Have Milk Fat Preferences Shifted? Structural Analysis of New York Milk Consumption

Takeshi Ueda and Darren L. Frechette

Consumption of lowfat and skim milk has increased substantially over the past decade. This study investigates whether the change is due to price and expenditure effects or to a more fundamental preference change in milk demand. Parametric and nonparametric analytical approaches provide a comprehensive analysis of structural change in milk consumption in New York State. A nonparametric approach first finds evidence of structural change. A parametric likelihood-ratio test then confirms the existence of structural change using a Kalman filter specification. The value of this technical analysis of milk preferences is its implication for labeling initiatives. Milk fat labels have allowed consumers to act on a new set of preferences, thereby improving consumer welfare.

Key Words: demand system, Kalman filter, milk demand, revealed preference, structural change

Fluid milk consumption patterns have changed considerably in recent decades. According to the U.S. Department of Agriculture (USDA), two major trends are indicated at a national level from 1970 through 1999. First, annual per capita total fluid milk consumption, not including flavored milk products, decreased by 24%, from 255 to 194 pounds. Second, whole milk's share of fluid milk consumption declined from 83% to 36%. The share of lowfat (1% and 2% milk fat) and skim milk increased from 17% to 64%. In particular, per capita consumption of skim milk rose significantly in the late 1980s and throughout the 1990s.

A similar trend away from whole milk consumption was also witnessed in New York State in the 1990s. Figure 1 displays monthly milk consumption ratios and relative prices in New York State from 1991 through 1998. The figure illustrates two facts: (*a*) lowfat and skim milk consumption both increased relative to whole milk consumption, and (*b*) relative price changes among the three products were small throughout the period.

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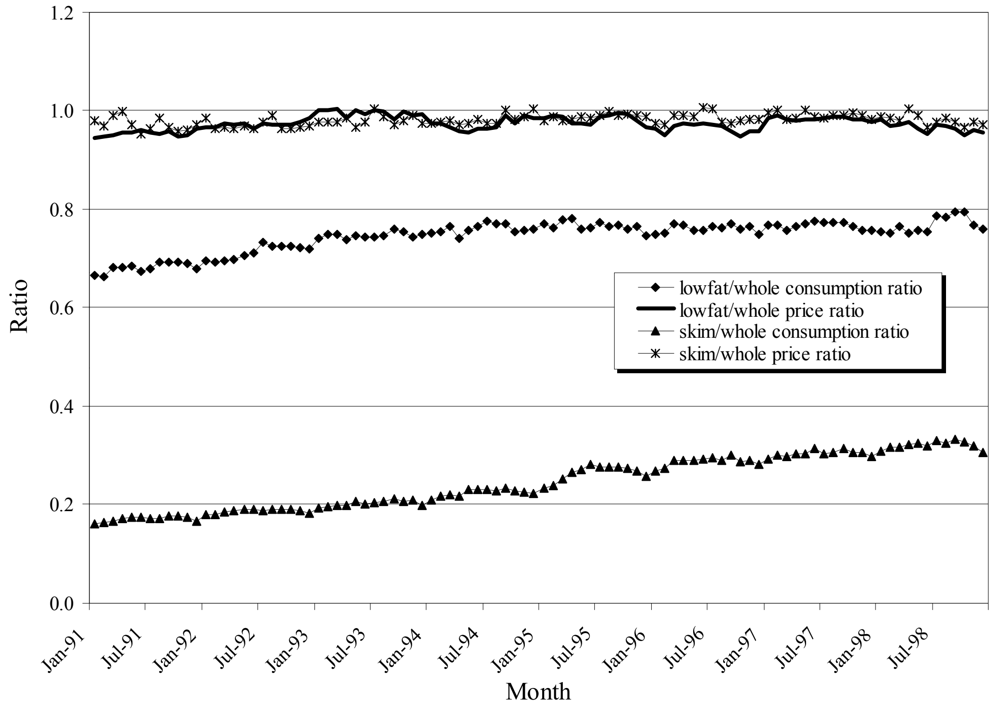
Figure 2 shows skim milk consumption increased relative to lowfat milk consumption over the 1991–1998 period. As observed from figures 1 and 2, more lowfat and skim milk and less whole milk were consumed in New York State throughout the period, but the changes do not appear to have been driven by relative prices.

The observed trend away from whole milk consumption has motivated scholars to perform structural studies of demand for fluid milk products. One type of study focuses on the effect of specific factors on the quantity and kinds of fluid milk products consumed using household data (e.g., Cornick, Cox, and Gould, 1994; Huang and Raunikar, 1983; Jensen, 1995; Raunikar and Huang, 1984).

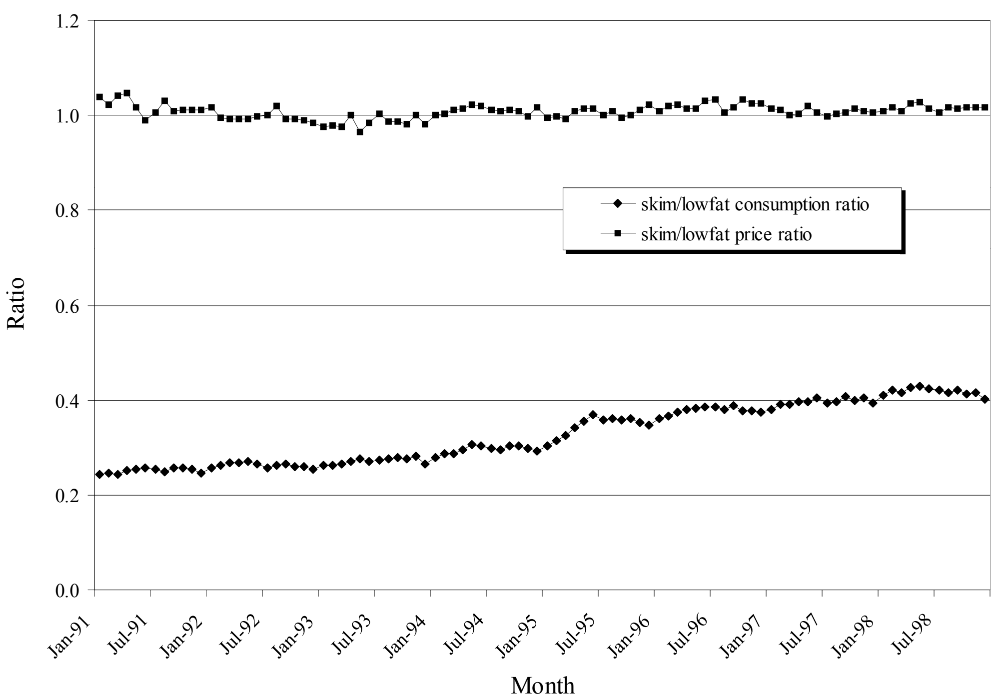
Another type of study is structural analysis using a demand system approach (e.g., Gould, 1996; Gould, Cox, and Perali, 1990). These analyses have identified various demand shifters related to consumption of fluid milk products: (*a*) increased public concern about cholesterol and animal fats, (*b*) demographic change, (*c*) change in substitute prices, (*d*) increased income, and (*e*) increased education.

Another well-explored direction of study examines the effect of advertising on milk sales (Kaiser et al., 1994; Kaiser and Reberte, 1996; Kinnucan, 1986; Lenz, Kaiser, and Chung, 1998; Vande Kamp and Kaiser, 2000). While most of the studies report



Source: New York State Department of Agriculture and Markets

Figure 1. Comparison of whole milk with lowfat and skim milk consumption: New York State, 1991–1998



Source: New York State Department of Agriculture and Markets

Figure 2. Comparison of skim milk with lowfat milk consumption: New York State, 1991–1998

effects of advertising on milk demand without considering fat content, Kaiser and Reberte (1996) focus on the milk demand structure by investigating differences in advertising effects on whole, lowfat, and skim milk demands. They conclude the effects were not statistically different.

In this paper, we investigate whether there is statistically measurable evidence of recent structural change in New York State fluid milk demands employing a demand system approach, and if so, what is the character of the change. The character of such a structural change would be important by itself, but a result confirming structural change would also indicate milk fat labels are effective.

Milk fat labels aim to improve consumer welfare by giving consumers a choice, by helping consumers to actualize their preferences. The labels themselves likely have not caused a structural change, but without labels consumers could not differentiate among milk products and could not form clear preferences in the first place. Labels can have multiple objectives, but this study is concerned only with their role in product differentiation. A lack of statistical evidence in favor of structural change may indicate there has been no measurable structural change in milk demand during the 1990s, or may suggest the labels are ineffective.

The methodological contribution of this paper is a structural analysis implementing both nonparametric and parametric analytical approaches. In both approaches, milk products are assumed to constitute a weakly separable group.[1] The nonparametric approach includes a revealed preference test (Chalfant and Alston, 1988; Varian, 1982) and a rank-sum test (Frechette and Jin, 2001) based on the revealed preference test results. The parametric analysis is performed to confirm the nonparametric results and attempt to characterize the nature of structural change, if it is found.

A nonnested model selection criterion developed by Barten (1993) is used to select the best model among four demand systems, which include the Rotterdam model and the almost ideal demand system (AIDS) model. The selected system is then reestimated with a Kalman filter specification, which allows parameters to vary with time, and compared with its fixed-parameter specification to identify structural change.

Nonparametric Approach

The nonparametric approach examines whether preferences are stable, i.e., whether consumption data are consistent with utility maximization by a representative consumer. The advantage of nonparametric approaches is that specification of functional forms is not an issue. We test the following null hypothesis: A set of preferences is stable and the variation in consumption can be explained fully by changes in relative prices or incomes. Rejection of the null hypothesis implies there is evidence of structural change in preferences.

The nonparametric approach is based on revealed preference theory (Houthakker, 1950; Samuelson, 1938; Varian, 1982, 1983). A revealed preference test for structural change in consumer demand was developed by Varian (1982) to examine whether demand is consistent with utility maximization. The axioms of revealed preference are the foundations of the test. If consumers who can afford the same two bundles of goods at different times are not consistent in their preferences between the bundles at all times, then there is evidence of structural change. Chalfant and Alston (1988) employ both the weak and strong axioms of revealed preference to investigate structural changes in meat consumption in the United States and in Canada.

Despite their generality, revealed preference tests have three drawbacks. Thurman (1987) and Varian (1982) contend the tests may have low power. For example, when budget lines fail to cross, there is little chance of finding observations inconsistent with the axioms, and therefore there can be little evidence of changes in preferences. For most goods, there has been steady growth in real expenditure, so budget lines in different time periods rarely cross.

A second drawback is that the tests do not provide any information about the nature of stable preferences, how to identify the functional form and elasticities of demand, or whether results from estimation will be plausible (Alston and Chalfant, 1991).

Finally, most revealed preference tests are restricted to deterministic demand systems or demand systems with linear shocks that do not affect the

[1] Separability has been well studied, especially in the 1960s and 70s (e.g., Goldman and Uzawa, 1964; Jorgenson and Lau, 1975). In structural demand analyses, weak separability is often assumed without being tested. However, this rather strong assumption ideally should be tested since incorrect grouping, such as ignoring substitute products, can cause misspecification of functional form and bias in estimation results. Eales and Unnevehr (1988), for example, tested separability in meat demand structural analysis. Separability was assumed and not tested in the present study because no reliable data were available to us for potential substitute goods at a comparable level of disaggregation to the monthly, state-level milk data used in this study.

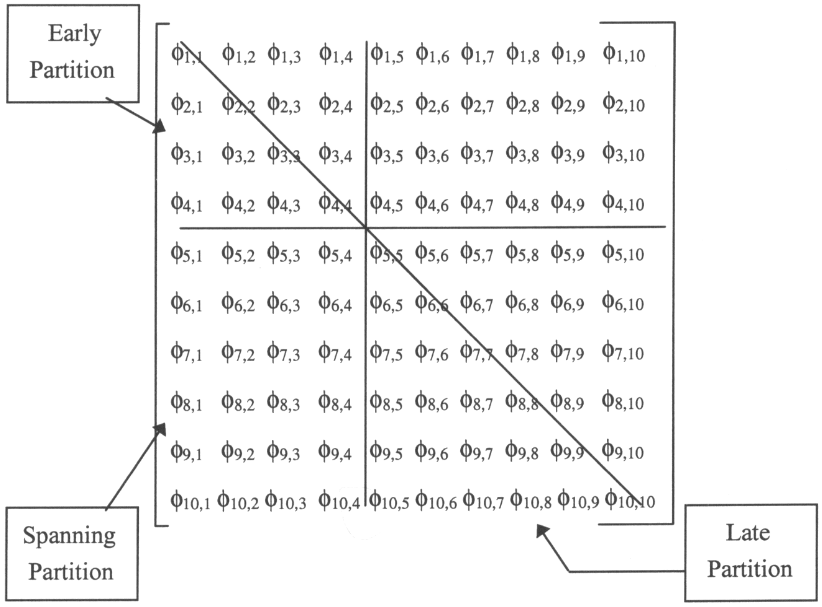


Figure 3. Illustration of matrix partitions (T = 10, τ = 5)

marginal rate of substitution between goods. Hence, fads, seasonality, and other transitory nonlinear shocks affecting preferences from period to period can result in a violation of the axioms of revealed preference, even in the absence of permanent structural change.

The Frechette and Jin Method

To address the third drawback, Frechette and Jin (2001) developed a method to distinguish between nonlinear shocks and permanent structural change. The first stage utilizes Varian's (1982) weak axiom of revealed preference (WARP) test to test the null hypothesis that observed data conform to utility maximization. The underlying assumptions are: (*a*) the goods constitute a weakly separable group; (*b*) there exists a well-behaved utility function which is nonsatiated, continuous, monotonic, and concave; and (*c*) shocks to the utility function are linear so they do not affect the marginal rates of substitution between any two goods.

Implementation of the WARP test is facilitated by constructing a matrix **Φ** (see figure 3). Suppose the number of observations is T, and a bundle of goods demanded and their prices are represented by vectors $\mathbf{q}_t$ and $\mathbf{p}_t$ at time t. The matrix **Φ** will be $\{T \times T\}$ with elements $\varphi_{st} = p_s' q_t / p_s' q_s$. The scalar φ_{st} represents the affordability of bundle $\mathbf{q}_t$ at time s, with φ_{st} less than or equal to one if $\mathbf{q}_t$ is affordable at time s, and φ_{st} greater than one if not. Each element φ_{st} below the diagonal is compared with its counterpart, φ_{ts}, above the diagonal. If both are less than one, a violation of the WARP is noted, indicating a preference reversal.

A preference reversal occurs when the consumer chooses a bundle of goods $\mathbf{q}_t$ over another bundle $\mathbf{q}_s$ at time t and chooses $\mathbf{q}_s$ over $\mathbf{q}_t$ at time s, even though both bundles are affordable at both times. If no preference reversal appears, then stable preferences cannot be rejected, and no further test is indicated. Otherwise, an additional step examines whether preference reversal occurred due to permanent structural change. The null hypothesis is that a transitory nonlinear shock caused the violation of WARP. The alternative is a permanent structural change.

The test is initiated by dividing the below-diagonal portion of the matrix **Φ** into three partitions based on a potential breakpoint, τ (figure 3). The upper left triangle represents an "early" partition including elements φ_{st} such that s and t are periods before the breakpoint ($s, t < \tau$). The lower right triangle represents a "late" partition including elements φ_{st} such that s and t are periods after the breakpoint ($s, t \geq \tau$). The portion remaining, the rectangle below the early partition, represents a "spanning" partition including elements φ_{st} from before and after the breakpoint ($t < \tau \leq s$).

Then the number of violations within each partition is calculated. For example, if the matrix $\mathbf{\Phi}$ is $\{10 \times 10\}$, it has 45 elements below the diagonal. If τ is 5, there are 6 possible violations in the early partition, 15 in the late partition, and 24 in the spanning partition, for a total of 45 possible violations (see figure 3 for an illustration). If preferences are fixed over the sample, the unconditional probability of observing violations is the same in each partition. If preferences shift permanently at some time τ, then the probabilities of observing violations in each partition may differ due to structural change.

In order to determine whether the probability of observing a violation differs from partition to partition, a Kruskal-Wallis test is performed. The Kruskal-Wallis test extends the concept of a rank-sum test to a comparison of more than two populations (Ott, 1988). In the test, violations in the three partitions are regarded as draws from three distinct distributions. The null hypothesis of the test is that the three distributions are identical.

The Kruskal-Wallis test statistic is written as:

$$K = \frac{12}{N(N+1)} \sum_i \frac{\theta_i^2}{N_i} - 3(N+1),$$

with

$$\theta_i = n_i\left(N - \frac{n-1}{2}\right) + (N_i - n_i)\,\frac{N-n+1}{2} = \frac{n_i N + N_i(N-n+1)}{2},$$

where n_i is the number of violations out of a possible N_i comparisons in partition i, where $i \in$ {early, spanning, late}; N is the total number of comparisons in all partitions and n is the total number of violations; and θ_i is the average rank sum for partition i. When there are a large number of ties in the ranks, as was found in this analysis, the adjusted Kruskal-Wallis statistic is used (Ott, 1988):

$$W = \frac{N^2 - 1}{3n(N-n)} K.$$

Under the null hypothesis, W has an asymptotic Chi-squared distribution with two degrees of freedom. W can be calculated at each possible breakpoint τ and a profile plotted. The test statistic becomes larger as the differences among the three distributions increase. As τ approaches the most likely breakpoint, the test statistic reaches its maximum (W^*). A permanent structural change is indicated if the null hypothesis is rejected for any τ.

The standard $\chi^2_{[2]}$ (Chi-squared with 2 degrees of freedom) critical value cannot be used for the hypothesis testing since W^* is a maximum statistic of W. For example, if $N = 100$, there are 97 different W statistics on the profile graph. If each of them were independent and identically distributed $\chi^2_{[2]}$ random variables, then the probability that $W^* < 5.99$ (the 95% critical value of $\chi^2_{[2]}$) would be $(0.95)^{97} = 0.0069$, meaning 99.31% of the time $W^* > 5.99$. The appropriate critical value is Z, where $[\text{prob}(W > Z)]^{N-3} = 0.95$ or 0.99. For $N = 100$, these critical values are $Z = 15.09$ or 18.34.

Data

Monthly data on prices and sales for New York fluid milk are used. The data were obtained from the New York State Department of Agriculture and Markets, partly from various issues of that Department's *New York State Dairy Statistics, Annual Summary* and partly from information supplied through personal contacts with the Department's staff.[2] Price data are available for whole, skim, 2%, and 1% milk.[3] Prices are retail, adjusted by the CPI, and cover the period from 1991 to 1998 (a total of 96 observations). Prices of lowfat milk are computed by taking a simple average of the prices of 1% and 2% milk since it was infeasible to compute quantity-weighted average prices without separate sales data for 1% and 2% milk.

Sales data are available for whole, skim, and lowfat (1% and 2% combined) milk. The data are for sales in New York State by New York plants, not sales in New York by all plants, because data for sales by all plants are not available monthly.[4] Quantities demanded are computed by converting pounds sold into gallons sold using conversion rates provided by the Division of Dairy Industry Services and Producer Security in the New York State Department of Agriculture and Markets, since

[2] Thanks go to Charles Huff of the New York State Department of Agriculture and Markets for promptly providing the data.

[3] Prices for half gallons and gallons are available for whole milk and 2% milk, but only prices of half gallons are available for 1% milk and skim milk. Prices used here are per gallon, so prices of 1% and skim milk are extrapolated from those of half gallons using a conversion ratio computed from whole milk and 2% milk prices.

[4] The data are observed monthly and aggregated over households in New York. Alternative specifications use household-level data aggregated over longer periods of time. From 1991 to 1998, sales by New York plants in New York State comprised approximately 70% to 80% of total sales in New York State. The use of this proxy should not bias the results because sales shares of whole, lowfat, and skim milk in New York State by New York plants reflect total sales shares in New York State fairly well in annual data.

Table 1. Nonparametric Approach: Results of the Weak Axiom of Revealed Preference (WARP) Tests

Number of Times $\varphi_{st} < 1$		
Above Diagonal ($t > s$)	Below Diagonal ($s > t$)	No. of Violations of WARP
1,565 of 4,560 (34.32%)	3,020 of 4,560 (66.23%)	26 (0.57%)

prices are indicated in dollars per gallon and sales are indicated in pounds. Expenditure shares for each product are derived by dividing expenditure for the product by total expenditure for all kinds of fluid milk.

Nonparametric Approach: Results and Interpretation

The results of the WARP test indicate preference reversals. In table 1, the first and second columns indicate how many different bundles q_t are affordable at a set of fixed prices p_s, and at how many different sets of prices p_t a bundle q_s is affordable. The third column is based on the results of the first and second columns. Out of 4,560 cases, 26 violations are confirmed, implying a 0.57% violation rate.[5] Further testing is needed to identify whether the violations are due to permanent structural change.

The adjusted Kruskal-Wallis statistic is computed and plotted in figure 4. The statistics are larger than 15.00 (the 95% critical value) from September 1992 to February 1997. In particular, the statistics from March 1993 to October 1996 are consecutively above 18.26 (the 99% critical value), and reach a maximum in December 1994.

Based on the adjusted Kruskal-Wallis test, the violation probability differs between pairs of partitions (early-late, early-spanning, or late-spanning), which implies the violations are caused by a permanent structural change. The test results also suggest the most probable structural breakpoint occurred around December 1994. More likely, the structural change was gradual throughout the period, and December 1994 is just a convenient mid-point. Gradual structural change is modeled using a Kalman filter as part of a parametric specification.

Parametric Approach

Analyses of structural change have commonly made use of parametric empirical analysis. A common procedure is to specify and estimate a system of demand equations defined over prices and quantities and then to examine stability of the parameters using a Chow test, dummy variables, and time-varying parameters. The legitimacy of these approaches depends on the fundamental assumptions that the demands comprise a weakly separable system and are a function of prices and expenditures only. The prices of other commodities are only relevant insofar as they determine the expenditure on the commodities of interest (Varian, 1992). The parametric approach, in general, pinpoints factors of structural change and measures their significance. However, all parametric test results are conditional on the functional form chosen, and so model selection is a key issue.

Considerable demand research, including the demand for dairy products, has made use of various functional forms in parametric structural analyses. Gould, Cox, and Perali (1990) incorporate demographic variables into the AIDS model to examine the impacts of changes in the demographic structure of the United States on fluid milk demand. In addition, they include juices, other beverages, and other food in the demand system. They conclude that whole milk and lowfat milk (skim, 1%, 2%) are substitutes for each other and that lowfat milk (skim, 1%, 2%) and fruit juices are substitutes.

Another analysis on fluid milk demand conducted by Gould (1996) found demands for whole milk, 2% milk, 1% milk, and skim milk combined are all substitutes for one another. Gould's findings also show demographic characteristics significantly affect U.S. milk demand.

Employing U.S. household food consumption survey data from 1948 and 1984, Heien and Wessells (1988) estimate the AIDS model to analyze the structure of dairy product demand, in which fluid milk is identified as a single commodity. They classify demand shifters into economic and demographic effects and perform a decomposition of the causes of demand changes over time. Based on their results, Heien and Wessells conclude demographic effects are significant and argue that very little taste change has occurred in dairy product demand.

[5] The percentage of violations of WARP varies across studies. For instance, Frechette and Jin (2001) found 1,093 violations out of 60,031 (1.82%) with Korean cereal data and then conducted the adjusted Kruskal-Wallis test. Jensen and Bevins (1991) found one to five violations out of 190 (0.52% to 2.63%) with U.S. data on butter, margarine, and salad and cooking oils, and concluded they needed further tests to establish whether or not structural change occurred.

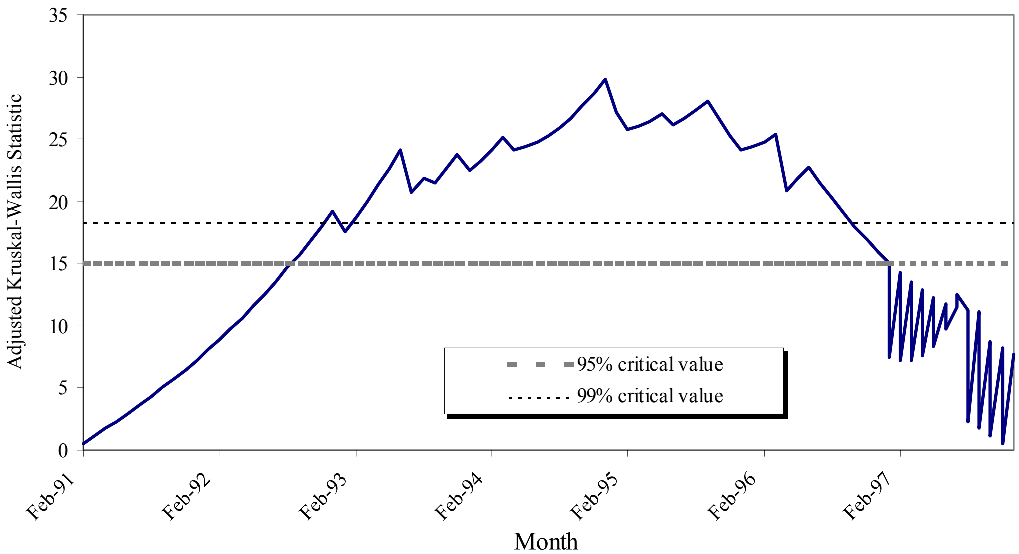


Figure 4. Adjusted Kruskal-Wallis statistics

In addition to dairy products, parametric analyses of demand structure have been extensively conducted on meat demand and provide a good reference point for further demand structure analysis. The literature includes investigations by Alston and Chalfant (1993); Choi and Sosin (1990); Eales and Unnevehr (1988, 1993); Kinnucan et al. (1997); and Thurman (1987).

Some analysts attempt to address the issue of misspecification of functional forms. Eales and Unnevehr (1993) demonstrate the inappropriateness of quantity-dependent specifications for the U.S. meat demand system and develop the inverse of the AIDS model (IAIDS). Alston and Chalfant (1993) devise pairwise tests for choosing between the Rotterdam model and the AIDS model.

Apart from meat demand studies, Barten (1993) develops a nonnested model selection criterion which enables one to compare four models (AIDS, Rotterdam, and hybrids of the AIDS and Rotterdam—the CBS and NBR models[6]). Lee, Brown, and Seale (1994) apply the method devised by Barten to a Taiwanese consumption study.

Barten's Nonnested Model Selection Criterion

Barten's (1993) model selection criterion rests upon a general model which nests models of four different functional forms. To take advantage of its generality, Barten's system is used here and can be expressed as:

$$(1)\quad w_i d\ln(q_i) = (d_i + \delta_1 w_i) d\ln(Q) + \sum_j [e_{ij} - \delta_2 w_i(\delta_{ij} - w_i)] d\ln(p_j), \quad i = 1, 2, 3,$$

where $d_i = \delta_1\beta_i + (1 - \delta_1)\theta_i$, $e_{ij} = \delta_2\gamma_{ij} + (1 - \delta_2)\pi_{ij}$, and $d\ln(Q) = \Sigma_i w_i d\ln(q_i)$. The index $\{i = 1, 2, 3\}$ represents whole, lowfat (1% and 2%), and skim milk. The variables w_i, q_i, and p_i denote, respectively, an expenditure share, a demand quantity, and a price of the ith commodity. The data for the nonparametric analysis are employed again in the parametric analysis.[7] The general model becomes the Rotterdam model when $\delta_1 = \delta_2 = 0$, the CBS model when $\delta_1 = 1$ and $\delta_2 = 0$, the AIDS model when $\delta_1 = 1$ and $\delta_2 = 1$, and the NBR model when $\delta_1 = 0$ and $\delta_2 = 1$.

The demand restrictions placed on the system are as follows:

[6] The CBS and NBR models are named after the Netherlands Central Bureau of Statistics and the National Bureau of Research, respectively.

[7] A demand system such as the AIDS or Rotterdam model conventionally requires only prices, consumption, and expenditure shares as explanatory variables, with some exceptions [e.g., Gould, Cox, and Perali (1990) incorporated demographic variables into a demand system of equations]. We used only prices, consumption, and expenditure shares since demographics (in terms of age and race) during the sample period do not show substantial changes. For instance, the under-18 age group has been steady at 23%. The only noticeable change is observed for the nonwhite group, which rose slightly from 32% to 35%. It is possible the nonwhite shift could have some effect in the long run, but the variation is too small to affect parameter estimates within the sample period.

(2) $\sum_i d_i = 1 - \delta_1$ and $\sum_i e_{ij} = 0$ (adding-up),

(3) $\sum_j e_{ij} = 0$ (homogeneity),

and

(4) $e_{ij} = e_{ji}$ (symmetry).

Barten's model selection criterion is a pairwise comparison between the general model and each of the four specific models using a likelihood-ratio test.

The Kalman Filter Specification

Applied parametric analysis has been performed widely with the fixed-parameter regression model. If parameters actually vary from time to time, how can models with fixed parameters capture gradual change? The Kalman filter specification is capable of accommodating gradual changes; hence, it can avoid misidentification of structural change caused by temporary fluctuations of coefficients.

In an application of the Kalman filter specification to structural analysis, Chavas (1983) investigates structural change in U.S. meat demand. The specification is based on the consideration that demand elasticities may vary over time. Tegene (1990) employs the Kalman filter specification for structural analysis of beverage demand in the United States.

In this study, the specification used by Chavas (1983) is employed for its tractability. The observation (or measurement) equation is specified as:

(5) $\mathbf{y}_t = \mathbf{x}_t \boldsymbol{\beta}_t + \mathbf{u}_t, \quad t = 1, \ldots, T,$

where $\mathbf{y}_t$ is a $\{T \times 1\}$ vector of observations on T dependent variables, $\mathbf{x}_t$ is a $\{T \times k\}$ matrix of T observations of k independent variables, $\boldsymbol{\beta}_t$ is a $\{k \times 1\}$ column vector of parameters, and $\mathbf{u}_t$ is a $\{T \times 1\}$ random vector, serially uncorrelated and distributed with mean zero and time-invariant covariance matrix $\boldsymbol{\sigma}$.

The parameter $\boldsymbol{\beta}_t$ is assumed to be generated by the process:

(6) $\boldsymbol{\beta}_t = \boldsymbol{\beta}_{t-1} + \mathbf{v}_t,$

where $\mathbf{v}_t$ is a $\{k \times 1\}$ column vector of serially uncorrelated disturbance terms with mean zero and covariance matrix $\boldsymbol{\Omega}_t$ (process noise), and is assumed to be uncorrelated with $\mathbf{u}_t$. This specification implies the parameters are allowed to follow a random walk.

Equation (6) is known as the state (or transition) equation. Equations (5) and (6) specify state space models for the Kalman filter. A brief description of the recursive Kalman filter algorithm to be used is provided in the appendix [see Meinhold and Singpurwalla (1983) for an approachable treatment with more detail].

In the Kalman filter specification described above, the process noise ($\boldsymbol{\Omega}_t$) is the key element for identification of structural change. In the absence of noise, $\boldsymbol{\Omega}_t = 0$ and the model is the classical fixed-coefficient model. On the other hand, a random coefficient model is obtained if process noise exists ($\boldsymbol{\Omega}_t \neq 0$). The model without the process noise can be interpreted as a restricted model, and the model with the process noise is an unrestricted model.

Identification of structural change is achieved by a likelihood-ratio test between the restricted model and its unrestricted counterpart. This approach differs from that of Chavas (1983) who assumed the process noise variance at time t ($\boldsymbol{\Omega}_t$) is proportional to the variance of the parameter estimate at time $t - 1$ (Σ_{t-1}), and then examined whether the ratio of the standard deviation of the process noise to the standard deviation of the parameter estimate is zero, which implies no structural change.

Using our approach, the null and alternative hypotheses are $\boldsymbol{\Omega}_t = 0$ and $\boldsymbol{\Omega}_t \neq 0$. Rejection of the null hypothesis indicates a structural change. If the null hypothesis cannot be rejected, the Kalman filter results are asymptotically equivalent to least-squares estimates (Chavas, 1983).

In this situation, the parameters are constant over time, and there is no structural change. The likelihood-ratio test statistic is distributed asymptotically as $\chi^2(k(k+1)/2)$, where k is the number of parameters.

Parametric Approach: Results and Interpretation

Each of the four alternative models is estimated with the seemingly unrelated regression (SUR) technique using all 96 observations. We applied Barten's criterion to the fixed-parameter model to identify the "best" model, as shown in table 2.[8] The AIDS model is the only one that cannot be rejected. Hence, the AIDS model is selected for the following structural analysis.

[8] Convergence was not achieved in the estimation of the general model with the Kalman filter due to the very large number of parameters to be estimated.

Table 2. Parametric Approach: Results of Likelihood-Ratio Test for Model Selection

Model	Log-Likelihood Value	Likelihood-Ratio Test Statistic
General	1,453.855	—
Rotterdam	1,347.305	213.100
CBS	1,435.245	37.221
AIDS	1,439.589	28.533
NBR	1,356.397	194.917

Note: The critical values at the 95% confidence interval are 21.026 for Rotterdam and CBS, and 32.671 for AIDS and NBR.

The AIDS model employing the Kalman filter specification is estimated and compared with its fixed-parameter SUR counterpart. For the estimation with the Kalman filter specification, the first 23 observations are used to obtain priors for the estimation, leaving 73 additional observations. The likelihood-ratio statistic (481.98) is larger than the 95% critical value (267.45), indicating a rejection of the fixed-parameter specification. The test provides evidence of structural change in fluid milk consumption, consistent with the results from the nonparametric analysis.

Table 3 shows estimation results for price and expenditure elasticities for whole, lowfat, and skim milk demands. All the expenditure elasticities are statistically significant; expenditure elasticities for lowfat and skim milk demands are positive, while those for whole milk demand are negative. The signs are consistent with findings reported by Cornick, Cox, and Gould (1994), and by Rauniker and Huang (1984). An increase in expenditure on fluid milk causes an increase in demands for lowfat and skim milk, but reduces demand for whole milk, ceteris paribus.

Regarding own-price elasticity estimates, whole and lowfat milk demands have negative signs with high standard errors. The estimates show that whole milk demand is more price elastic than lowfat milk demand. Therefore, consumers of whole milk are affected more by its own price change than are consumers of lowfat milk. Skim milk demand shows substantially positive own-price elasticity estimates with high standard errors. The insignificant estimates of own-price elasticities likely resulted from collinearity of the milk prices. A plot of the elasticity estimates revealed random movement with an upward trend. Although the average is positive, 27% of the 73 own-price elasticities computed using the Kalman filter are negative for skim milk.

One way to interpret the prevalence of positive skim milk own-price elasticities is that a significant structural change occurred in skim milk demand during the estimation period, or it could be the AIDS model with the Kalman filter was not able to provide statistically significant estimates. It is possible the results could be changed by inclusion of potential substitutes to skim milk (such as fruit juice and soft drinks), or by allowing the coefficient of $\beta_{t!1}$ in the state equation (6) to be estimated rather than fixing it equal to one.

On the other hand, skim milk demand may be just inelastic enough not to be affected by an increase of its own price in an economically significant way. Most likely, the high standard error and the relatively large negative cross-price elasticity with respect to lowfat milk indicate simply that collinear data caused imprecision in the estimates.

Table 4 displays estimated demand elasticities before and after the structural breakpoint suggested by the nonparametric analysis (December 1994) and the statistical significance of the difference. In terms of expenditure elasticity, the changes in whole and lowfat milk demands are statistically significant at the 1% level, and the change in skim milk is also significant, but at the 5% level. All the demands became less sensitive to expenditure changes after December 1994. The negative sign of the whole milk expenditure elasticity and positive signs of lowfat and skim milk expenditure elasticities are consistent with findings reported by Cornick, Cox, and Gould (1994), and by Rauniker and Huang (1984).

Some changes in price elasticities are also statistically significant. The change in own-price elasticity of whole milk demand is significant at the 1% level. Whole milk demand became more elastic with respect to its own price. The changes in both whole milk price elasticity of lowfat milk demand and lowfat milk price elasticity of skim milk demand are significant at the 5% level. Lowfat milk demand became less elastic with respect to whole milk price. Skim milk demand became more elastic with respect to lowfat milk price.

Tables 3 and 4 make it clear the estimated elasticities are somewhat imprecise, and in some cases own-price elasticity estimates are positive. For comparison, the fixed parameter SUR estimates are displayed in table 5. Cases 1 and 2 show the results obtained without differencing the data. Differencing is required because the data are nonstationary; therefore, cases 3 and 4 show the results obtained after differencing. Note that the standard errors are

Table 3. Demand Elasticity Estimates

		Price Elasticity			
Milk Product	Summary Statistic	Whole	Lowfat	Skim	Expenditure Elasticity
Whole	Mean	!0.562	!0.556	0.064	!0.013
	Maximum	0.505	0.484	1.426	!0.008
	Minimum	!1.974	!1.248	!1.541	!0.020
	Standard Deviation	0.445	0.302	0.562	0.003
	Standard Error	0.625	0.378	0.378	0.001
Lowfat	Mean	!0.714	!0.218	0.003	0.043
	Maximum	2.070	2.410	2.799	0.052
	Minimum	!3.105	!2.103	!2.390	0.031
	Standard Deviation	0.966	0.664	1.025	0.005
	Standard Error	1.330	1.074	0.679	0.001
Skim	Mean	0.211	!2.941	1.435	0.053
	Maximum	9.443	9.448	8.372	0.122
	Minimum	!6.227	!16.337	!4.386	0.016
	Standard Deviation	2.592	3.343	2.619	0.030
	Standard Error	2.075	1.718	1.190	0.001

Notes: Mean, maximum, minimum, and standard deviation are for the elasticities computed using observations from November 1992 to December 1998. Standard errors are for the mean values of the elasticity estimates.

Table 4. Means of Demand Elasticity Estimates Before and After Structural Change

	Price Elasticity			
Milk Product	Whole	Lowfat	Skim	Expenditure Elasticity
Before the structural change (November 1992−December 1994):				
Whole	!0.340	!0.610	!0.097	!0.016
Lowfat	!1.036	!0.094	0.290	0.047
Skim	0.162	!1.819	0.937	0.069
After the structural change (January 1995−December 1998):				
Whole	!0.685	!0.526	0.154	!0.011
Lowfat	!0.536	!0.287	!0.155	0.041
Skim	0.238	!3.562	1.711	0.044
***t*-statistics for the null hypothesis that the elasticities did not change:**				
Whole	3.025***	!1.160	!1.751	!11.057***
Lowfat	!1.979**	1.110	1.688	7.822***
Skim	!0.108	2.286**	!1.349	2.932**

Note: ** and *** denote statistical significance at the 5% and 1% levels, respectively.

biased toward zero for the raw data, compared to the differenced data. The important comparison to make among the tables is that the own-price elasticity estimates are mostly positive using the fixed parameter model with the differenced data, compared to the Kalman filter estimates, the signs of which are more in line with theory. The complete set of parameter estimates using the Kalman filter is available upon request from the authors. In any case, the elasticity estimates themselves are of only indirect importance to the findings of structural change.

Table 5. SUR Fixed Parameter Estimates

	Price Elasticity			
Milk Product	Whole	Lowfat	Skim	Expenditure Elasticity
CASE 1: Demand Elasticity Estimates with Level Data without Restrictions				
Whole	!1.154	!0.467	!0.858	0.935
	(0.361)	(0.359)	(0.064)	(0.060)
Lowfat	0.451	!2.113	!0.987	0.953
	(0.293)	(0.301)	(0.044)	(0.034)
Skim	0.548	!2.300	!1.017	0.963
	(0.325)	(0.319)	(0.046)	(0.031)
CASE 2: Demand Elasticity Estimates with Level Data with Restrictions Imposed				
Whole	!3.834	!0.017	0.081	1.078
	(0.361)	(0.359)	(0.064)	(0.060)
Lowfat	1.788	!2.113	!2.240	0.953
	(0.293)	(0.301)	(0.044)	(0.034)
Skim	0.652	!2.300	!1.017	0.963
	(0.325)	(0.319)	(0.046)	(0.031)
CASE 3: Demand Elasticity Estimates with Differenced Data without Restrictions				
Whole	0.002	!1.510	0.381	0.987
	(0.054)	(1.257)	(0.041)	(0.004)
Lowfat	!0.764	1.179	!0.590	1.072
	(3.962)	(3.334)	(2.304)	(0.006)
Skim	!0.187	!0.682	1.322	0.959
	(1.018)	(1.092)	(0.757)	(0.708)
CASE 4: Demand Elasticity Estimates with Differenced Data with Restrictions Imposed				
Whole	!1.834	!0.543	0.865	2.999
	(0.054)	(1.257)	(0.041)	(0.004)
Lowfat	!0.638	1.179	1.294	1.072
	(3.962)	(3.334)	(2.304)	(0.006)
Skim	0.266	!0.682	1.322	0.959
	(1.018)	(1.092)	(0.757)	(0.708)

Notes: Standard errors are reported in parentheses. Restrictions are adding-up, homogeneity, and symmetry.

Conclusions and Implications

Both nonparametric and parametric analytical methods succeeded in disentangling price and expenditure effects from the effects of structural change. Primarily, these results indicate there was an economically meaningful and statistically measurable structural change in fluid milk demand in New York State between 1991 and 1998. Both methods rely upon statistical tests of the null hypothesis that the structure did not change, and the null hypothesis was rejected at the 5% level of significance in each case.

Aggregation and collinearity of prices caused imprecision in the elasticity estimates, which may raise questions about the robustness of the results. However, both parametric and nonparametric methods confirm the occurrence of a structural change, and that consumers were still actualizing a change in preferences long after lowfat and skim milk were introduced into the market.

No single demand parameter can be identified to summarize the nature of the structural change. Notably, all demands became more expenditure inelastic, and whole milk demand became more own-price elastic. On the other hand, the exact nature of the structural change may not be identifiable using the approach taken here. It appears there was not one single parametric shift, but rather a more subtle change in structure that was difficult to characterize. The parametric and nonparametric approaches are well suited for identifying structural change, but they may not be the most well suited for characterizing its nature.

Instead, other a priori knowledge about milk consumption may elucidate the matter more easily. Skim and lowfat milk consumption have increased relative to whole milk, even as their relative prices have been steady. Clearly, the structural change has resulted in a shift toward lowfat and skim milk consumption, whatever its effect on the parametric model. Future work might concentrate on developing a new approach to characterize this change more precisely.

Other natural extensions for future research would be to include potential substitutes for fluid milk products and to incorporate demographic variables and an indicator representing consumers' knowledge about the relationship between fat intake and health. Increasing the number of observations could lead to the identification of long-term patterns in fluid milk consumption. The difficulty of such an approach is that it may require incorporating additional explanatory variables into every parameter estimate, which may reduce the degrees of freedom considerably as the number of parameters increases two-, three-, or four-fold in a model already plagued by high standard errors.

One implication of the structural change result reported here is that further health education, information, and advertising may trigger increased structural change in fluid milk consumption. On one hand, consumers who are more informed about fat content are better able to make choices among milk products. On the other hand, consumers could not act upon new information without labels which effectively differentiate milk products.

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Appendix: A Brief Description of the Recursive Kalman Filter Algorithm

The Kalman filter is a tool to estimate equations with stochastic coefficients. Suppose that $\mathbf{b}_{t-1}$ is an estimate of β_{t-1} based on the first $t-1$ observations, and $\mathbf{\Sigma}_{t-1}$ is the covariance matrix of $\mathbf{b}_{t-1}$. The prior estimate of $\boldsymbol{\beta}_t$ is

$$\text{(A1)}\quad \mathbf{b}_{t|t-1} = \mathbf{b}_{t-1}$$

and the prior covariance of $\mathbf{b}_t$ is

$$\text{(A2)}\quad \mathbf{\Sigma}_{t|t-1} = \mathbf{\Sigma}_{t-1} + \mathbf{\Omega}_t.$$

When a new observation for time t becomes available, the Kalman filter provides the updating equation. The following is the posterior estimate of $\boldsymbol{\beta}_t$:

$$\text{(A3)}\quad \mathbf{b}_t = \mathbf{b}_{t|t-1} + \mathbf{G}_t[\mathbf{y}_t - \mathbf{x}_t\mathbf{b}_{t|t-1}],$$

with the posterior covariance matrix of $\mathbf{b}_t$ specified as

$$\text{(A4)}\quad \mathbf{\Sigma}_t = \mathbf{\Sigma}_{t|t-1} - \mathbf{G}_t\mathbf{x}_t\mathbf{\Sigma}_{t|t-1},$$

where $\mathbf{G}_t = \mathbf{\Sigma}_{t|t-1}\mathbf{x}_t'[\mathbf{x}_t\mathbf{\Sigma}_{t|t-1}\mathbf{x}_t' + \boldsymbol{\sigma}]^{-1}$, known as the gain of the filter.