Short-Run Demand Relationships in

the U.S. Fats and Oils Complex *

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Paper to be presented at the NCR-134 Conference on Applied Commodity Analysis, Forecasting, and Market Risk Management Chicago, Illinois, April 17-18, 2000.

May 10, 2000

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Practioners' Abstract

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. We consider short run (monthly) demand relationships for edible fats and oils. In that monthly quantities of fats and oils are likely to be relatively fixed, we utilize an inverse AIDS specification. Our analysis consists of two components. In the first, we utilize a smooth transition function to model a switching inverse almost ideal demand system (IAIDS) that assesses short-run demand conditions for edible fats and oils in the U.S. Our results suggest that short-run demand conditions for fats and oils experienced a rather rapid structural shift in the early 1990s. Although this shift generally made price flexibilities more elastic, differences in flexibilities across regimes are modest in most cases. Our 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. An important distinction occurs for lard and tallow, which exhibit a very elastic scale response. This suggests that scale increases in the consumption of edible fats and oils will significantly decrease consumers' marginal valuation of these animal fats. A second segment of our analysis considers dynamic extensions to the IAIDS model that recognize habit effects. Although nested hypothesis testing supports the dynamic specification over the static IAIDS model, price and scale flexibilities are quite similar to the static case.

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1 Introduction

Fats and oils play an important role in the diet of the typical American consumer. Park and Yetley (1990) estimated that direct consumption of fats and oils accounts for 33 percent 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 twenty years. For example, total annual consumption of fats and oils increased from 57.4 pounds per person in 1981 to 68.2 pounds per person in 1995 (USDA-ERS, 1999). 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 per-capita fats and oils consumption are illustrated in Figure 1.

Existing research on the demand for fats 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, Cox, and Perali (1991) 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.

Demand conditions for individual fats and oils were evaluated by Goddard and Glance (1989), Yen and Chern (1992) and Chern, Loehman, and Yen (1995). 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, Cox, and Perali (1991) suggested that changes in the distribution of demographic factors over time had shifted demand system parameters. Chern, Loehman, and Yen (1995) used a Bayesian model of information and health risk belief based on FDA health survey data and the cholesterol information index of Brown and Schrader (1990) to represent increasing

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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 while healthier vegetable fats and oils were positively affected by health information.[2] Yen and Chern (1992) 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 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.

To our knowledge, all existing research on the demand for fats and oils evaluates long-run demand relationships (i.e., by using quarterly or annual data collected over a long period). A somewhat different approach is taken in this analysis. The focus of our analysis is on short-run (monthly) patterns of consumption. We suspect that, because of biological production lags, the short-run (monthly) supply of individual fats and oils is likely to be very inelastic. Thus, we treat quantities as being fixed and estimate an inverse demand system model. We consider 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 (comprised of the sum of lard and beef tallow consumption figures). Our inverse demand system is applied to monthly data covering the period from October 1981 through May 1999. In an approach similar to that taken in earlier studies, we allow our demand system to vary in accordance with structural shifts that may have impacted short-run demand relationships. Our approach differs from existing studies, however, in that we utilize a smooth transition function to model gradual shifts in the structural parameters of the inverse demand system. Rather than tying the shift to proxy variables, we endogenously model the timing and speed of structural shifts.

The plan of this paper is as follows. The next section describes the demand model chosen to represent preferences for edible fats and oils—the inverse almost ideal demand system (IAIDS) of Eales and Unnevehr (1994). The third section discusses our econometric approach to modeling parameter shifts that may reflect the presence of structural changes.

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[1] The cholesterol information index of Brown and Schrader (1990) is 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 (1991) report 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.

The fourth section contains a discussion of the application of the short-run demand models to monthly consumption data. The fifth section considers a dynamic extension of the inverse AIDS model that allows for habit effects in fats and oils consumption. The final section offers some concluding remarks. In addition to providing new information about demand conditions for edible fats and oils, we believe that our analysis makes two original contributions. The first involves 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.

2   An Inverse Demand Model

The inverse almost ideal demand system was introduced by Eales and Unnevehr (1994). The demand model is derived by differentiating a logarithmic distance function that is fully analogous to Deaton and Muellbauer's (1980) 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

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

Differential of the logarithmic distance function yields compensated share equations, which, following Deaton and Muellbauer (1980), 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

$$\gamma_{ij} = (\gamma_{ij}^* + \gamma_{ji}^*)/2 \quad \text{and} \quad \ln Q = \alpha_0 + \sum_{i=1}^{k} \alpha_i \ln q_i + 0.5 \sum_{i=1}^{k} \sum_{j=1}^{k} \gamma_{ij} \ln q_i \ln q_j. \tag{5}$$

Standard adding-up and homogeneity conditions imply an analogous set of conditions in the case of inverse demands.[3] In the case of the inverse AIDS model, these conditions require:

$$\sum_i \alpha_i = 1, \sum_i \beta_i = 0, \sum_i \gamma_{ij} = 0 \quad \text{(adding-up);} \tag{6}$$

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[3]See Anderson (1980) for a detailed development of adding up conditions for inverse demand systems.

$$\sum_j \gamma_{ij} = 0 \quad \text{(homogeneity)}; \tag{7}$$

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

Eales and Unnevehr (1994) derive price and scale flexibilities for the inverse AIDS model and discuss linear approximate versions that use a linear quantity aggregator index rather than the nonlinear index implied by the full model.[4] Flexibilities represent the percentage decrease in the marginal value of the commodity (i.e., its expenditure-normalized price) that occurs in response to a one percent increase in consumption of the commodity. Hicks (1956) termed commodities to be gross "q-complements" if their cross price flexibilities are positive and "q-substitutes" if the cross-price flexibilities are negative.[5] 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 one percent. 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 (1999) 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.

3   Econometric Framework

The standard inverse AIDS system is entirely analogous to the direct AIDS system and is amenable to standard nonlinear estimation techniques. As we have 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 have been developed.

In this analysis, we apply smooth transition functions 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 (1971) and has been applied by Tsurumi, Wago, and Ilmakunnas (1986), Moschini and Meilke (1989), and Goodwin and Brester (1995). In contrast to many earlier applications of transition functions, we utilize a functional representation of the tran-

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[4]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 (1994) note, appeals to correlated prices which are typically used to justify a linear approximation are not reasonable for quantities.

[5]An alternative interpretation of substitutes and complements in inverse demand systems in presented by Barten and Bettendorf (1989).

sition that is smooth and differentiable in both directions. This permits us 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:

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

where e_{it} is a mean zero error term, which 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. We allow this shift to occur gradually and identify the timing and speed of the shift using our estimation data. Thus, we represent structural change 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. Our specification of the mixing problem allows us to rewrite the share equations as:

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

The mixing term λ_t is given by:

$$\lambda_t = \Phi((t - \mu)/\sigma) \quad t = 1, ..., N; \tag{11}$$

where Φ is the normal cumulative distribution function (cdf) and μ and σ are parameters to be estimated.[6] Note that μ represents the observation lying one-half way 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), we assume 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.[7]

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, though the switch is gradual in our 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 unidentified under the null hypothesis of no structural change. Thus, conventional test statistics have nonstandard distributions.

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[6]Our smooth transition function approach has much in common with the smooth threshold modeling techniques of Terasvirta (1994). A similar approach to specification and estimation is undertaken there, though in that case observations may switch between regimes more than once. In our approach, the regime switch is permanent.

[7]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.

Hansen (1996) has 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) recommends 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. We follow such an approach to testing the significance of threshold effects here.

Finally, we should acknowledge the likelihood of autocorrelation in our application to monthly consumption data. To address this concern, we allow for first-order autocorrelation in the residuals by applying the methods developed by Berndt and Savin (1975). As Berndt and Savin (1975) demonstrated, invariance of the estimates with respect to the deleted equation is guaranteed only when each equation has the same autoregressive root. We estimate a diagonal autoregressive matrix with a common autoregressive term in each equation. Thus, each share equation is rewritten as:

$$
\begin{aligned}
w_{it} = \rho w_{it-1} + (1 - \lambda_t)g(\theta^{(1)}, q_t) + \lambda_t g(\theta^{(2)}, q_t) - \\
\rho((1 - \lambda_{t-1})g(\theta^{(1)}, q_{t-1}) + \lambda_{t-1}g(\theta^{(2)}, q_{t-1})) + \nu_t
\end{aligned}
\tag{12}
$$

where ρ is the autoregressive parameter (identical across equations) and ν_t is a serially independent, normally distributed residual error.

4   Empirical Application and Results

Monthly edible consumption figures and prices were collected from standard USDA sources (USDA-ERS, 1999) for the period covering October 1981 through 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 our analysis due to a lack of data.[8] It should also be noted that, due to nonreporting of consumption figures, a number of observations were missing throughout our sample. Our estimation sample contained 178 nonmissing observations. Any observation for which the current or lagged (due to our autocorrelation correction) values of model variables were missing was given zero weight in the likelihood function. We assume that our group of fats and oils is weakly separable from all other products and thus consider these goods in isolation from other commodities. As Eales and Unnevehr (1994)

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[8]Over the period of our study, these minor oils typically accounted for less than 5 percent 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 our data often do not report consumption figures for minor oils because of disclosure considerations.

note, 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 our sample, together accounting for nearly 78 percent of expenditures (53 percent by soybean oil and 25 percent by butter). Corn oil is the next most prominent oil, typically accounting for about 4 percent of total fats and oils expenditures. The remaining fats and oils had average budget shares ranging from 1.5 - 3 percent.

A standard inverse AIDS demand model was estimated for the full sample. Parameter estimates and summary statistics are presented in Table 2.[9] Nearly every parameter is 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.

We pursued two estimation strategies in our regime switching analysis—both of which yielded very similar results. In the first, following standard practice for the estimation of transition functions, we used a grid search to estimate parameters defining the transition function (μ and σ). Under this approach, a two dimensional grid search was used to specify the transition function parameters. The remaining parameters of the switching demand system were then estimated conditional on these parameters. The combination of transition function parameters the yielded the highest maximized conditional log-likelihood function were chosen as the optimal estimates. In that our transition function is smooth and continuously differentiable, standard nonlinear estimation techniques are also applicable. Thus, we also estimate μ and σ along with the other parameters of the model using conventional maximum likelihood techniques.[10]

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 138.3 and 8.2, respectively. Estimates obtained using a grid search were similar, though the grid search estimate of μ was slightly smaller (133) and the estimate of σ was somewhat higher (21). The transition functions for both the ML and grid search estimates are presented in Figure 2. Note that both sets of estimates suggest a very similar pattern of structural change, centered around the 1992-93 period. The larger bandwidth parameter suggests a more gradual transition, though adjustment is nearly complete by mid-1994 in both cases. Estimates of the inverse AIDS model obtained using the grid search estimates of

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[9]Note that, following convention, α_0 is fixed at zero in estimation of the other parameters.

[10]One may ask why a grid search was considered in light of the fact that conventional estimation techniques are feasible and must, be 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, our experience was that our 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.

μ and σ were nearly identical to those presented here. Further, the elasticity estimates were nearly identical to those presented here. 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 142.359, 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 less than 0.01 for this test statistic, confirming the significance of the parameter differences across regimes.[11]

Table 3 presents price and scale flexibilities, evaluated at the data means. For the full sample, the estimates all appear reasonable, though own-price flexibilities of coconut oil, corn oil, and cottonseed oil are very small and, in fact, are not statistically different from zero.[12] This suggests that consumers' marginal valuations of these oil products are not significantly affected when quantities increase. As expected, nearly all cross-price flexibilities are negative, suggesting that all fats and oils in our analysis are gross q-substitutes. These cross-price flexibilities are, however, often close to zero, suggesting a relatively low degree of substitutability.[13]

Scale flexibilities indicate the extent to which marginal valuations are affected when consumption of all products is increased one percent. As expected, all scale flexibilities are negative, indicating that increased consumption lowers the marginal valuation of all goods. However, considerable variation exists in scale commodities across goods. Recall that scale flexibilities greater than one in absolute value correspond to "necessities" while scale flexibilities less than one in absolute value are "luxuries."[14] The scale flexibility for animal fats (lard and tallow) is very large in absolute value, indicating that marginal values for lard and tallow decrease substantially more than those for other goods as consumption of all fats and oils rises. This suggests that animal fats are a "less-preferred" commodity relative to other fats and oils.

The own-price flexibility for soybean oil, by far the most prominent commodity in our group of fats and oils, is -0.58. This estimate, suggests that increasing consumption of soybean oil by one percent lowers consumers' marginal valuation of soybean oil by 0.58 percent. The own-price flexibility for butter was considerably smaller at -0.29. Animal fats had an own-price flexibility of -0.47.

Flexibility estimates for the alternative regimes implied by the gradual switching model are also presented in Table 3. In most cases, the flexibilities are similar across the two regimes, though 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,

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[11]In particular, the bootstrap implied critical values of 34.08 and 39.56 at the $\alpha = .05$ and .01 levels, respectively. The bootstrap sampling was limited to 100 replications due to the computationally intensive nature of the simulation. In addition, the grid search was conducted on a somewhat coarser grid than we used in estimation for the original sample.

[12]Standard errors for elasticities were obtained using Geweke's (1986) sampling procedures.

[13]Barten and Bettendorf (1989) are critical of the use of cross-price flexibilities in categorizing goods as substitutes or complements and recommend an alternative approach using Allais coefficients.

[14]Park and Thurman (1999) demonstrate that a negative scale elasticity that 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.

corn, and cottonseed oils) are actually positive in the first regime. This result violates quasi-concavity of the underlying distance function and thus makes the estimates questionable. Estimates for the second regime are much more reasonable and suggest more elastic responses of normalized prices to increases in quantities. The scale flexibilities are quite similar across the alternative regimes, with animal fats again showing a very elastic response of normalized prices to increases in the scale of consumption.

The fact that several own-price flexibilities for minor oils are actually positive in the first regime may suggest that our switching methods are inadequate for capturing the structural changes which shifted the demands for fats and oils in the 1980s. Flexibility estimates for the second regime are quite similar to what is frequently observed for food commodities. If we concentrate our estimation 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 our models.

5   A Dynamic Extension

In light of our use of monthly data, one may suspect the potential for dynamic habit or stock effects. A variety of methods for incorporating dynamics into a direct or inverse demand system have been developed and applied in recent years. At a fundamental level, our recognition of autocorrelation represents a dynamic specification in that shares are influenced by residuals from the preceding period. Alternative approaches to recognizing dynamic habit effects typically involve the inclusion of lagged consumption levels in the share equations (see, for example, Pollak (1970) and Blanciforti and Green (1983)).

A more general approach to incorporating habit effects in a dynamic specification of the direct AIDS model was considered by Ray (1984). Holt and Goodwin (1997) applied this specification to a consideration of quarterly meat demand in the U.S. Ray's (1984) approach involved augmenting the share equations with lagged aggregate consumption. In particular, in the direct AIDS model, the augmentation permits price and real income responses to vary with lagged consumption. As Holt and Goodwin (1997) note, in the indirect AIDS model, this augmentation implies that the level of the distance function required to achieve a given level of utility will depend upon lagged quantities as well as current quantities. The intuition underlying this specification is that habit effects relate current distance to lagged consumption levels.

Following Ray (1984) and Holt and Goodwin (1997), the dynamic inverse AIDS model allows quantity responses to vary with lagged quantities according to the following specification:

$$w_i = \alpha_i + \sum_{j=1}^{k} (\gamma_{ij} + \theta_{ij} \mu_{t-1}) \ln q_j + (\beta_i + \nu_i \mu_{t-1}) \ln Q \tag{13}$$

where

$$\mu_{t-1} = \sum_{i=1}^{k} \ln q_{it-1} \tag{14}$$

and

$$\ln Q = \alpha_0 + \sum_{i=1}^{k} \delta_i \mu_{t-1} + \sum_{i=1}^{k} \alpha_i \ln q_i + 0.5 \sum_{i=1}^{k} \sum_{j=1}^{k} (\gamma_{ij} + \theta_{ij} \mu_{t-1}) \ln q_i \ln q_j. \tag{15}$$

The μ_{t-1} term represents aggregate consumption, or the 'standard of living,' in the previous period.[15] Inclusion of this term in the share equations allows price and scale flexibilities to vary with lagged aggregate consumption, thus incorporating habit persistence. In addition to the parametric restrictions discussed above for the static IAIDS model, the dynamic specification includes the following restrictions:

$$\sum_{i=1}^{k} \theta_{ij} = \sum_{j=1}^{k} \theta_{ij} = 0, \quad \sum_{i=1}^{k} \nu_i = 0, \quad \theta_{ij} = \theta_{ji}. \tag{16}$$

In light of the preceding results indicating parameter instability for a simple static IAIDS model, we limited our application of the dynamic IAIDS model to the set of observations roughly corresponding to the latter regime (i.e., from 1988 forward).[16] The dynamic IAIDS model was estimated using maximum likelihood procedures. Following our analysis of the static model, the estimates were again corrected for first-order autocorrelation using the procedures of Berndt and Savin (1975). Parameter estimates and summary statistics are presented in Table 4.

Although the parameters added to represent dynamic effects are statically significant at the $\alpha = .10$ or smaller level in only 7 of 26 cases, a nested likelihood ratio test of the dynamic specification has the value of 43.57, which exceeds the chi-square critical value at the $\alpha = .05$ level. Thus, the results indicate that a static IAIDS specification omits relevant dynamic terms representing habit effects. Significant autocorrelation appears to again be present in the dynamic IAIDS specification, indicating that the addition of parameters allowing for dynamic habit effects does not eliminate autocorrelation.

Price and scale flexibilities for the dynamic specification, evaluated at the data means, are presented in Table 5. Although the estimates are quite similar to those obtained for the static IAIDS specifications considered above, several differences do exist. All flexibilities appear to be of the correct sign, with all own-price flexibilities being negative. Own-price flexibilities for coconut oil, corn oil, and cottonseed oil, though negative, are again close to zero. When compared to the full sample results for the static IAIDS model, the butter and soybean own-price flexibilities are slightly larger in absolute value, suggesting slightly higher marginal

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[15]See Holt and Goodwin (1997) for a detailed discussion of the corresponding distance function and the derivation of the dynamic inverse AIDS share equations.

[16]Of course, omission of significant dynamic effects represents a specification error that may reveal itself in the form of parameter instability in a simple static specification. Our ability to examine structural change in a static specification is limited by our available degrees of freedom. In particular, both the switching regression specification and the dynamic IAIDS specification involve roughly twice the number of parameters as what is implied by a standard IAIDS specification.

valuations for these products. The scale flexibilities are very similar to those obtained in the static models. Exceptions occur for coconut oil, which rises (in absolute value) to -1.23 and animal fats, which rise (in absolute value) to -5.57. Again, these results indicate that marginal valuations for these goods fall substantially as aggregate consumption of all fats and oils increase, implying that these products are "less-preferred" relative to the other fats and oils.

Overall, in spite of their statistical significance as a group, the incorporation of parameters representing dynamic effects results in similar price and scale flexibilities. Of course, at the data means, the variable representing lagged aggregate consumption (μ_{t-1}) approaches zero since it is made up of logarithmic normalized quantities. Thus, dynamic effects may have a more significant influence on observations away from the mean values.

6   Concluding Remarks

Fats and oils play a prominent role in U.S. dietary patterns. Recent concerns over the negative health consequences associated with 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 Gould, Cox, and Perali (1991), Yen and Chern (1992), and Chern, Loehman, and Yen (1995) suggested that increased health concerns and changing demographics may have shifted consumer demands for fats and oils.

We utilize a gradually switching inverse AIDS demand model to assess short-run demand conditions for edible fats and oils in the U.S. Our results suggest that short-run demand conditions for fats and oils experienced a rather rapid structural shift in the early 1990s. Although this shift generally made price flexibilities more elastic, differences in flexibilities across regimes are modest in most cases. A dynamic extension to the static IAIDS model implies that, although parameters representing dynamic effects are statistically significant, the dynamic specification results in relatively similar price and scale flexibilities.

Our 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. An important distinction occurs for lard and tallow, which exhibits a very elastic scale response. This suggests that increasing the scale of consumption of all fats and oils will result in significant decreases in consumers' marginal valuation of lard and tallow.

Our research effort was hampered to some extent by nondisclosure of consumption data for minor oils. Future research will consider quarterly data to attempt to address this limitation. In addition, greater attention to dynamic demand relationships and persistence in consumption may be warranted.

Table 1. Variable Definitions and Summary Statistics

Variable	Definition	Mean	Std. Dev.
q_{butter}	Monthly butter consumption (lb./capita)	0.3272	0.0573
$q_{coconut}$	Monthly coconut oil consumption (lb./capita)	0.0771	0.0298
q_{corn}	Monthly corn oil consumption (lb./capita)	0.2640	0.0819
$q_{cottonseed}$	Monthly cottonseed oil consumption (lb./capita)	0.2094	0.0496
$q_{soybean}$	Monthly soybean oil consumption (lb./capita)	3.5975	0.2852
q_{animal}	Monthly lard and tallow consumption (lb./capita)	0.3039	0.1011
p_{butter}	Butter Price (cents/lb.)	121.7956	33.5521
$p_{coconut}$	Coconut oil price (cents/lb.)	31.1489	10.7563
p_{corn}	Corn oil price (cents/lb.)	24.7622	3.8894
$p_{cottonseed}$	Cottonseed oil price (cents/lb.)	24.2333	5.2313
$p_{soybean}$	Soybean oil price (cents/lb.)	22.7400	4.7439
p_{lard}	Lard price (cents/lb.)	17.2826	3.6999
p_{tallow}	Tallow price (cents/lb.)	15.5252	3.4810
w_{butter}	Budget share for butter	0.2526	0.0710
$w_{coconut}$	Budget share for coconut oil	0.0151	0.0067
w_{corn}	Budget share for corn oil	0.0407	0.0145
$w_{cottonseed}$	Budget share for cottonseed oil	0.0323	0.0078
$w_{soybean}$	Budget share for soybean oil	0.5260	0.0663
w_{animal}	Budget share for lard and tallow	0.0307	0.0079

Table 2. Standard and Switching Inverse AIDS Demand Systems:

Parameter Estimates and Summary Statistics[a]

Parameter	Full Sample	Regime I	Regime II
γ_{11}	0.1645	0.2001	0.1110
	(0.0126)*	(0.0125)*	(0.0221)*
γ_{12}	−0.0043	−0.0051	−0.0010
	(0.0010)*	(0.0011)*	(0.0019)
γ_{13}	−0.0097	−0.0133	−0.0050
	(0.0018)*	(0.0019)*	(0.0032)
γ_{14}	−0.0097	−0.0122	−0.0032
	(0.0012)*	(0.0013)*	(0.0023)
γ_{15}	−0.1415	−0.1553	−0.1105
	(0.0118)*	(0.0126)*	(0.0225)*
γ_{22}	0.0140	0.0179	0.0101
	(0.0008)*	(0.0012)*	(0.0011)*
γ_{23}	−0.0016	−0.0003	−0.0002
	(0.0008)*	(0.0012)	(0.0011)
γ_{24}	−0.0006	−0.0032	0.0019
	(0.0007)	(0.0010)*	(0.0010)
γ_{25}	−0.0064	−0.0058	−0.0098
	(0.0017)*	(0.0024)*	(0.0036)*
γ_{33}	0.0392	0.0528	0.0245
	(0.0018)*	(0.0024)*	(0.0022)*
γ_{34}	−0.0030	−0.0064	−0.0035
	(0.0010)*	(0.0013)*	(0.0013)*
γ_{35}	−0.0202	−0.0263	−0.0098
	(0.0030)*	(0.0038)*	(0.0053)
γ_{44}	0.0303	0.0352	0.0229
	(0.0013)*	(0.0016)*	(0.0022)*
γ_{45}	−0.0117	−0.0068	−0.0156
	(0.0021)*	(0.0028)*	(0.0050)*
γ_{55}	0.1889	0.2050	0.1722
	(0.0147)*	(0.0170)*	(0.0306)*

[a]Subscripts correspond to $(i = 1)$ butter, $(i = 2)$ coconut oil, $(i = 3)$ corn oil, $(i = 4)$ cottonseed oil, $(i = 5)$ soybean oil, and $(i = 6)$ lard and tallow. Numbers in parentheses are standard errors. An asterisk indicates statistical significance at the $\alpha=.05$ or smaller level.

Table 2. (continued)

Parameter	Full Sample	Regime I	Regime II
α_1	0.2614	0.2890	0.1740
	$(0.0068)^*$	$(0.0066)^*$	$(0.0158)^*$
α_2	0.0156	0.0159	0.0156
	$(0.0006)^*$	$(0.0007)^*$	$(0.0017)^*$
α_3	0.0445	0.0435	0.0381
	$(0.0010)^*$	$(0.0012)^*$	$(0.0026)^*$
α_4	0.0322	0.0318	0.0331
	$(0.0007)^*$	$(0.0008)^*$	$(0.0021)^*$
α_5	0.5190	0.5025	0.5900
	$(0.0065)^*$	$(0.0071)^*$	$(0.0166)^*$
β_1	0.0543	0.0231	0.0473
	$(0.0274)^*$	(0.0286)	(0.0422)
β_2	0.0007	0.0016	-0.0005
	(0.0022)	(0.0026)	(0.0038)
β_3	-0.0013	-0.0008	0.0023
	(0.0041)	(0.0043)	(0.0063)
β_4	0.0038	0.0084	0.0001
	(0.0027)	$(0.0030)^*$	(0.0044)
β_5	0.0597	0.0745	0.0658
	$(0.0264)^*$	$(0.0296)^*$	(0.0435)
ρ	0.8964	0.9159	
	$(0.0173)^*$	$(0.0165)^*$	
μ		138.3416	
		$(2.5500)^*$	
σ		8.2105	
		$(2.8533)^*$	
R^2_{Butter}	0.8751	0.9141	
$R^2_{Coconut}$	0.9128	0.9247	
R^2_{Corn}	0.9346	0.9551	
$R^2_{Cottonseed}$	0.9045	0.9238	
$R^2_{Soybean}$	0.8715	0.8958	

[a]Subscripts correspond to $(i = 1)$ butter, $(i = 2)$ coconut oil, $(i = 3)$ corn oil, $(i = 4)$ cottonseed oil, $(i = 5)$ soybean oil, and $(i = 6)$ lard and tallow. Numbers in parentheses are standard errors. An asterisk indicates statistical significance at the $\alpha = .05$ or smaller level.

Table 3. Price and Scale Flexibilities

Normalized Price	Quantity						Scale
	Butter	Coconut	Corn	Cottonseed	Soybean	Animal	
................................Full Sample................................							
Butter	−0.2946	−0.0137	−0.0295	−0.0313	−0.4470	0.0091	−0.7849
	(0.0428)*	(0.0043)*	(0.0093)*	(0.0065)*	(0.0926)*	(0.0187)	(0.1154)*
Coconut	−0.2713	−0.0723	−0.1043	−0.0362	−0.3988	−0.0738	−0.9517
	(0.0536)*	(0.0519)	(0.0529)*	(0.0461)	(0.1592)*	(0.0762)	(0.1472)*
Corn	−0.2458	−0.0399	−0.0372	−0.0735	−0.5134	−0.1193	−1.0324
	(0.0380)*	(0.0199)*	(0.0395)	(0.0240)*	(0.1072)*	(0.0484)*	(0.0999)*
Cottonseed	−0.2701	−0.0159	−0.0866	−0.0582	−0.2999	−0.1639	−0.8825
	(0.0311)*	(0.0214)	(0.0295)*	(0.0393)	(0.0892)*	(0.0409)*	(0.0841)*
Soybean	−0.2403	−0.0105	−0.0338	−0.0185	−0.5811	−0.0139	−0.8865
	(0.0182)*	(0.0034)*	(0.0062)*	(0.0045)*	(0.0485)*	(0.0131)	(0.0543)*
Animal	−0.9427	−0.0944	−0.3116	−0.2989	−2.3035	−0.4701	−4.8123
	(0.0922)*	(0.0382)*	(0.0663)*	(0.0465)*	(0.3800)*	(0.1748)*	(0.3922)*
................................Regime I................................							
Butter	−0.1850	−0.0189	−0.0491	−0.0455	−0.5667	−0.0528	−0.9087
	(0.0387)*	(0.0049)*	(0.0094)*	(0.0069)*	(0.0970)*	(0.0194)*	(0.1122)*
Coconut	−0.3139	0.1860	−0.0132	−0.2071	−0.3329	−0.2258	−0.8962
	(0.0603)*	(0.0764)*	(0.0765)	(0.0585)*	(0.2014)	(0.1064)*	(0.1723)*
Corn	−0.3327	−0.0067	0.2971	−0.1589	−0.6568	−0.1593	−1.0193
	(0.0377)*	(0.0284)	(0.0576)*	(0.0329)*	(0.1239)*	(0.0622)*	(0.1034)*
Cottonseed	−0.3139	−0.0944	−0.1891	0.0999	−0.0755	−0.1946	−0.7410
	(0.0318)*	(0.0271)*	(0.0410)*	(0.0503)*	(0.1142)	(0.0549)*	(0.0933)*
Soybean	−0.2595	−0.0090	−0.0443	−0.0084	−0.5358	−0.0160	−0.8584
	(0.0187)*	(0.0044)*	(0.0077)*	(0.0058)	(0.0536)*	(0.0157)	(0.0559)*
Animal	−1.3339	−0.1646	−0.3512	−0.3246	−2.1732	0.2332	−4.4702
	(0.1284)*	(0.0533)*	(0.0842)*	(0.0605)*	(0.3889)*	(0.2360)	(0.3579)*
................................Regime II................................							
Butter	−0.5133	−0.0010	−0.0122	−0.0064	−0.3390	0.0399	−0.8130
	(0.0860)*	(0.0082)	(0.0147)	(0.0116)	(0.1377)*	(0.0329)	(0.1670)*
Coconut	−0.0739	−0.3278	−0.0145	0.1265	−0.6715	−0.0710	−1.0359
	(0.1316)	(0.0721)*	(0.0730)	(0.0687)	(0.2760)*	(0.1438)	(0.2503)*
Corn	−0.1092	−0.0040	−0.3963	−0.0834	−0.2111	−0.1459	−0.9441
	(0.0786)	(0.0275)	(0.0534)*	(0.0330)*	(0.1643)	(0.0795)	(0.1535)*
Cottonseed	−0.0968	0.0597	−0.1073	−0.2910	−0.4824	−0.0796	−0.9972
	(0.0759)	(0.0320)	(0.0415)*	(0.0672)*	(0.1836)*	(0.0824)	(0.1367)*
Soybean	−0.1785	−0.0168	−0.0135	−0.0257	−0.6069	−0.0464	−0.8750
	(0.0420)*	(0.0067)*	(0.0105)	(0.0102)*	(0.0799)*	(0.0272)	(0.0837)*
Animal	−0.6628	−0.0906	−0.3472	−0.2042	−2.8239	−0.2227	−4.7345
	(0.2640)*	(0.0715)	(0.1065)*	(0.0910)*	(0.5878)*	(0.3475)	(0.5459)*

[a]Numbers in parentheses are standard errors. An asterisk indicates statistical significance at the α=.05 or smaller level.

Table 4. Dynamic Inverse AIDS Demand System:

Parameter Estimates and Summary Statistics[a]

Parameter	Estimate	Parameter	Estimate
γ_{11}	0.1265	γ_{45}	-0.0132
	(0.0151)*		(0.0033)*
γ_{12}	-0.0010	γ_{55}	0.1770
	(0.0007)		(0.0232)*
γ_{13}	-0.0072	θ_{11}	0.0175
	(0.0021)*		(0.0165)
γ_{14}	-0.0091	θ_{12}	0.0004
	(0.0016)*		(0.0008)
γ_{15}	-0.1150	θ_{13}	-0.0006
	(0.0157)*		(0.0023)
γ_{22}	0.0114	θ_{14}	-0.0028
	(0.0005)*		(0.0016)
γ_{23}	0.0000	θ_{11}	-0.0163
	(0.0007)		(0.0169)
γ_{24}	0.0006	θ_{22}	0.0011
	(0.0007)		(0.0005)*
γ_{25}	-0.0079	θ_{23}	0.0001
	(0.0016)*		(0.0006)
γ_{33}	0.0378	θ_{24}	0.0004
	(0.0023)*		(0.0007)
γ_{34}	-0.0042	θ_{25}	-0.0009
	(0.0014)*		(0.0011)
γ_{35}	-0.0215	θ_{33}	0.0070
	(0.0041)*		(0.0021)*
γ_{44}	0.0302	θ_{34}	-0.0024
	(0.0019)*		(0.0013)

[a]Subscripts correspond to ($i = 1$) butter, ($i = 2$) coconut oil, ($i = 3$) corn oil, ($i = 4$) cottonseed oil, ($i = 5$) soybean oil, and ($i = 6$) lard and tallow. Numbers in parentheses are standard errors. An asterisk indicates statistical significance at the α=.05 or smaller level.

Table 4. (continued)[a]

Parameter	Estimate	Parameter	Estimate
θ_{35}	-0.0001	δ_4	-0.1854
	(0.0031)		(0.1281)
θ_{44}	0.0040	δ_5	0.0857
	$(0.0018)^*$		(0.0609)
θ_{45}	0.0033	β_1	0.0640
	(0.0023)		(0.0336)
θ_{55}	0.0131	ν_1	0.0549
	(0.0208)		(0.0322)
α_1	0.2140	β_2	-0.0027
	$(0.0088)^*$		(0.0017)
α_2	0.0118	ν_2	-0.0014
	$(0.0004)^*$		(0.0017)
α_3	0.0474	β_3	0.0041
	$(0.0013)^*$		(0.0050)
α_4	0.0332	ν_3	-0.0015
	$(0.0009)^*$		(0.0050)
α_5	0.5563	β_4	0.0101
	$(0.0090)^*$		$(0.0036)^*$
δ_1	-0.0411	ν_4	0.0036
	(0.0395)		(0.0035)
δ_2	0.0262	β_5	0.0525
	(0.0352)		(0.0357)
δ_3	0.0881	ν_5	-0.0477
	(0.0461)		(0.0354)
δ_4	0.0283	ρ	0.8984
	(0.0560)		$(0.0231)^*$

R^2_{Butter}	0.8374
$R^2_{Coconut}$	0.9179
R^2_{Corn}	0.9629
$R^2_{Cottonseed}$	0.9356
$R^2_{Soybean}$	0.8050

[a]Subscripts correspond to $(i = 1)$ butter, $(i = 2)$ coconut oil, $(i = 3)$ corn oil, $(i = 4)$ cottonseed oil, $(i = 5)$ soybean oil, and $(i = 6)$ lard and tallow. Numbers in parentheses are standard errors. An asterisk indicates statistical significance at the $\alpha=.05$ or smaller level.

Table 5. Price and Scale Flexibilities for Dynamic Inverse AIDS Model

Normalized Price	Quantity						Scale
	Butter	Coconut	Corn	Cottonseed	Soybean	Animal	
Butter	−0.3705	−0.0012	−0.0207	−0.0313	−0.3562	0.0345	−0.7140
	(0.0617)*	(0.0037)	(0.0115)	(0.0090)*	(0.1294)*	(0.0287)	(0.1507)*
Coconut	−0.1367	−0.0541	−0.0103	0.0391	−0.7808	−0.2597	−1.2275
	(0.0538)*	(0.0447)	(0.0580)	(0.0577)	(0.1744)*	(0.0762)*	(0.1408)*
Corn	−0.1554	0.0009	−0.0664	−0.0988	−0.4729	−0.1172	−0.8986
	(0.0470)*	(0.0174)	(0.0557)	(0.0341)*	(0.1450)*	(0.0648)	(0.1227)*
Cottonseed	−0.2100	0.0209	−0.1148	−0.0645	−0.2335	−0.1235	−0.6915
	(0.0434)*	(0.0214)	(0.0418)*	(0.0595)	(0.1388)	(0.0583)*	(0.1094)*
Soybean	−0.1868	−0.0131	−0.0350	−0.0207	−0.6275	−0.0324	−0.9051
	(0.0252)*	(0.0028)*	(0.0077)*	(0.0063)*	(0.0663)*	(0.0212)	(0.0644)*
Animal	−0.8096	−0.1637	−0.3599	−0.3027	−3.2185	−0.2103	−5.5675
	(0.1995)*	(0.0333)*	(0.0966)*	(0.0728)*	(0.6395)*	(0.3161)	(0.5655)*

[a]Numbers in parentheses are standard errors. An asterisk indicates statistical significance at the $\alpha=.05$ or smaller level.
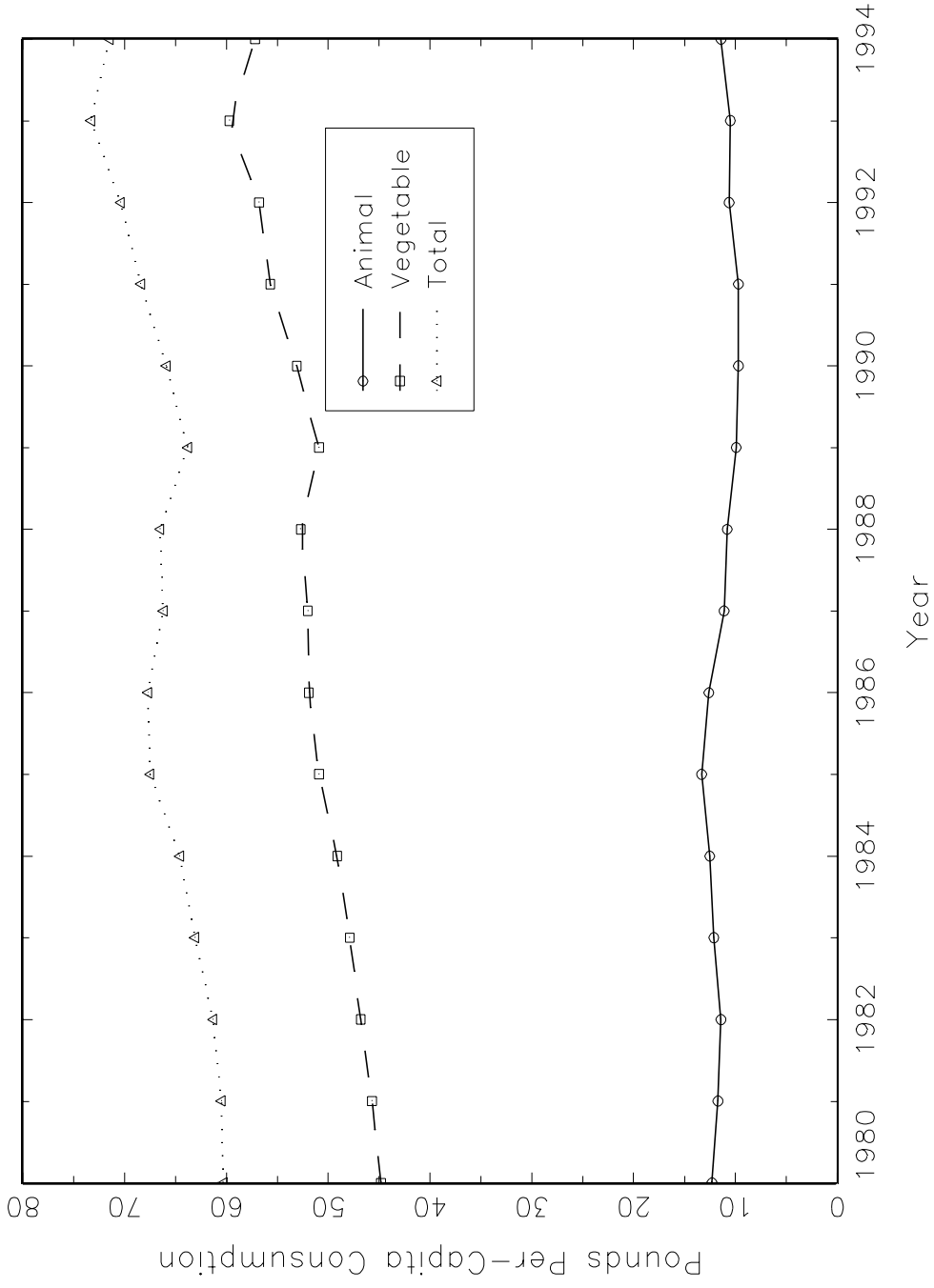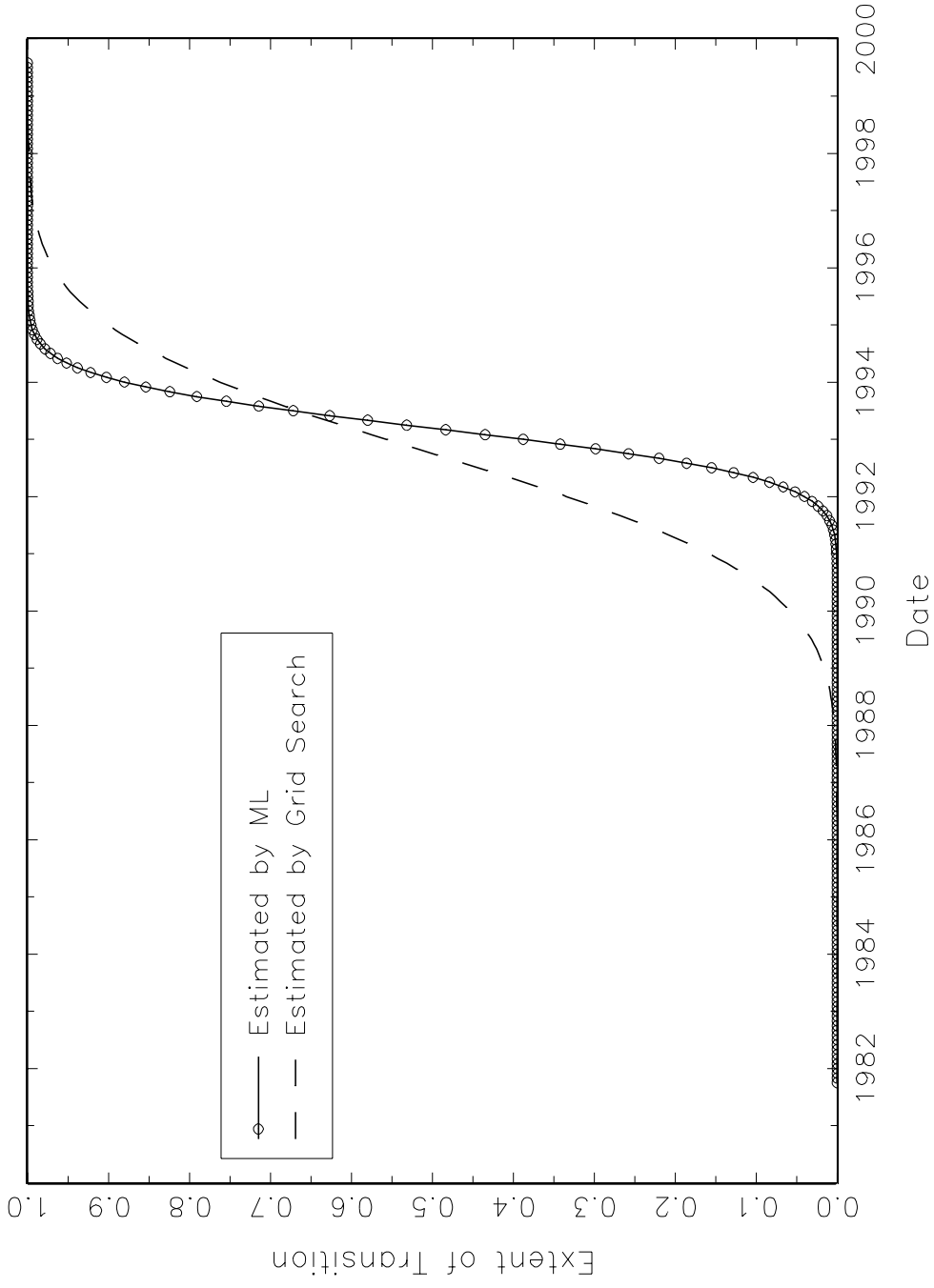
Figure 1: Consumption of Fats and Oils: 1981-1999

Figure 2: Timing and Speed of Transition Between Regimes

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