1999

and oils is rather sparse, and thus current knowledge of demand parameters is rather limited. One line of research has considered modeling demand relationships for aggregated groups of commodities such as butter, margarine, shortenings, and cooking oils. Gould et al. used demographic scaling of demand system parameters to evaluate the role of changing demographics in the aggregate demand for fats and oils between 1962 and 1987. Their results indicated that demographic variables such as education, race, and age were important determinants of preferences for fats and oils and thus that changes in these factors lead to structural changes in aggregate demand patterns for fats and oils.

Demand conditions for individual fats and oils were evaluated by Chern et al., Goddard and Glance, and Yen and Chern. In each case, annual consumption data on the most prominent individual fats and oils were used to evaluate long-run demand conditions. These studies revealed that individual fats and oils are both substitutes and complements for one another in consumption. In addition, considerable variation in own-price and expenditure elasticities was found across individual oils.

A central theme inherent in the existing literature on the demand for fats and oils is the suspicion that exogenous factors (either demographic factors or greater health awareness) have brought about structural shifts in demand relationships. For example, the findings of Gould et al. suggested that changes in the distribution of demographic factors over time had shifted demand system parameters. Chern et al. used a Bayesian model of information and health risk belief based on Food and Drug Administration health survey data and the cholesterol information index of Brown and Schrader to represent increasing consumer awareness of the health implications of fats and oils consumption.[1] Their results indicated that consumption of fats and oils perceived to be less healthy (such as butter, lard, and coconut oils) was negatively affected by the cholesterol index, whereas healthier vegetable fats and oils were positively affected by health information.[2] Yen and Chern used a similar health information index and found that increased information about the consequences of dietary fats was correlated with increased consumption of corn, cottonseed, and soybean oil and decreased consumption of butter and lard.

Although the existing research has established that the demand for fats and oils experienced structural change in response to changes in these exogenous factors, the timing and pace of shifting preferences was restricted to correspond to certain observable variables that were rough proxy measures of changing attitudes and preferences regarding fats and oils. For example, the dissemination of health information can only imperfectly be represented by counting journal pages. It is possible that information regarding health concerns reached consumers through other avenues, and thus that restricting shifts to correspond to dates of article publications may be restrictive. Of course, any approach to capturing unobservable shifts in preferences is subject to these same concerns.

[1] The cholesterol information index of Brown and Schrader was constructed by taking the difference between articles in the basic health literature that suggest a link between cholesterol and coronary disease and those articles that question such a link.

[2] Fats and oils that are relatively low in saturated fats and high in polyunsaturated fats are generally considered to be more healthy. McCance and Widdowson reported the following ratios of polyunsaturated to saturated fats in common oils: 0.03 for butter, 0.02 for coconut oil, 0.23 for lard, 1.9 for cottonseed oil, 3.9 for soybean oil, and 4.6 for corn oil. The presence of cholesterol in butter and animal fats also has negative health implications.

To our knowledge, all existing research on the demand for fats and oils has evaluated long-run demand relationships (i.e., by using quarterly or annual data collected over a long period). A somewhat different approach is taken in the present analysis. The focus of the analysis is on short-run (monthly) patterns of consumption. It is suspected that, because of biological production lags, the short-run (monthly) supply of individual fats and oils is likely to be very inelastic.[3] Thus, quantities are treated as being fixed, and thus an inverse demand system model is estimated. The analysis considers monthly demands for six important fats and oils—butter, coconut oil, corn oil, cottonseed oil, soybean oil, and an aggregate commodity representing other animal fats (composed of the sum of lard and beef tallow consumption figures). An inverse demand system is applied to monthly data covering the period from January 1970 through May 1999. In an approach similar to that taken in earlier studies, the analysis allows the demand system to vary in accordance with structural shifts that may have affected short-run demand relationships. This approach differs from existing studies, however, in that it uses a smooth, continuous transition function to model gradual shifts in the structural parameters of the inverse demand system. Rather than tying the shift to proxy variables, the timing and speed of structural shifts are endogenously modeled.

The overall objective of the present article is to evaluate short-run demand relationships within the U.S. edible fats and oils complex. In addition to providing new information about demand conditions for edible fats and oils, the analysis makes two original contributions. The first involves the development and application of a smooth transition function that provides a flexible approach to the incorporation of gradual structural change that occurs at an unknown point in the data series. The second includes an illustration of the methods developed by Hansen (1996) for testing structural change under conditions where nuisance parameters are unidentified under the null hypothesis of no structural change.

[3] Although, as a reviewer has correctly pointed out, the supply of fats and oils may be seasonal, especially for products like butter. As is noted below, the analysis explicitly modeled such seasonality in consumption and did not reveal large effects.

An Inverse Demand Model

The inverse almost ideal demand system was introduced by Eales and Unnevehr. The demand model is derived by differentiating a logarithmic distance function that is fully analogous to Deaton and Muellbauer's price-independent logarithmic (PIGLOG) cost function. In particular, the distance function for a system of k goods is given by

$$\ln d(u, q) = (1 - u)a \ln(q) + u \ln b(q), \tag{1}$$

where

$$\ln a(q) = \alpha_0 + \sum_{i=1}^{k} \alpha_i \ln q_i + 0.5 \sum_{i=1}^{k} \sum_{j=1}^{k} \gamma_{ij}^{*} \ln q_i \ln q_j \tag{2}$$

and

$$\ln b(q) = \beta_0 \prod_{i=1}^{k} q_j^{-\beta_j} + \ln a(q). \tag{3}$$

Differentiation of the logarithmic distance function yields compensated share equations, which, according to the method of Deaton and Muellbauer, can be "uncompensated" by inverting the distance function and solving for the utility index, which is then substituted into the share equation to yield

$$w_i = \alpha_i + \sum_{j=1}^{k} \gamma_{ij} \ln q_j + \beta_i \ln Q, \tag{4}$$

where

$$\gamma_{ij} = (\gamma_{ij}^{*} + \gamma_{ji}^{*})/2 \quad \text{and} \tag{5}$$

$$\ln Q = \alpha_0 + \sum_{i=1}^{k} \alpha_i \ln q_i + 0.5 \sum_{i=1}^{k} \sum_{j=1}^{k} \gamma_{ij} \ln q_i \ln q_j.$$

Standard adding-up and homogeneity conditions imply an analogous set of conditions in the case of inverse demands.[4] In the case of the inverse almost ideal demand system (AIDS) model, these conditions require

$$(6)\quad \sum_i \alpha_i = 1, \qquad \sum_i \beta_i = 0,$$

$$\sum_i \gamma_{ij} = 0 \quad \text{(adding-up)},$$

$$(7)\quad \sum_j \gamma_{ij} = 0 \quad \text{(homogeneity), and}$$

$$(8)\quad \gamma_{ij} = \gamma_{ji} \quad \text{(symmetry).}$$

Eales and Unnevehr derived price and scale flexibilities for the inverse AIDS model and discussed linear approximate versions that used a linear quantity aggregator index rather than the nonlinear index implied by the full model.[5] Flexibilities represent the percentage decrease in the marginal value of the commodity (i.e., its expenditure-normalized price) that occurs in response to a 1% increase in consumption of the commodity. Hicks termed commodities to be gross "*q*-complements" if their cross price flexibilities are positive and "*q*-substitutes" if the cross-price flexibilities are negative.[6] Changes in the overall scale of consumption on normalized prices are evaluated using scale flexibilities. Scale flexibilities indicate the percentage change in normalized prices that will occur if consumption of all goods in the system is scaled up by 1%. Scale flexibilities are generally expected to be negative, and, in fact, in a fashion completely analogous to Engel's adding-up condition, the weighted sum of the scale flexibilities must be -1. Although it is tempting to consider scale elasticities as inverse versions of expenditure elasticities, they are by no means the same (excepting the restrictive cases of homothetic preferences and unitary elasticities of substitution). Park and Thurman provide a detailed discussion of the relationship between scale flexibilities and expenditure elasticities. Commodities are considered as necessities if scale flexibilities are less than -1 and luxuries otherwise.

[4] See Anderson for a detailed development of adding up conditions for inverse demand systems.

[5] In light of the extensive criticisms of linear approximate AIDS models that have come to light in recent years, the merits of the linear approximation are dubious. As Eales and Unnevehr noted, appeals to correlated prices that are typically used to justify a linear approximation are not reasonable for quantities.

[6] An alternative interpretation of substitutes and complements in inverse demand systems was presented by Barten and Bettendorf.

Econometric Framework

The standard inverse AIDS system is entirely analogous to the direct AIDS system and is amenable to standard nonlinear estimation techniques. As has been noted above, however, considerable evidence exists (both anecdotally and from earlier research) to suspect that consumer preferences for edible fats and oils are not stable. Thus, some method of allowing for structural change, in the form of shifts in the parameters, is necessary. A wide variety of methods for allowing parameters to shift to accommodate structural change has been developed.

In the present analysis, a smooth transition function is used to model the transition between regimes that characterizes structural change in the demand for fats and oils. The use of transition functions to model movements between alternative structural regimes was introduced by Bacon and Watts and has been applied by Goodwin and Brester, Moschini and Meilke, and Tsurumi et al. In contrast to many earlier applications of transition functions, the present analysis uses a functional representation of the transition that is smooth, continuous, and differentiable in both directions. This permits one to apply standard maximum-likelihood (ML) procedures to estimate the parameters of the transition function.

Each of the share equations of the inverse AIDS demand model may be written as

$$(9)\quad w_{it} = g(\theta, q_t) + e_{it},$$

where e_{it} is a mean zero error term that is assumed to be normally distributed. The parameter set defined by $\theta = (\alpha, \gamma, \beta)$ characterizes the functional preference relationships represented by the inverse AIDS model. The residual covariance matrix of the share equations will be singular, and thus one equation must be omitted when estimating the system. Structural change is usually characterized as a regime shift involving a change in these parameters over time. This shift is allowed to occur gradually, and the analysis identifies the timing and speed of the shift using the estimation data. Thus, structural change is represented in terms of a shift in the parameter set from $\theta^{(1)}$ to $\theta^{(2)}$. A mixing term λ_t that is constrained by construction to lie in the open interval (0, 1) is used to represent shifting between regimes. This specification of the mixing problem allows us to rewrite the share equations as

$$(10) \quad w_{it} = (1 - \lambda_t)g(\theta^{(1)}, q_t) + \lambda_t g(\theta^{(2)}, q_t) + e_{it}.$$

The mixing term λ_t is given by

$$(11) \quad \lambda_t = \Phi[(t - \mu)/\sigma] \qquad t = 1, \ldots, N,$$

where Φ is the normal cumulative distribution function and μ and σ are parameters to be estimated.[7] Note that μ represents the observation lying halfway between regimes 1 and 2 (i.e., for which $\lambda_t = 0.50$). The bandwidth parameter σ represents the speed of adjustment between regimes, with larger values of σ corresponding to more gradual adjustments between regimes. Note that $\lim_{x\to\infty} \Phi(x) = 1$ and $\lim_{x\to-\infty} \Phi(x) = 0$. In that the share equations of the system are intimately related to one another through the cross-equational restrictions given by Equation (6), it is assumed that the share equations all share the same value of the mixing term λ_t. This ensures that the restrictions hold at every point in the data, including those observations falling between regimes.[8]

A test of the statistical significance of the differences in parameters across alternative regimes is desirable. A standard test of parameter differences across regimes is analogous to a conventional Chow test, although the switch is gradual in this case rather than instantaneous, as is the case with standard Chow tests. As is well known, testing for structural breaks in cases where the break point is unknown a priori is complicated by the fact that parameters characterizing the break (μ and σ) are not identified under the null hypothesis of no structural change. Thus, conventional test statistics have nonstandard distributions. Hansen (1996) developed an approach to testing the statistical significance of parameter differences across alternative regimes in threshold autoregressive models. Under his approach, simulation methods are used to approximate the asymptotic null distribution of a test of parameter differences and to identify appropriate critical values. Hansen (1996, 1997) recommended running a number of simulations whereby the dependent variables are replaced by standard normal random draws. For each simulated sample, the regime-switching model is estimated and a standard Chow-type test is used to test the significance of the regime switch. From this simulated sample of test statistics, the asymptotic p value is approximated by taking the percentage of test statistics for which the test taken from the estimation sample exceeds the observed test statistics. Such an approach to testing the significance of threshold effects is adopted herein.

The likelihood of autocorrelation in the application to monthly consumption data should also be acknowledged. To address this concern, a rich specification that allows for a general form of first-order autocorrelation within and across equations is adopted. In particular, the general autocorrelation correction procedures for singular demand systems developed by Moschini and Moro is used. Moschini and Moro demonstrated that this procedure guarantees invariance with respect to the deleted equation and preserves adding up conditions. The general estimation approach involves share equations of the form

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[7] The smooth transition function has much in common with the smooth threshold modeling techniques of Terasvirta. A similar approach to specification and estimation is undertaken there, although in that case observations may switch between regimes more than once. In the present approach, the regime switch is permanent.

[8] In reality, all observations fall between regimes given the asymptotic nature of the transition function, which never actually reaches zero from above or one from below.

$$(12)\quad w_{it} = (1 - \lambda_t)g_i(\theta^{(1)}, q_t) + \lambda_t g_i(\theta^{(2)}, q_t) - \sum_j R_{ij}[w_{jt-1} - \{[(1 - \lambda_{t-1})g_j(\theta^{(1)}, q_{t-1}) + \lambda_{t-1}g_j(\theta^{(2)}, q_{t-1})]\}] + v_t,$$

where R_{ij} is the autoregressive parameter for the jth lagged residual in the ith equation and v_t is a serially independent, normally distributed residual error. As Moschini and Morro noted, R_{ij} is defined as

$$(13)\quad R_{ij} = \delta_{ij}\lambda_i - \frac{\lambda_i(\lambda_j - \lambda_n)}{\sum_s \lambda_s},$$

where δ_{ij} is 1 if $i = j$ and 0 otherwise. Although a number of alternative specifications are nested within this specification (including the Berndt and Savin specification of a single autoregressive parameter), this analysis allows the autocorrelation correction to be as general as possible by not imposing any restrictions.[9]

Finally, when working with finely sampled consumption or demand data, as in the present analysis using monthly data, one is often concerned with capturing deterministic seasonal fluctuations that may influence demand. The simple ad hoc addition of seasonal components may be problematic however, because, in a demand model, this implicitly assumes that the underlying structure of demand fluctuates in a deterministic fashion.[10] An alternative version of the demand model that included a second-order Fourier series approximation to the unknown seasonal component of demand was also considered. In particular, the model included seasonal terms of the form

$$(14)\quad \sum_{j=1}^{k} [\theta_j\cos(2\pi jd_t/12) + \phi_j\sin(2\pi jd_t/12)],$$

where $k = 2$ and d_t indicates the month of the year.[11] As is discussed in detail below, although statistically significant, these terms had almost no effect on the implied flexibilities. The specification containing the seasonal components did imply a faster process of adjustment, which is discussed below.

Empirical Application and Results

Monthly edible consumption figures and prices were collected from standard U.S. Department of Agriculture (USDA) sources for the period covering January 1970–May 1999. Minor oils, including palm oil, peanut oil, sunflower seed oil, and rapeseed oil account for a small share of the market and were omitted from the analysis because of a lack of data.[12] It should also be noted that, because of nonreporting of consumption figures, a number of observations were missing throughout the sample. The estimation sample contained 316 nonmissing observations. Any observation for which the current or lagged (because of the autocorrelation correction) values of model variables were missing was given zero weight in the likelihood function. It is assumed that the group of fats and oils is weakly separable from all other products, and thus these goods are considered in isolation from other commodities. Thus, conditional inverse demands are estimated under an assumption of two-

[9] In the interest of maintaining a parsimonious specification, we have limited our analysis to first-order autocorrelation. In light of the use of monthly data, more complex forms of autocorrelation could exist. The results were very robust to the autocorrelation specification.

[10] Note that simple seasonality in the supply of a commodity, such as is certainly the case for fats and oils as well as most food commodities, does not necessarily justify the inclusion of seasonal components in a demand model. In fact, such seasonality in supply is advantageous in uncovering and identifying the underlying consumer preferences, because the seasonality contributes variation in exogenous prices (or, in the inverse demand model, quantities) that helps in estimating preference relationships.

[11] For a discussion of the use of such terms to model harmonic seasonality, see Nerlove.

[12] Over the period of the present study, these minor oils typically accounted for <5% of total fats and oils consumption. A small number of firms produce these minor oils. The Census Department surveys that are the original sources of the data often do not report consumption figures for minor oils because of disclosure considerations.

Table 1. Variable Definitions and Summary Statistics

Variable	Definition	Mean	SD
q_{butter}	Monthly butter consumption (lb./capita)	0.3488	0.0647
q_{coconut}	Monthly coconut oil consumption (lb./capita)	0.1071	0.0459
q_{corn}	Monthly corn oil consumption (lb./capita)	0.2305	0.0688
$q_{\text{cottonseed}}$	Monthly cottonseed oil consumption (lb./capita)	0.2370	0.0659
q_{soybean}	Monthly soybean oil consumption (lb./capita)	3.2394	0.5063
q_{animal}	Monthly lard and tallow consumption (lb./capita)	0.3491	0.1059
p_{butter}	Butter Price (cents/lb.)	109.4343	36.0467
p_{coconut}	Coconut oil price (cents/lb.)	29.6350	12.4653
p_{corn}	Corn oil price (cents/lb.)	25.6433	6.3078
$p_{\text{cottonseed}}$	Cottonseed oil price (cents/lb.)	24.0612	6.5785
p_{soybean}	Soybean oil price (cents/lb.)	22.2856	6.2439
p_{lard}	Lard price (cents/lb.)	31.0413	12.0049
p_{tallow}	Tallow price (cents/lb.)	14.4072	4.2351
w_{butter}	Budget share for butter	0.2916	0.0799
w_{coconut}	Budget share for coconut oil	0.0231	0.0107
w_{corn}	Budget share for corn oil	0.0452	0.0127
$w_{\text{cottonseed}}$	Budget share for cottonseed oil	0.0439	0.0148
w_{soybean}	Budget share for soybean oil	0.5452	0.0832
w_{animal}	Budget share for lard and tallow	0.0510	0.0093

stage budgeting.[13] As Eales and Unnevehr noted, assuming that quantities are predetermined for some aggregate commodity category is likely to be suspect. Following convention, quantity terms were normalized using the data means to have mean values of one. Summary statistics and variable definitions are presented in Table 1.

Soybean and butter are the most prominent fats and oils in the sample, together accounting for nearly 84% of expenditures (55% by soybean oil and 29% by butter). Lard and tallow (meat fats) were the next most prominent oil category, together accounting for ~5.1% of total fats and oils expenditures. The prominence of animal fats, especially lard and tallow, has diminished substantially in recent years. The remaining fats and oils had average budget shares ranging from 2.3 to 4.5%.

A standard inverse AIDS demand model was estimated for the full sample. Parameter estimates and summary statistics are presented in Table 2.[14] Most parameter estimates are highly significant, and the estimates appear to fit the data very well, as is evidenced by the R^2 measures of correlation between actual and fitted shares. Table 2 also contains estimates of the regime switching model intended to capture and model structural change in the estimates.[15]

Two estimation strategies are pursued in the regime switching analysis, both of which yielded very similar results. In the first, following standard practice for the estimation of transition functions, a grid search was used to estimate parameters defining the transition function (μ and σ). Under this approach, a

[13] As a reviewer noted, this implicitly assumes homothetic preferences in the first stage of the more general consumption model. The analysis does not address issues related to the allocation of budgets in the first stage across aggregate goods categories. The extent to which any structural changes may have affected the role of fats and oils in the full consumption vector is a topic for further research.

[14] Note that, following convention, α_0 is fixed at zero in estimation of the other parameters. Estimates were not especially sensitive to this normalization.

[15] In light of the similarities between the two alternative models (with and without deterministic seasonality) and in the interest of a parsimonious specification, only results for the model that omits the seasonal components are presented. Results for the model containing seasonal terms are available on request.

Table 2. Standard and Switching Inverse AIDS Demand Systems: Parameter Estimates and Summary Statistics

Parameter	Full Sample	Regime I	Regime II
γ_{11}	0.2224 (0.0098)*	0.2352 (0.0117)*	0.2020 (0.0274)*
γ_{12}	−0.1551 (0.0088)*	−0.1517 (0.0097)*	−0.1220 (0.0226)*
γ_{13}	−0.0261 (0.0026)*	−0.0316 (0.0038)*	−0.0180 (0.0064)*
γ_{14}	−0.0210 (0.0018)*	−0.0213 (0.0024)*	−0.0142 (0.0057)*
γ_{15}	−0.0082 (0.0016)*	−0.0110 (0.0022)*	−0.0119 (0.0042)*
γ_{22}	0.1994 (0.0095)*	0.2083 (0.0100)*	0.1328 (0.0234)*
γ_{23}	−0.0104 (0.0017)*	−0.0121 (0.0020)*	−0.0088 (0.0044)*
γ_{24}	−0.0115 (0.0013)*	−0.0145 (0.0014)*	−0.0039 (0.0033)
γ_{25}	−0.0060 (0.0010)*	−0.0086 (0.0012)*	0.0007 (0.0027)
γ_{33}	0.0419 (0.0018)*	0.0491 (0.0027)*	0.0321 (0.0035)*
γ_{34}	−0.0035 (0.0010)*	−0.0046 (0.0013)*	−0.0035 (0.0019)*
γ_{35}	−0.0009 (0.0009)	0.0001 (0.0012)	0.0002 (0.0016)
γ_{44}	0.0404 (0.0011)*	0.0440 (0.0012)*	0.0244 (0.0031)*
γ_{45}	0.0002 (0.0007)	−0.0012 (0.0009)	0.0023 (0.0015)
γ_{55}	0.0176 (0.0008)*	0.0228 (0.0012)*	0.0093 (0.0019)*
α_1	0.5308 (0.0060)*	0.5043 (0.0074)*	0.6346 (0.0230)*
α_2	0.3095 (0.0064)*	0.3464 (0.0078)*	0.1769 (0.0265)*
α_3	0.0461 (0.0009)*	0.0450 (0.0013)*	0.0480 (0.0035)*
α_4	0.0409 (0.0008)*	0.0386 (0.0010)*	0.0432 (0.0034)*
α_5	0.0224 (0.0007)*	0.0211 (0.0008)*	0.0243 (0.0026)*
β_1	0.0031 (0.0179)	−0.0100 (0.0193)	−0.1043 (0.0445)
β_2	0.0032 (0.0193)	0.0103 (0.0198)	0.0272 (0.0453)
β_3	−0.0037 (0.0035)	−0.0016 (0.0040)	−0.0079 (0.0092)
β_4	0.0008 (0.0026)	0.0020 (0.0027)	−0.0031 (0.0063)
β_5	−0.0021 (0.0022)	0.0007 (0.0024)	−0.0053 (0.0054)
λ_1	0.9459 (0.0188)*	0.9660 (0.0161)*	
λ_2	0.9551 (0.0175)*	0.9741 (0.0141)*	
λ_3	0.8146 (0.0331)*	0.8434 (0.0304)*	
λ_4	0.8623 (0.0264)*	0.8801 (0.0246)*	
λ_5	0.8820 (0.0278)*	0.8902 (0.0265)*	
λ_6	0.8819 (0.0313)*	0.7549 (0.0399)*	
μ		265.2369 (8.1242)*	
σ		38.0696 (7.8974)*	
R^2_{soybean}	0.9202	0.9298	
R^2_{butter}	0.8999	0.9203	
R^2_{corn}	0.8847	0.8894	
$R^2_{\text{cottonseed}}$	0.9727	0.9607	
R^2_{coconut}	0.9365	0.9454	

Notes: Subscripts correspond to (i = 1) soybean oil, (i = 2) butter, (i = 3) corn oil, (i = 4) cottonseed oil, (i = 5) coconut oil, and (i = 6) lard and tallow. Numbers in parentheses are standard errors. An asterisk indicates statistical significance at the α = 0.10 or smaller level.

two-dimensional grid search was used to specify the transition function parameters. The remaining parameters of the switching demand system were then estimated conditionally on these parameters. The combination of transition function parameters that yielded the highest maximized conditional log-likelihood function were chosen as the optimal estimates. In that the transition function is smooth and continuously differentiable, standard nonlinear

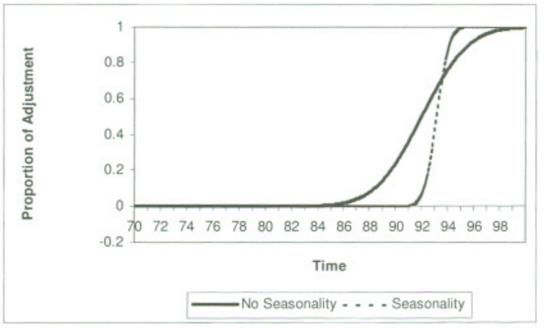

Figure 2. Timing and Speed of Transition Between Regimes

estimation techniques are also applicable. Thus, it is possible to estimate μ and σ along with the other parameters of the model using conventional maximum-likelihood techniques.[16]

Parameter estimates for the gradual switching model are also presented in Table 2. These estimates were obtained using conventional ML estimation procedures. ML estimates of μ and σ were 265.2 and 38.1, respectively. Not surprisingly, the estimates obtained using a grid search were very similar (265 and 38, respectively). The alternative specification containing deterministic seasonal terms (not presented) obtained estimates of 277.20 and 11.73, respectively. Thus, a somewhat faster pattern of adjustment is implied when an allowance is made for deterministic seasonality, although the general timing of the switch is very similar. The transition functions are presented in Figure 2. The functions imply a gradual structural change that commenced in the late 1980s to early 1990s (1986 in the first model and 1990 in the second) and took ~4–8 years to near completion. The shifts are centered at about 1992–1993. In contrast to conventional evaluations and tests of structural change, such as the discrete breaks implied by standard Chow-type tests, the switching models imply a structural shift that was of a gradual nature. Intuitively, one would certainly expect the preferences of consumers that underlie functional demand relationships to shift in a gradual fashion. This is especially true for aggregate demand models, because the rate of shift and adoption of new consumption habits may differ across individuals, such that aggregate changes appear to occur at a gradual pace.

A standard likelihood-ratio test of the significance of the differences in the standard model and the regime switching model (estimated via grid search) had the value of 240.40, which strongly rejects the null hypothesis of parameter stability using conventional chi-square critical values. Application of Hansen's bootstrapping methods implied a probability value <0.01 for this test statistic, confirming the significance of the parameter differences across regimes. In particular, the bootstrap implied a critical value of ~30.6 at the $\alpha = .05$ level. The bootstrap sampling was limited to 100 replications because of the computationally intensive nature of the simulation. In addition, the grid search was conducted on a somewhat coarser grid than was used in estimation for the original sample.[17]

The individual parameters underlying the autocorrelation correction are all highly significant and generally close to 0.9 in value. The matrices of implied autocorrelation parameters for the general model specification of Moschini and Moro are presented in Table 3. Note the high degree of autocorrelation within an equation represented in the estimates. In particular, the diagonal elements are all large and highly significant. In contrast, the off-di-

[16] One may ask why a grid search was considered in light of the fact that conventional estimation techniques are feasible and must, by construction, yield estimates that are as good as or better (in terms of the maximized likelihood function value) than the grid search estimates. Estimation of the transition function parameters by conventional means presents a difficult estimation problem, whereas estimation via grid search is straightforward. The grid search approach provides ideal starting values for use in the ML estimation, although the ML estimates of the transition function parameters were reasonably robust with respect to start values. Finally, estimation of the transition function parameters via conventional ML is not really feasible in the simulation of test statistics given the complexity of the estimation problem.

[17] The magnitude by which the test statistic exceeds those simulated under the null hypothesis suggests that the simulation is likely sufficient to verify the significance of the test.

Table 3. Autocorrelation Parameter Estimates

Equation	Error Term				
	Soybean	Butter	Corn	Cottonseed	Coconut
Model I					
Soybean	0.9345 (0.0162)*	−0.0131 (0.0067)*	0.0119 (0.0080)	0.0035 (0.0068)	0.0000 (0.0071)
Butter	−0.0115 (0.0068)*	0.9419 (0.0152)*	0.0120 (0.0080)	0.0035 (0.0069)	0.0000 (0.0071)
Corn	−0.0098 (0.0057)*	−0.0112 (0.0057)*	0.8247 (0.0289)*	0.0030 (0.0059)	0.0000 (0.0061)
Cottonseed	−0.0103 (0.0061)*	−0.0118 (0.0060)*	0.0109 (0.0072)	0.8653 (0.0233)*	−0.0001 (0.0064)
Coconut	−0.0106 (0.0062)*	−0.0121 (0.0061)*	0.0111 (0.0074)	0.0032 (0.0064)	0.8819 (0.0247)*
Model II					
Soybean	0.9275 (0.0146)*	−0.0400 (0.0083)*	−0.0161 (0.0090)*	−0.0228 (0.0081)*	−0.0246 (0.0082)*
Butter	−0.0388 (0.0084)*	0.9338 (0.0132)*	−0.0163 (0.0090)*	−0.0230 (0.0082)*	−0.0248 (0.0083)*
Corn	−0.0336 (0.0071)*	−0.0349 (0.0071)*	0.8292 (0.0262)*	−0.0199 (0.0072)*	−0.0215 (0.0072)*
Cottonseed	−0.0350 (0.0074)*	−0.0364 (0.0073)*	−0.0147 (0.0082)*	0.8592 (0.0219)*	−0.0225 (0.0075)*
Coconut	−0.0354 (0.0074)*	−0.0368 (0.0073)*	−0.0148 (0.0082)*	−0.0210 (0.0075)*	0.8674 (0.0233)*

Notes: Numbers in parentheses are standard errors. An asterisk indicates statistical significance at the $\alpha = 0.10$ or smaller level.

agonal elements, representing autocorrelation across equations, are generally negative, although small in value.

Table 4 presents price and scale flexibilities, evaluated at the data means, for the model omitting the seasonal components. Again, flexibilities for the model containing the seasonal terms were almost identical and thus are not presented here. For the full sample, the estimates all appear reasonable and are, in every case, statistically significant.[18] The relatively small values (in absolute value terms) of the flexibilities suggests that increasing the quantity of fats and oils consumed does not have a large impact on the marginal valuations (prices). This is analogous to a situation where demands are relatively price elastic in a direct (q-dependent) demand model. The largest flexibility (−0.59) is obtained for soybean oil, by far the most prominent commodity. This implies that prices are relatively flexible for soybean oil in response to changes in the quantity of soybean oil consumed. Again, in a direct-demand case, this would be analogous to a price-elastic demand function. As expected, nearly all cross-price flexibilities are negative, suggesting that all fats and oils in the analysis are gross q-substitutes. These cross-price flexibilities are, however, often close to zero, suggesting a relatively low degree of substitutability.[19] The own-price flexibilities for corn and cottonseed are quite close to zero, suggesting that marginal valuations of these commodities would not have to change considerably to induce additional consumption. Butter and other animal fats (lard and tallow) also have relatively small price flexibilities (−0.31 and −0.28, respectively).

Scale flexibilities indicate the extent to which marginal valuations are affected when the quantity consumed of all products is increased to 1. As expected, all scale flexibilities are negative, indicating that increased consumption lowers the marginal valuation of all

[18] Standard errors for elasticities were obtained using Geweke's sampling procedures.

[19] Barten and Bettendorf are critical of the use of cross-price flexibilities in categorizing goods as substitutes or complements and recommend an alternative approach using Allais coefficients.

Table 4. Price and Scale Flexibilities

Normalized Price	Quantity						
	Soybean	Butter	Corn	Cottonseed	Coconut	Animal	Scale
Full Sample							
Soybean	−0.5889 (0.0304)*	−0.2829 (0.0140)*	−0.0475 (0.0049)*	−0.0382 (0.0038)*	−0.0149 (0.0031)*	−0.0219 (0.0051)*	−0.9942 (0.0329)*
Butter	−0.5260 (0.0571)*	−0.3130 (0.0280)*	−0.0350 (0.0067)*	−0.0391 (0.0057)*	−0.0203 (0.0040)*	−0.0555 (0.0067)*	−0.9890 (0.0665)*
Corn	−0.6202 (0.0787)*	−0.2527 (0.0318)*	−0.0775 (0.0386)*	−0.0819 (0.0217)*	−0.0206 (0.0191)	−0.0282 (0.0288)	−1.0811 (0.0778)*
Cottonseed	−0.4681 (0.0579)*	−0.2580 (0.0246)*	−0.0800 (0.0219)*	−0.0777 (0.0249)*	0.0060 (0.0155)	−0.1050 (0.0233)*	−0.9826 (0.0578)*
Coconut	−0.4048 (0.0931)*	−0.2860 (0.0397)*	−0.0409 (0.0368)	0.0066 (0.0298)	−0.2402 (0.0370)*	−0.1267 (0.0405)*	−1.0920 (0.0930)*
Animal	−0.2516 (0.0662)*	−0.3281 (0.0266)*	−0.0225 (0.0249)	−0.0921 (0.0200)*	−0.0558 (0.0182)*	−0.2758 (0.0393)*	−1.0258 (0.0629)*
Regime I							
Soybean	−0.5785 (0.0344)*	−0.2835 (0.0150)*	−0.0589 (0.0071)*	−0.0399 (0.0047)*	−0.0206 (0.0041)*	−0.0369 (0.0060)*	−1.0183 (0.0353)*
Butter	−0.5008 (0.0609)*	−0.2753 (0.0285)*	−0.0399 (0.0078)*	−0.0481 (0.0062)*	−0.0288 (0.0043)*	−0.0716 (0.0067)*	−0.9645 (0.0682)*
Corn	−0.7183 (0.1044)*	−0.2773 (0.0370)*	0.0839 (0.0601)	−0.1021 (0.0290)*	0.0016 (0.0278)	−0.0221 (0.0404)	−1.0342 (0.0876)*
Cottonseed	−0.4611 (0.0694)*	−0.3171 (0.0264)*	−0.1017 (0.0295)*	0.0048 (0.0283)	−0.0259 (0.0197)	−0.0540 (0.0283)*	−0.9551 (0.0631)*
Coconut	−0.4603 (0.1163)*	−0.3653 (0.0427)*	0.0060 (0.0539)	−0.0499 (0.0373)	−0.0129 (0.0522)	−0.0892 (0.0542)*	−0.9715 (0.1017)*
Animal	−0.4003 (0.0748)*	−0.4279 (0.0282)*	−0.0193 (0.0353)	−0.0497 (0.0242)*	−0.0417 (0.0245)*	−0.0897 (0.0472)*	−1.0286 (0.0669)*
Regime II							
Soybean	−0.6439 (0.0729)*	−0.2315 (0.0429)*	−0.0342 (0.0121)*	−0.0271 (0.0112)*	−0.0224 (0.0080)*	−0.0673 (0.0153)*	−1.0263 (0.0819)*
Butter	−0.3677 (0.1259)*	−0.5176 (0.0818)*	−0.0260 (0.0170)	−0.0092 (0.0135)	0.0047 (0.0100)	0.0088 (0.0171)	−0.9069 (0.1555)*
Corn	−0.4929 (0.1899)*	−0.2456 (0.1040)*	−0.2979 (0.0772)*	−0.0840 (0.0429)*	−0.0001 (0.0359)	−0.0544 (0.0559)	−1.1748 (0.2004)*
Cottonseed	−0.3605 (0.1561)*	−0.1084 (0.0760)	−0.0818 (0.0429)*	−0.4457 (0.0710)*	0.0498 (0.0341)	−0.1230 (0.0611)*	−1.0696 (0.1438)*
Coconut	−0.6387 (0.2310)*	−0.0349 (0.1217)	−0.0025 (0.0687)	0.0877 (0.0649)	−0.6010 (0.0830)*	−0.0387 (0.0841)	−1.2282 (0.2336)*
Animal	−0.6681 (0.1768)*	0.0428 (0.0910)	−0.0373 (0.0479)	−0.0997 (0.0526)*	−0.0107 (0.0380)	−0.1600 (0.0940)*	−0.9330 (0.1560)*

Notes: Numbers in parentheses are standard errors. An asterisk indicates statistical significance at the α = 0.10 or smaller level.

goods. Recall that scale flexibilities >1 in absolute value correspond to "necessities," whereas scale flexibilities <1 in absolute value are "luxuries."[20] A surprising result is that the scale flexibilities are all quite close to 1 in absolute value. If all scale flexibilities are equal to −1, the demand system estimates imply that preferences are homothetic. In other words, increasing the scale of total consumption tends to increase consumption of each of the individual fats and oils commodities by about the same proportion. In no cases are the scale flexibilities significantly different from −1.

Flexibility estimates for the alternative regimes implied by the gradual switching model are also presented in Table 4. In most cases, the flexibilities are similar across the two regimes, although the flexibilities are uniformly larger (in absolute value) in the second regime. In several cases, own-price flexibilities that were close to zero for the full sample (coconut, corn, and cottonseed oils) are actually positive in the first regime, although in the positive estimates are very close to zero and in no case are the positive flexibilities significantly different from zero. Positive own-price flexibilities violate quasi concavity of the underlying distance function, although the fact that these estimates are essentially zero moderates this concern. It should be noted that, of the six goods, three of the own-price flexibilities are not statistically different from zero. Estimates for the second regime are more in line with expectations and suggest more elastic responses of normalized prices to increases in quantities. The scale flexibilities are quite similar across the alternative regimes and are again quite close to one in absolute value, again implying that homothetic preferences characterize the demand for fats and oils in both regimes.

Flexibility estimates for the second regime are quite similar to what is frequently observed for food commodities. If estimation is concentrated solely on the post-1992 sample, estimates nearly identical to those presented for the second regime are obtained. Thus, these may offer the most reasonable assessment of current demand conditions for edible fats and oils. Scale flexibilities do not appear to be significantly influenced by the structural shifts revealed by the models. A more intuitive interpretation of the preferences underlying the flexibilities may be garnered from a consideration of the price elasticities. As Anderson has shown, the matrix of price elasticities can be obtained by inversion of the matrix of flexibilities. We inverted the flexibilities implied for the second regime and, as expected, obtained relatively elastic price elasticities. In particular, own-price elasticities for soybean oil, butter, corn oil, cottonseed oil, coconut oil, and animal fats were −7.2, −4.8, −3.8, −3.1, −1.9, and −23.9. This interpretation of the inverted flexibilities must be tempered in light of a recent exchange between Eales and Huang. Huang argued that it may be inappropriate to undertake such inversion using statistical demand parameter estimates because such inversion may ignore important statistical properties associated with the estimates. Both Eales and Huang pointed out that separability assumptions, such as those adopted in the present analysis, may not be transparent to such inversion since separability for inverse demands may not imply separability for direct demand parameters obtained by inverting the indirect parameters.

Overall, the regime-switching model suggests that price flexibilities have increased substantially in response to a gradual structural change that began in the late 1980s and proceeded through the early 1990s. The results suggest that scale flexibilities for all commodities have remained close to −1, suggesting that demand conditions for edible fats and oils are consistent with homothetic preferences.

Concluding Remarks

Fats and oils play a prominent role in U.S. dietary patterns. Recent concerns over the negative health consequences associated with

[20] Park and Thurman demonstrate that a negative scale elasticity that is less than one in absolute value will have an expenditure elasticity that is greater than one. Likewise, goods with large scale elasticities (in absolute value) will have small expenditure elasticities.

consumption of certain fats and oils have led many to suspect that demand conditions for fats and oils may have undergone structural change. Indeed, previous research by Chern et al., Gould et al., and Yen and Chern suggested that increased health concerns and changing demographics may have shifted consumer demands for fats and oils.

The present analysis uses a gradually switching inverse AIDS demand model to assess short-run demand conditions for edible fats and oils in the United States. The results suggest that short-run demand conditions for fats and oils experienced a rather gradual structural shift in the late 1980s to the early 1990s. Although this shift generally made price flexibilities more elastic, differences in scale flexibilities across regimes were modest in most cases.

The results suggest that decreases in marginal valuations for most fats and oils in response to consumption increases are rather small. Scale flexibilities are relatively close to -1, suggesting near-homothetic preferences for fats and oils. This suggests that increasing the scale of consumption of all fats and oils results in equivalent proportional decreases in consumers' marginal valuations of individual fat and oil commodities. The results of our analysis should be interpreted within the context of a number of underlying assumptions and limitations. In particular, we assume that inverse demand conditions for edible fats and oils are weakly separable from other goods. In addition, the analysis assumes a specific structural representation (the inverse AIDS model), a particular model of structural change, and a specific correction for first-order autocorrelation. Extensions to this research may benefit from a consideration of a more general modeling approach that eases the restrictions implied by these assumptions.

In all, the results suggest the presence of structural change occurring in 1992, and thus an analysis focused on post-1992 data yields the best representation of the current short-run demand conditions for edible fats and oils. The results suggest that inverse demand conditions largely reflect homothetic preferences in that increases in the scale of consumption of aggregate fats and oils tend to increase consumption of each of the individual fats and oils in equal proportions. This may suggest that the health concerns that may underlie structural changes have not effectively shifted consumption patterns toward "healthier" fats and oils and thus may imply a role for future nutritional education.

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