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A STUDY OF STRUCTURAL CHANGE:
THE DEMAND FOR MEAT

by

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Abstract: A Kalman filter specification is proposed to handle parameter variations in a study of structural change. The method is applied to the U.S. demand for meat in the 1970's. One of the result is that the income elasticity of demand for beef appears to have decreased sharply during the last few years.

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I - Introduction

Economists have long been suspicious that shocks in the economy lead to sometimes permanent changes in supply-demand relationships. The source of such structural change may be technological progress, a shift in consumer preferences or any institutional change. Alternatively, this structural change may also be associated with econometric modeling. Indeed, exclusion of relevant variables, functional form specification, the use of proxy variables, poor data quality or aggregation problems are some of the factors which imply that econometric models are misspecified. One way to handle this problem in linear models is to allow the parameters to vary. This approach has become an attractive way to deal with structural change problems in econometrics. Indeed, econometricians have extended the classical fixed-parameter model by allowing systematic parameter variations and/or assuming that the parameters are random (Singh, et al.). Recently, Rausser et al. have argued in favor of a Kalman filter specification to study structural change. In particular, they have shown that basically all known cases of parameter changes in a linear model are a special case of the Kalman filter specification. Furthermore, the equivalence between Kalman filtering techniques, generalized least squares (Sant) and Bayesian estimation (Sarris) gives added flexibility to the approach.

Although numerous examples of structural change exist, a recent case appears to concern the demand for meat in the late 1970's. Indeed, such structural change has been suspected for several reasons. First, the recent concern of consumers about cholesterol may have had a profound impact on consumer preferences toward meat. Second, a change in beef grading in the mid-1970's may have had some influence on beef demand (Purcell and Nelson). Finally, large fluctuations in the prices for meat in the 1970's could have altered the economic relationships among alternative sources of animal proteins for consumers. These elements suggest that important changes in meat demand may have occured in the 1970's. In such a case, there is a need to investigate this structural change. First, it would be useful to be able to identify when did the changes occured. Second, there is a need to update the estimates of demand elasticities in attempt to describe what happened. Appropriate econometric methods can help analyze this structural change.

The objective of this paper is to develop a method for the investigation of structural change. This is presented in the context of a linear model. The methodological approach is based on the Kalman filter, as discussed in section II. In order to estimate the variance of the random coefficients, use is made of the one step ahead prediction error of the model as proposed by Akaike. This procedure gives a practical way of updating econometric models that are subject to structural change. The method is illustrated in section III, in the context of meat demand in the 1970's. Finally, concluding remarks are presented in section IV.

II - The Model

Consider the linear model

$$Y_t = X_t \beta_t + e_t \quad (1)$$

where Y_t is a (nxl) vector of observations on n dependent variables, X_t is a (nxk) matrix of n observations on k predetermined variables, β_t is a (kxl) vector of parameters, and t denotes the t^{th} time period. The term e_t is a (nxl) random vector, serially uncorrelated, and distributed with mean zero and covariance matrix $E(e_t e_t') = \sigma$. The vector of parameters β_t is assumed to be generated by the difference equation

$$\beta_t = \phi_t \beta_{t-1} + Z_t \delta_t + u_t \quad (2)$$

where ϕ_t is a (kxk) matrix, Z_t is a (kxm) matrix of observations on m non-stochastic variables, and δ_t is a (mxl) vector. The process noise u_t is a (kxl) random vector, serially uncorrelated, independent of e_t, and distributed with mean zero and covariance matrix $E(u_t u_t') = \Omega_t$. For $\Omega_t \neq 0$, the parameter vector is random. Similarly, for $\phi_t \neq I$ or $\delta_t \neq 0$, we have the case of systematic parameter variation. Thus, as argued by Rausser et.al., the specification (2) is very general and appears suitable for the investigation of changes in structural parameters. Indeed, the parameters ϕ_t, δ_t and the covariance Ω_t may be assumed to change for each time period. Although such assumptions increase the complexity of the model, they give great flexibility for the analysis of structural change. In particular, they can handle the case where parameters change during certain periods but are constant during other periods. This approach has been common in the engineering literature (e.g. Sage and Melsa), where ϕ_t, δ_t and Ω_t are typically assumed known, as engineers often have strong a priori information on such parameters.

If we let b_t be the estimate of β_t using observations through t, and Σ_t the covariance matrix of b_t, the Kalman filter gives the following sequential estimate of β_t in the model (1) and (2) (Sage and Melsa)

$$b_t = b_{t|t-1} + G_t \left[Y_t - X_t \, b_{t|t-1}\right] \tag{3}$$

with covariance matrix

$$\Sigma_t = \Sigma_{t|t-1} - G_t \, X_t \, \Sigma_{t|t-1} \tag{4}$$

where $G_t = \Sigma_{t|t-1} \; X_t' \left[X_t \, \Sigma_{t|t-1} \, X_t' + \sigma\right]^{-1}$ is the gain of the filter, $b_{t|t-1} = \phi_t \, b_{t-1} + Z_t \, \delta_t$ is the prior estimate of β_t, and $\Sigma_{t|t-1} = \phi_t \, \Sigma_{t-1} \, \phi_t' + \Omega_t$ is the prior covariance of b_t. Thus, the posterior estimate of β_t given in (3) is simply the prior estimate $b_{t|t-1}$, plus the prediction error $(Y_t - X_t \, b_{t|t-1})$ weighted by the gain of the filter G_t. Similarly, the posterior variance Σ_t in (4) is the prior variance $\Sigma_{t|t-1}$ minus the positive semi-definite matrix $G_t \, X_t \, \Sigma_{t|t-1}$. If the parameters involved in (2) are known, then the estimate (3) gives the minimum variance unbiased estimate of β_t. Note that given the recursivity of (3) and (4), it requires that some initial estimates $b_\circ$ and $\Sigma_\circ$ are available.

One problem that arises in econometrics is that economists have in general little prior information on the parameters ϕ_t, δ_t and Ω_t. In order to simplify the estimation, these parameters are often assumed to be time-invariant (e.g. Singh et al.; Sant). For example, when $\Omega_t = 0$ (no process noise) and $\phi_t = I$, then the specification (1) and (2) becomes a classical linear model with interaction effects between the variables X_t and Z_t. To illustrate, if the vector Z_t takes the value 1 for the t^{th} period and zero otherwise, then we have a model where dummy variables allow the parameter to take new values starting at time t. Because it can be easily implemented in empirical work, this approach has been very common in the investigation of structural change. However, it requires that the model builder knows when and how structural change occurs, information which may not always be available in economic models.

An alternative approach is to assume that $\phi_t = I$ and $\delta_t = o$ (Sant). It implies from (2) that the parameters follow a random walk model, i.e. that structural change cannot be predicted ahead of time. In this case, the magnitude of the change at time t is measured by the magnitude of Ω_t. The problem is then to estimate the covariance matrix Ω_t. Here, we propose an estimation method based on prediction error. Indeed, expression (3) gives the best linear unbiased estimation of β_t, conditional on the variance Ω_t. Since the correct value of Ω_t is expected to help improve the model prediction, we propose to choose Ω_t such that the prediction error at time t is minimized in some sense. In order to make the estimation tractable, the variance of the process noise at time t is assumed to be proportional to the variance of the parameter estimates at time t - 1, i.e.

$$\Omega_t = (K \otimes I_k)\ \Sigma_{t-1}(K \otimes I_k) \tag{5}$$

where K is a (nxn) diagonal matrix with non-negative diagonal elements $K_1, \ldots, K_n$, and $\otimes$ is the Kronecker product. Thus, K measures the ratio of the standard deviation of the process noise to the standard deviation of the parameter estimates. For example, K = 0 implies no process noise ($\Omega_t = 0$) i.e. no change in the population parameters, while large values of K suggest important structural changes. In this case, the choice of Ω_t reduces to the choice of the K matrix. More specifically, we propose to choose the matrix K that minimizes the weighted error sum of squares of the prediction error one time period ahead during some time interval $\{t_0$ to $t_1\}$, defined as

$$\sum_{t=t_0}^{t_1} \left[(y_{t+1} - X_{t+1}\, b_t)'\ \sigma^{-1}\ (y_{t+1} - X_{t+1}\, b_t)\right] \tag{6}$$

Such use of prediction error in specification and estimation of econometric model appears attractive. For example, one-step ahead prediction error has been successfully used in the identification of time series models (Akaike). This approach has several advantages. First, it eliminates any possibility of divergence in the empirical use of the Kalman filter (Sage and Melsa, p. 412). Second, it provides a simple way to investigate the existence and/or magnitude of structural change during different periods. Third, it does not require that the model builder knows when or how the change occurs. This approach is further illustrated in the next section, where structural changes for U.S. meat demand in the 1970's are investigated.

III - Application to the Demand for Meat

Because Pope et. al. found that the linear and double-log specifications are frequently inadequate, the demand function selected for our analysis of U.S. meat consumption is specified as follows

$$\frac{\Delta Q_{it}}{Q_{i,t-1}} = \beta_{i0} + \sum_{j=1}^{N} \beta_{ij} \frac{\Delta P_{jt}}{P_{j,t-1}} + \delta_i \frac{\Delta I_t}{I_{t-1}} + e_{it} \tag{7}$$

where t denotes time, Q_i is the consumption of the i^{th} commodity, P_j is the price of the j^{th} commodity, I is consumer income, and $\Delta X_t = X_t - X_{t-1}$. Thus expression (7) expresses the percentage change in quantity consumed as a function of the percentage change in prices and income. The parameters β_{ij} $(j > 0)$ and δ_i then represent respectively the price elasticities and income elasticity of demand for the i^{th} commodity. This specification has the advantage of being linear in the parameters. Also, by including both the current and lag values of quantities, prices and income, it may be able to capture dynamic effects.

Assuming that the error term e_{it} is serially uncorrelated, and distributed with mean zero and covariance

$$E\,(e_{it}\,e_{jt'}) = \begin{cases} 0 \text{ for } t \neq t' \\ \sigma_{ij} \text{ for } t \neq t' \end{cases}$$

the demand functions (7) can then be estimated efficiently by seemingly unrelated regression (SUR). Furthermore, demand theory provides theoretical restrictions derived from the utility maximization hypothesis. These restrictions include homogeneity, symmetry and the Engel aggregation restriction (Phlips, p. 51). Only the first two restrictions are relevant in the investigation of meat demand since we are concerned only with a subset of the commodities involved in the budget constraint. The homogeneity of degree zero in prices and income of the demand functions can be expressed in terms of the demand elasticities as

$$\sum_{j=1}^{N} \beta_{ij} + \delta_i = 0 \tag{8}$$

where β_{ij} is the elasticity of the i^{th} commodity with respect to the j^{th} price and δ_i is the income elasticity of the i^{th} commodity. Similarly, the symmetry restriction of the Marshallian demand functions in elasticity form is

$$W_i(\beta_{ij} + W_j\ \delta_i) = W_j(\beta_{ji} + W_i\ \delta_j) \tag{9}$$

where $W_i = \dfrac{p_i x_i}{y}$ is the budget share of the i^{th} commodity. Such restrictions can be tested and/or imposed in the estimation of the model (Byron).

The data used to estimate the model consist in U.S. per-capita food consumption of poultry, beef and pork, as well as per-capita disposible income. Prices are nominal retail prices for poultry, beef and pork.

The following analysis proceeds in two steps. First, data-based prior information on the elasticities of demand for meat is obtained by estimating meat demand using data up to 1970. Second, this prior information is used to investigate structural change in meat demand in the 1970's.

Data-Based Prior Information (1970):

The model was estimated for three meat items (poultry, beef and pork) by Seemingly Unrelated Regression based on data from 1950 to 1970. The symmetry and homogeneity restrictions imposed at the 1970's level were tested. The test statistic, F with 6 and 48 degrees of freedom, was 2.1138 which implies acceptance of the theoretical restrictions at the 5 percent significance level. Imposing these restrictions, the restricted estimates for 1970 are presented in table 1.

Except for the income elasticity of poultry, all estimated elasticities are significantly different from zero. In general, they have the expected sign and magnitude and compare favorably with results of previous research (e.g. Pope et al., Brandow, George and King), which suggests that the model may give a reasonable approximation to the demand for meat. It provides prior information on the meat demand elasticities for 1970 that can now be used in the investigation of structural change during the last decade, through the use of the Kalman filter.

Structural Change in the 1970's:

The elasticity estimates and their variances obtained from the 1950-1970 period can be taken as the prior information $b_\circ$ and $\Sigma_\circ$ in the Kalman filter. Furthermore, assuming that the variance of the measurement error e_t is time-invariant, $\sigma = [\sigma_{ij}]$ can be unbiasedly estimated from the 1950-1970 period. Under such assumptions, the problem is then to determine the variance of the process noise Ω_t as discussed in Section II.

If the variance of the process noise vanishes ($\Omega_t = 0$), then, the parameters are assumed to be constant over time and there is no structural change. In such a case, the corresponding estimated demand elasticities for meat are presented in table 1 for the years 1970 through 1979. Note that, although the population parameters are assumed constant, the sample estimates may still vary. This is the case for the own price elasticity and the income elasticity of poultry that tend to decrease over time (in absolute value) (see table 1).

However, in the case of structural change, the process noise variance Ω_t is not zero and the parameters follow a random walk model. As discussed in section II, we propose to identify Ω_t by using as a criterion the one-step ahead forecast error (6) that is minimized by a numerical gradient method. In order to identify when a structural change could have occurred in meat demand, the proposed approach is applied to the 1970-74 period first, then to the 1975-79 period.

For the 1970-74 period, it was found that the one-step ahead forecast error (6) was minimized when $K = 0$ thus implying no structural change in meat demand in the first part of the decade ($\Omega_t=0$, t=1970 to 1974). This suggests that a classical model with fixed parameters would be appropriate to represent U.S. meat consumption in the early 1970's. It follows that the elasticities reported in table 1 from 1970 to 1974 are the best estimates of the economic relationships in meat demand during that period. Thus, although most elasticity estimates remain close to their 1970 level, the estimated income elasticity of poultry decreases from .17 in 1970 to .034 in 1974, while the own price elasticity of demand for poultry changes from -.761 to -.543 in the same period.

For the period 1975-79 period, the use of the one-step ahead forecast error criterion (6) discussed in section II gave different results. Indeed, the criterion was minimized for $K_1 = 4.06$, $K_2 = 1.48$ and $K_3 = 0$ for poultry, beef and pork respectively. This implies that random elements were introduced in the poultry and beef equations but not in the pork equation. In other words, important structural change was identified for poultry and beef demand in the late 1970's. This suggests that information available before 1975 may not be very useful in understanding the demand for poultry and beef in the 1980's. Using the variance of the process noise Ω_t corresponding to the above K, (from (5)) Kalman filter estimates of demand elasticities for the second part of the 1970's are presented in table 2. Compared to the estimates presented in table 1, these elasticities are characterized by a substantial improvement in forecasting error for all years but 1975. They also suggest how the structural change affects income and price elasticities of demand. This has important implications for the analysis and forecast of meat demand.

As may be expected, little change happens in the elasticities of demand for pork where no structural change was identified. However, substantial changes occur in the beef demand. The most important change appears to be the sharp decrease in the income elasticity of beef from .655 in 1975 to .183 in 1979. It is accompanied by an increase of the cross-price elasticity with respect to pork (from .137 to .355) as well as a change in the own-price elasticity (from -.870 to -.617) during the same period. This suggests that beef consumption has become more influenced by the pork market in the last few years. Also, the decrease in the beef own price elasticity indicates that the beef market may exhibit larger price variations as supply follows the cattle cycle. Finally, the decline in income elasticity suggests a possible decrease in the long term rate of growth of the U.S. beef industry.

Structural change in poultry demand is found to be associated with an increase in income elasticity from .012 in 1975 to .275 in 1979, and a decrease in the cross-price elasticity with respect to pork from .185 to .001 during the same period (table 2). Thus, poultry consumption appears to become less affected by the pork market. These results (particularly the rise in income elasticity) indicate that, given an improvement in consumer income, one may expect future long term growth in the poultry industry.

IV - Concluding Remarks

This paper has presented a method to investigate structural change in economic relationships in the context of a linear model. The approach is based on the minimization of a prediction error criterion. It provides a flexible way of dealing with structural change in the sense that structural change may occur in some periods but not others. The approach has also the attractive feature of Bayesian learning associated with the Kalman filter. It gives a practical way of updating the parameter estimates of econometric models that are subject to structural change while optimizing their forecasting power.

Application of the method to U.S. meat demand in the 1970's identified structural change occurring for beef and poultry (but not pork) in the last part of the decade. For example, the empirical results suggest that the income elasticity of beef has been sharply decreasing in the last few years, while the income elasticity of poultry has been increasing. This has important implications for the analysis and forecast of meat demand. For instance, it may help explain the decreasing share of beef expenditures in the consumer budget over the last few years. The above results illustrate the potential applications of the proposed method in econometric modeling under structural change.

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Table 1 - Estimates of Demand Elasticities for Meat (1970 - 1979) without structural change [a]

Elasticity of	Poultry				Beef				Pork				
with respect to	Poultry	Beef	Pork	Income	Poultry	Beef	Pork	Income	Poultry	Beef	Pork	Income	SSE_p [b]
1970	-.761 (.093)	.296 (.061)	.296 (.056)	.170 (.101)	.085 (.018)	-.916 (.077)	.225 (.054)	.606 (.104)	.082 (.016)	.217 (.051)	-.734 (.068)	.435 (.092)	
1971	-.759 (.093)	.297 (.061)	.287 (.052)	.175 (.100)	.085 (.018)	-.916 (.077)	.224 (.052)	.606 (.102)	.079 (.015)	.217 (.050)	-.727 (.063)	.431 (.087)	7.56
1972	-.738 (.093)	.280 (.060)	.254 (.050)	.203 (.099)	.081 (.018)	-.906 (.077)	.231 (.051)	.594 (.099)	.070 (.014)	.224 (.048)	-.733 (.061)	.439 (.083)	32.40
1973	-.562 (.058)	.232 (.058)	.277 (.049)	.053 (.066)	.065 (.017)	-.960 (.072)	.207 (.047)	.688 (.087)	.076 (.014)	.203 (.044)	-.685 (.053)	.405 (.071)	8.72
1974	-.543 (.058)	.230 (.058)	.278 (.049)	.034 (.065)	.064 (.017)	-.967 (.072)	.197 (.046)	.705 (.086)	.076 (.014)	.194 (.044)	-.697 (.053)	.427 (.070)	16.82
1975	-.545 (.058)	.258 (.055)	.258 (.048)	.029 (.065)	.072 (.016)	-.935 (.070)	.181 (.044)	.681 (.086)	.070 (.013)	.177 (.042)	-.718 (.050)	.471 (.069)	5.10
1976	-.554 (.057)	.256 (.055)	.255 (.047)	.044 (.064)	.072 (.016)	-.937 (.069)	.176 (.044)	.688 (.085)	.069 (.013)	.172 (.042)	-.727 (.050)	.485 (.068)	16.20
1977	-.538 (.057)	.241 (.055)	.230 (.046)	.066 (.062)	.068 (.016)	-.906 (.069)	.208 (.043)	.630 (.083)	.063 (.013)	.202 (.041)	-.706 (.048)	.441 (.066)	3.68
1978	-.536 (.057)	.235 (.052)	.231 (.046)	.069 (.060)	.066 (.015)	-.868 (.064)	.213 (.042)	.587 (.078)	.063 (.013)	.206 (.040)	-.704 (.048)	.434 (.064)	6.49
1979	-.537 (.057)	.259 (.048)	.223 (.045)	.055 (.059)	.074 (.014)	-.860 (.060)	.225 (.040)	.562 (.076)	.060 (.013)	.216 (.038)	-.714 (.047)	.438 (.063)	1.88

[a] Standard errors are in parentheses.

[b] SSE_p is the weighted error sum of squares of one-step ahead prediction error.

Table 2 - Estimates of Demand Elasticities for Meat Under Structural Change (1975-79)

Elasticity of	Poultry				Beef				Pork				
with respect to	Poultry	Beef	Pork	Income	Poultry	Beef	Pork	Income	Poultry	Beef	Pork	Income	SSE_p [a]
1975	-.551	.353	.185	.012	.079	-.870	.137	.655	.075	.186	-.723	.463	5.89
1976	-.696	.322	.116	.258	.077	-.889	.116	.696	.074	.180	-.732	.477	11.73
1977	-.449	.210	.037	.201	.077	-.683	.317	.288	.074	.194	-.709	.441	.830
1978	-.478	.210	.055	.213	.080	-.593	.323	.189	.075	.199	-.707	.433	4.81
1979	-.581	.296	.001	.275	.079	-.617	.355	.183	.076	.217	-.723	.429	1.30

[a] SSE_p is the weighted error sum of square of one-step ahead prediction error.