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Dynamics and Long-run Structure in U.S. Meat Demand

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Empirical analysis, based on a general dynamic Almost Ideal Demand System, shows the commonly used autoregressive and partial adjustment processes are restrictive to meat demand data. This study derives a linear specification in levels form to investigate dynamics in a general framework. Merging a long-run steady state structure with short-run dynamics results in consistent and robust long-run demand elasticities.

Une analyse empirique, basée sur un système dynamique général de demande quasi optimale, montre que les mécanismes courants d'ajustement autorégressif et d'ajustement partiel ont un effet restrictif sur l'évaluation des données de la demande de viande. Les auteurs proposent une spécification linéaire par niveaux pour examiner la dynamique du cadre général. La combinaison d'une structure stable de longue durée avec une dynamique de courte période a produit des élasticités cohérentes et solides de la demande à long terme.

INTRODUCTION

Economic studies of demand often show that consumers do not adjust instantaneously to changes in prices, income or other determinants of demand. Lagged values of certain variables cause changes in consumer behavior in the current period. Psychological causes of consumer inertia, which include habit formation or persistence, institutional factors such as inventory adjustments and intertemporally separate budgeting contribute to the observed lagged effects in consumers' decision making (see Brown 1952; Houthakker and Taylor 1970; Blundell 1988; Phlips 1983; Johnson, Hassan and Green 1984). Clearly, the assumption of instantaneous adjustment to change by consumers is very restrictive.

A standard procedure for incorporating dynamic processes is to assume an adjustment process, such as partial adjustment, with a focus only on the short-run dynamics. The long-run parameters are based on the ratio of short-run and adjustment coefficients. Since this ratio is derived from regression coefficients, a problem arises in calculating standard errors for the long-run coefficients (Bewley and Fiebig 1990). An alternative for identifying the "correct" model specification for demand is to develop a relatively general framework incorporating the alternative hypotheses related to dynamics and allowing for direct estimation of long-run coefficients (Anderson and Blundell 1983; Hendry, Pagan and Sargan 1984; Hendry and Richard 1982).

The purpose of this study is to evaluate dynamics and the long-run structure in U.S. meat demand within a general framework. The general dynamic demand framework is extended to the Almost Ideal Demand System (AIDS). This approach allows merging of the short-run dynamics and long-run steady-state structure much like the study by Anderson and Blundell (1982; 1983). In addition, the proposed model provides a convenient form and relatively straightforward way of investigating dynamics within a general framework.

The paper is organized as follows. First is a discussion of dynamic adjustments and the Almost Ideal Demand System. Next, an appropriate and convenient form of the long-run AIDS model is derived to estimate the meat demand parameters by using quarterly data. The general dynamic demand model is then estimated and tested against alternative forms of the partial adjustment process, autoregressive and static versions. The estimated total and group elasticities are discussed. Finally, the last section provides a discussion of some of the study's implications.

DYNAMIC ADJUSTMENTS AND THE ALMOST IDEAL DEMAND SYSTEM

Dynamic Adjustments to Static Models

Consider the linear approximate Almost Ideal Demand System (see Deaton and Muellbauer 1980):

$$W_t = \gamma_0 + \sum_{i=1}^{n} \gamma_i \log (p_{it}) + \beta \log (y_t / P_t^*) + u_t \qquad (1)$$

where

W = the vector of budget shares,
p = a vector of n commodity prices,
y = total expenditure, and
P^* = the Stone price index.

Typically, this static version is applied to data on hand and, as appropriate, the model is corrected for autocorrelation.[1]

To understand the implications of such a correction for first-order autocorrelation, substitute $u_t = \delta u_{t-1} + \epsilon_t$ in Eq. 1, noting that:

$$u_{t-1} = W_{t-1} - (\gamma_0 + \sum_{i=1}^{n} \gamma_i \log p_{it-1} + \beta \log (y_{t-1} / P_{t-1}^*))$$

Eq. 1 can be rewritten to account for first-order autocorrelation as:

$$W_t = \delta W_{t-1} + \gamma_0^* + \sum_{i=1}^{n} \gamma_i (\log p_{it} - \delta \log p_{it-1}) + \beta (\log (y_t / P_t^*) - \delta \log (y_{t-1} / P_{t-1}^*)) + \epsilon_t \qquad (2)$$

where

δ = the first-order autocorrelation coefficient for the system and
$\gamma_0^* = (\gamma_0 - \delta)$.

The important feature to note in Eq. 2 is that the imposition of an autocorrelated error structure in the static model implies the presence of lagged dependent variables and, hence, some sort of adjustment process.[2]

In general, the introduction of lagged budget shares directly into the static model leads to estimation of only the short-run parameters. The long-run parameters are usually derived by dividing the estimated short-run coefficients by one minus the (sum of the) lag adjustment coefficient(s). Although the coefficients are easy to estimate in this procedure, it is rather cumbersome to generate standard errors for the long-run estimates. Moreover, since the calculation of long-run parameters involves the ratio of two regression coefficients, the sample moments may not exist (see Greenberg and Webster 1983 for a discussion on this). While approximation methods can be used to generate such information, considerable small-sample bias may exist, overshadowing statistical inference on long-run estimates. Bewley and Fiebig (1990) have shown that the nonexistence of finite moments is of sufficient consequence to produce a wide range of long-run estimates in empirical application. New methods are available that allow estimation of long-run parameters directly and also provide a way of combining steady-state economic theory and time series properties of data. This is the basis for adopting a general dynamic framework in our study.

Dynamics and the Long-run Structure

Eq. 2 also suggests that a distributed lag model may provide the basis for formulating a general dynamic framework.[3] This can be achieved by including lagged dependent (budget shares) and lagged independent variables (prices and deflated total expenditure) in the original formulation of the AIDS in Eq. 1. A justification for including such lagged variables can be given by the consumer's inability to react instantaneously to changes in prices and income owing to adjustment costs or lack of information. Given this, a general dynamic representation of the AIDS model in the distributed lag form is given by:

$$W_t = \sum_{k=1}^{L} \alpha_k W_{t-k} + \sum_{k=0}^{L} B_k X_{t-k} + u_t \tag{3}$$

where

X = a vector of prices and expenditure (deflated by the Stone price index),

k = the order of the lag structure for exogenous and dependent variables, $k = 1, \ldots L$, and

B = the matrix of parameters in the system.

Eq. 3 is in the form of a stochastic difference equation. By repeated substitution, the final form or steady-state relationship between the budget shares and exogenous variables (for the deterministic part of the difference equation) is given by:

$$W_t = \sum_{k=0}^{L} \frac{B_k}{(1 - \sum_{k=1}^{L} \alpha_k)} X_t$$

$$= \Phi X_t \tag{4}$$

The vector Φ represents the long-run parameters defined as the sum of the coefficients of current and lagged values for each exogenous variable (prices and expenditures) divided by one minus the sum of the lag coefficients of the dependent variable. Eq. 4 can be treated as the long-run steady-state structure for the AIDS model (see Harvey 1981).

The main idea in investigating the dynamics of a demand structure is to reformulate the original distributed lag model, specified in Eq. 3, so that the long-run structure defined in Eq. 4 can be identified directly. Such a transformation could be done in a number of ways. One model is derived by subtracting ($\Sigma_{k=1}^{L} \alpha_k W_t$) from both sides of Eq. 3 and manipulating algebraically to obtain (see Wickens and Breusch 1988; Bewley 1979):

$$W_t = -\theta \sum_{k=1}^{L} \alpha_k \Delta_k W_t + \Phi X_t - \theta \sum_{k=1}^{L} B_k \Delta_k X_t + \theta u_t \tag{5}$$

where

$$\theta = \frac{1}{(1 - \sum_{k=1}^{L} \alpha_k)}$$

Δ = the difference operator.

Eq. 5 identifies the long-run, steady-state condition parameters, Φ, directly along with the short-run dynamics. This model is referred to as the general dynamic AIDS (GD/AIDS).[4] The important characteristics of the GD/AIDS are summarized in Table 1. The partial adjustment, autoregressive and static versions of AIDS are nested within the GD/AIDS. Thus, the model provides an opportunity to test alternatively model specifications.[5]

GD/AIDS provides an appropriate representation of a general dynamic framework in the sense that it allows merging of long-run information along with the short-run effects. Anderson and Blundell (1983) adopted such an integrated approach mainly

Table 1. Summary of basic characteristics of the general dynamic AIDS

Description	General dynamic (GD) AIDS
Model	$W_t = \Sigma \alpha_k \Delta_k W_t + \Phi x_t - \Sigma B_k \Delta_k x_t + u_t$
Nested models	
Autoregressive	$B_k = -\Phi \alpha_k \quad k = 1, \ldots L$
Partial adjustment	$\alpha_k = 0$ for $k \neq 1$; and $B_k = 0$ for $k = 1, 2, \ldots L$
Static model	$\alpha_k = 0 \ \forall k$ and $B_k = 0 \ \forall k$
Estimation	Linear in parameters
Long-run structure	The GD/AIDS merges short-run behavior with long-run steady-state structure; the static long-run structure is usually depicted with current values.

to explain the failure of static models in accepting theoretical restrictions.[6] The linear nature and levels form of the GD/AIDS specification, however, provide a viable alternative to Anderson and Blundell's model in terms of achieving the desirable aspects of flexibility, simplicity and identification of long-run parameters.

DATA AND MODEL SPECIFICATION FOR U.S. MEAT DEMAND

Data

The data used to analyze U.S. meat demand are on a quarterly basis starting from the first quarter of 1965 through the fourth quarter of 1988. The commodities considered in the study are beef (including veal), pork and chicken. Per-capita retail equivalent quantities and retail prices for the commodities come from the Livestock and Meat Situation reports (USDA, various issues), Poultry and Egg Situation reports (USDA, various issues) and other special bulletins published by the USDA (USDA 1989; USDA 1974). The data are specified as follows. The quantity of chicken used is the sum of the per-capita retail equivalents of young chicken and other chicken quantities. Monthly retail prices are aggregated to a quarterly basis by using simple averages. None of the variables is seasonally adjusted.

Meat Expenditure

A two-stage budgeting process is assumed where in Stage I the total expenditure is allocated among meat, other food and nonfood expenditures; and in Stage II the meat expenditure is allocated among different meat items. This facilitates the specification of consumer demand within the meat group as a function of prices of meat commodities and total meat expenditure alone. The meat group expenditure is computed as the sum of beef, pork and chicken expenditures.

However, the two-step budgeting process also implies relations between Stage I (meat group expenditure allocation) and Stage II (within-meat-group allocation). For this study, we assume that the theoretical relationships between the two stages of the budgeting process are derived under static conditions. Accordingly, for the first stage, we specify a static function that allocates total expenditure among meat, other food and nonfood. The purpose of specifying the first stage is to be able to differentiate between total and group effects on meat commodities. The system (AIDS) used in the second stage permits a general way of estimating within-meat-group allocation without imposing restrictive *a priori* assumptions with regard to expenditure effects (see Deaton and Muellbauer 1980).

The dynamic approach (described above) allows for direct identification of the long-run structure in the second (within-group) stage taking into consideration the short-run dynamics and steady-state relation between the two stages of the budgeting process. In this connection, the long-run estimates can be used to compute group price indexes to capture the effect of general price movements of each commodity on the meat expenditure allocation in the first stage. Thus, from a practical point of view and for exposition of the distinction between total and group elasticities for meat commodities, a simple log-linear equation for the meat group expenditure allocation is deemed sufficient.[7] This is specified as:

$$\log M_t = S_0 + S_1\, JS(1) + S_2\, JS(2) + S_3\, JS(3) + E_1 \log GP_{1t} + E_2 \log GP_{2t} + E_3 \log POF_t + E_4 \log PNF_t + E_y \log PCE_t + E_T\, TREND + h_t \qquad (6)$$

where

M = the meat group expenditure (in per-capita terms),
GP_1 and GP_2 = meat group price indexes,
POF = the price of food less meat,
PNF = price of nonfood goods,
PCE = the per-capita personal consumption expenditure,
$TREND$ = a time trend variable,
$JS(r)$ = a quarterly dummy for the rth quarter,
$S_0, S_1, S_2, S_3, E_1, E_2, E_3, E_4, E_y$, and E_T = parameters to be estimated, and
h = the disturbance term.

The meat group price is represented by two group indexes in Eq. 6: GP_1 and GP_2. This is consistent with the generalized polar form of the conditional meat demand system in Stage II and is less restrictive than using only one group price index (Gorman 1959; Deaton and Muellbauer 1980). Following Barten and Turnovsky (1966), GP_1 and GP_2 are defined as:

$$\log GP_{1t} = \sum_{i=1}^{n} W_{it} \log P_{it}$$

$$\log GP_{2t} = \sum_{i=1}^{n} W_{it}\, \eta^G_{imt} \log P_{it}$$

where

W_i = group budget share of the ith commodity, and
η^G_{im} = group expenditure elasticities.

The first index, GP_1, is the geometric weighted index of prices, where the weights are based on within-group budget shares, whereas the second index, GP_2, is weighted by within-group expenditure elasticities. Thus, GP_1 reflects the "substitution" effects of a within-group price change, while GP_2 reflects the "expenditure" effects due to changes in relative prices within the group.

Data for the food and nonfood consumer price indexes and personal consumption expenditure were collected from various issues of Survey of Current Business (U.S. Department of Labor). The price index for food less meat was calculated based on the price indexes for meat and food using their relative weights in the food budget.

Dynamic Specification

The first step in the dynamic specification is to establish a lag structure. Lags up to eighth order are considered along with three seasonal dummies for the last three quarters; log-likelihood tests are performed by omitting one or more specific lags. After some initial testing, which took account of Laitinen's (1978) work showing that small sample bias may lead to overrejections, the model with first- and fourth-order lags is taken as the maintained general model[8]; inclusion of second- and third-order lags is not necessary. This dynamic specification is also appealing because it reflects adjustments based on both a quarter-to-quarter and a year-to-year basis.

The GD/AIDS structure for U.S. meat demand in the equivalent form of Eq. 5 is specified for the distributed lag model with first- and fourth-order lag structure as:

$$W_{it} = SD_i + \sum_{r=2}^{4} SD_{ir}\, JS(r) + \tilde{\alpha}_{i1}\, \Delta_1\, W_{it} + \tilde{\alpha}_{i4}\, \Delta_4\, W_{it} + \sum_{j=1}^{n+1} \Phi_{ij}\, X_{ijt} - \sum_{j=1}^{n+1} \tilde{B}_{ij}\, \Delta_1\, X_{ijt} - \sum_{j=1}^{n+1} \tilde{C}_{ij}\, \Delta_4\, X_{ijt} + V_{it} \quad (7)$$

where

Δ = the difference operators,
$\tilde{\alpha}_{i1} = -\theta\, \alpha_{i1}$,
$\tilde{\alpha}_{i4} = -\theta\, \alpha_{i4}$,
$\tilde{B}_{ij} = \theta\, B_{ij}$,
$\tilde{C}_{ij} = \theta\, C_{ij}$,
Φ_{ij}, SD_i and SD_{it} = parameters to be estimated,
$JS(r)$ = seasonal dummies,
X_{ijt} = meat prices and meat expenditures (deflated by the Stone price index), and
V_{it} = disturbance terms.

Eq. 7 states that the current level of the meat budget share is a function of both levels and differences of prices and meat expenditures with year-to-year and quarter-to-quarter changes.

The introduction of lags in the dependent variables to generalize the dynamic process poses certain identification and estimation problems. This situation is analogous to the autoregressive structures discussed by Berndt and Savin (1975). Anderson and Blundell (1982) have demonstrated that in a budget share system such as GD/AIDS the identification restrictions are related to the adding-up requirements. For the invariance of results due to arbitrary deletion of an equation within a system such as GD/AIDS, where only own-commodity lags are allowed, Anderson and Blundell (1982) have pointed out that the adjustment parameters should be identical for all equations. That is, $1 - \tilde{\alpha}_{i1} - \tilde{\alpha}_{i4}$ should be equal for both the beef ($i = 1$) and pork ($i = 2$) equations. Accordingly, adding-up restrictions for GD/AIDS are given by:

$$\begin{gathered}
\sum_{i=1}^{n} SD_i = 1 \\
\sum_{i=1}^{n} SD_{ir} = 0; \qquad r = 2, 3, 4 \\
\sum_{i=1}^{n} \tilde{\alpha}_{ik} = 0 \\
\tilde{\alpha}_{11} = \tilde{\alpha}_{21} = \alpha_1^* \\
\tilde{\alpha}_{14} = \tilde{\alpha}_{24} = \alpha_4^* \\
\sum_{i=1}^{n} \Phi_{ij} = 0; \ \sum_{i=1}^{n} \tilde{B}_{ij} = 0; \ \sum_{i=1}^{n} \tilde{C}_{ij} = 0.
\end{gathered} \quad (8)$$

The main point to note here is that the lag coefficients should be restricted to be equal across equations if the maximum likelihood methods are to be invariant to arbitrary deletion of one of the equations in the system.

As pointed out earlier, popular forms of dynamic representations, such as the partial adjustment, autoregressive and static AIDS models, are nested within the general GD/AIDS model of Eq. 7. With the adding-up restriction (that is, $\tilde{\alpha}_{11} = \tilde{\alpha}_{21}$, and $\tilde{\alpha}_{14} = \tilde{\alpha}_{24}$) for Eq. 7, an autoregressive model (AR/AIDS) is derived through the common factor restrictions $\tilde{B}_{ij} = -\alpha_1^*\, \phi_{ij}$ and $\tilde{C}_{ij} = -\alpha_4^*\, \phi_{ij}$. The partial adjustment model (PA/AIDS) is derived by setting $\alpha_4^* = 0$ and $\tilde{B}_{ij} = \tilde{C}_{ij} = 0$. To derive the static AIDS (ST/AIDS) model would also require $\alpha_1^* = 0$. These restrictions provide the opportunity to test the autoregressive, partial adjustment and static models within the general dynamic model represented by GD/AIDS (see Table 1).

EMPIRICAL RESULTS

The GD/AIDS (Eq. 7), AR/AIDS, PA/AIDS and static AIDS are applied to the quarterly U.S. data. A maximum likelihood procedure in SHAZAM version 6.1 (White 1988) is used to estimate the system, with the chicken equation deleted due to adding-up restrictions

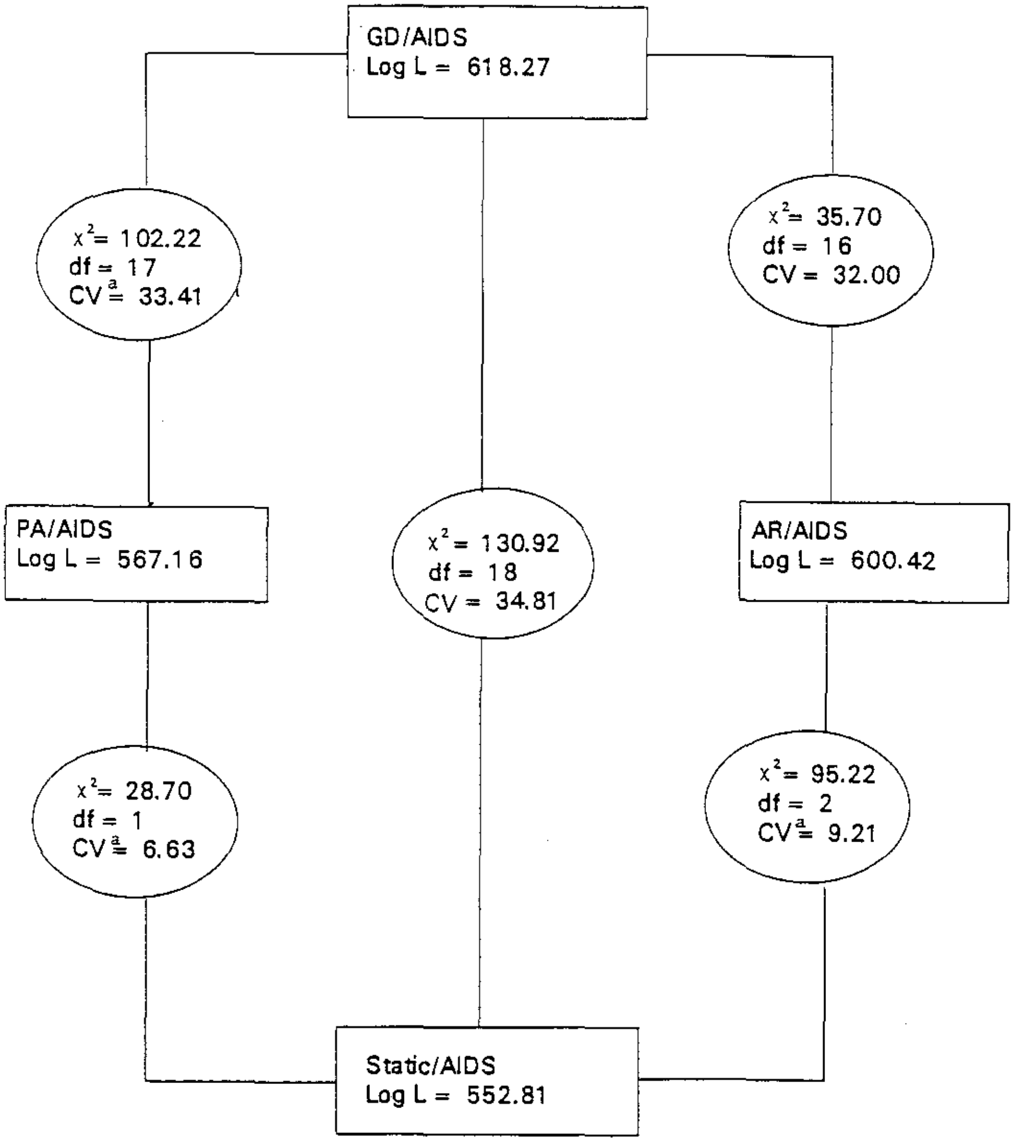

Figure 1. Tests of alternative models
[a]CV indicates critical value at the 0.01 level.

(maintaining the lag adjustment coefficients to be equal across equations).

Figure 1 shows the log likelihood ratio tests performed to discriminate among the alternative models. Apart from the adding-up requirements, the symmetry and homogeneity restrictions are also maintained in comparing the different models.[9] Following Anderson and Blundell (1983), these restrictions are imposed only on the long-run parameters (of the GD/AIDS), leaving nonhomogeneous and nonsymmetric responses in the short run. The homogeneity and symmetry restrictions are given by:

$$\sum_{j=1}^{n} \Phi_{ij} = 0$$

$$\Phi_{ij} = \Phi_{ji}.$$

As a test for the restricted lag adjustments, a generalized partial adjustment model[10] (GP/AIDS) with cross-commodity lag effects is estimated. The likelihood ratio test statistics indicate that the null hypothesis of a (restricted) partial adjustment model

Table 2. Maximum likelihood parameters of the general dynamic AIDS with homogeneity and symmetry restrictions imposed in the long run

Parameters[a]	Coefficient	Standard error	t-ratio
α_{11}	0.4275	0.1269	3.37
α_{14}	0.4021	0.0943	4.26
B_{11}	0.0518	0.0885	0.59
B_{12}	−0.0457	0.0664	−0.69
B_{13}	−0.0151	0.0508	−0.30
B_{1M}	−0.0040	0.0120	−0.33
C_{11}	−0.0602	0.0444	−1.36
C_{12}	−0.0196	0.0273	−0.72
C_{13}	0.0262	0.0278	0.94
C_{1M}	0.0050	0.0080	0.63
SD_1	0.5007	0.3491	1.43
SD_{12}	0.0070	0.0057	1.23
SD_{13}	0.0051	0.0061	0.83
SD_{14}	0.0008	0.0072	0.11
Φ_{11}	−0.0195[b]	—	—
Φ_{12}	0.0011	0.0101	0.11
Φ_{13}	0.0184	0.0124	1.49
Φ_{1M}	0.0260	0.0917	0.26
α_{21}	0.4275	0.1269	3.37
α_{24}	0.4021	0.0943	4.26
B_{21}	−0.0299	0.0392	−0.76
B_{22}	0.0501	0.0338	1.48
B_{23}	−0.0148	0.0245	−0.60
B_{2M}	−0.0026	0.0056	−0.48
C_{21}	0.0277	0.0200	1.38
C_{22}	0.0035	0.0144	0.24
C_{23}	0.0134	0.0133	1.01
C_{2M}	0.0051	0.0037	1.36
SD_2	0.6730	0.1700	3.96
SD_{22}	−0.0142	0.0027	−5.31
SD_{23}	−0.0164	0.0032	−5.14
SD_{24}	−0.0013	0.0055	−0.24
Φ_{21}	0.0011	0.0101	0.11
Φ_{22}	−0.0267[b]	—	—
Φ_{23}	0.0256	0.0070	3.65
Φ_{2M}	−0.0893	0.0447	−2.00
Log-likelihood function = 618.27			
Beef:	$R^2 = 0.62$	$Q^c(12) = 20.79$	$Q(24) = 34.47$
Pork:	$R^2 = 0.82$	$Q(12) = 20.38$	$Q(24) = 24.65$

[a]For parameters α, B, C and Φ, the subscript ij refers to the ith commodity with respect to the jth variable: $i = 1$ for beef; $i = 2$ for pork; $j = 1, 2, 3$ for beef, pork, and chicken prices, respectively; and $j = M$ for the meat expenditure variable.

[b]Derived based on the homogeneity restriction.

[c]Q denotes the Box-Pierce Q statistic for serial correlation in the residuals. The figures in the parentheses are the degrees of freedom for chi-square statistics. The critical values at the 5% level of significance are 21.03 and 36.42, respectively, for 12 and 24 degrees of freedom.

cannot be rejected over GP/AIDS. However, PA/AIDS and the autoregressive (AR/AIDS) version of the model fail acceptance over GD/AIDS.[11] Thus, the hypotheses of partial adjustment or autoregressive forms seem to be too restrictive for the data. As reported in Figure 1, all the dynamic adjustment specifications (namely, the GD/AIDS or AR/AIDS or PA/AIDS) are preferred over the static AIDS model for the U.S. meat demand data. To be consistent with the data, the dynamic nature of meat demand is best represented by the more flexible framework.

The estimated coefficients with homogeneity and symmetry imposed only on the long-run structure of GD/AIDS are presented in Table 2. The R^2 values, 0.62 and 0.82 for the beef and pork equations, respectively, indicate that the model performs reasonably well in terms of explanatory power. The computed Box-Pierce Q statistics for the residuals are not statistically significant, suggesting that the null hypothesis of white noise residuals cannot be rejected.

All estimated coefficients for the differenced dependent variables are statistically significant, indicating the presence of habit formation or persistence effects in meat consumption. Thus, dynamic lag adjustments are found important for the meat demand system. Stability checks indicate that the model is dynamically stable.[12]

Estimated Elasticities

Table 3 presents the estimated conditional (group) price and expenditure elasticities for the GD/AIDS, AR/AIDS, PA/AIDS and static AIDS models. The group or conditional (long-run) expenditure and price elasticities

Table 3. Estimated conditional elasticities for different AIDS models

	Uncompensated price elasticities[a] with respect to:			Expenditure elasticity[a]
Model/commodity	beef group	pork group	chicken group	meat group
General dynamic (GD/AIDS)[b]				
Beef	−1.022	−0.009	−0.003	1.035
Pork	0.152	−0.994	0.122	0.719
Chicken	−0.250	0.020	−1.252	1.483
Restricted partial adjustment model (PA/AIDS)				
Beef	−1.061	−0.029	0.012	1.072
Pork	0.071	−1.007	0.075	0.856
Chicken	0.054	0.099	−1.205	1.053
Autoregressive model (AR/AIDS)[c]				
Beef	−1.020	0.013	0.015	0.992
Pork	0.009	−0.968	−0.056	1.014
Chicken	0.051	−0.117	−0.933	0.999
Static model (ST/AIDS)				
Beef	−1.084	−0.044	0.008	1.120
Pork	0.079	−0.968	0.055	0.834
Chicken	0.133	0.089	−1.148	0.927

[a]The reported elasticities are the average of the values from the 1986 through 1988 periods.
[b]Only the long-run elasticities are reported.
[c]No distinction can be made between short run and long run.

are given by (see Green and Alston 1991; Foster, Green and Alston 1990)[13]:

$$\eta_{iM}^{G} = \frac{\Phi_{iM}}{\hat{W}_i} + 1$$

$$\eta_{ij}^{G} = (\Phi_{ij} - \Phi_{iM}\,\hat{W}_j) / \hat{W}_i - \delta_{ij}$$

where

δ = the kronecker delta,
subscript M = the expenditure,
superscript G = group (conditional), and
$\hat{W}$ = the predicted budget shares.

Note that the reported conditional elasticities are averaged over the values calculated for every sample point between 1986 and 1988. The conditional own-price elasticities are negative, with rather elastic own-price responses for chicken in the long run. Because chicken consumption has increased significantly over the past decade as relative prices have fallen, this finding is not surprising.

The long-run group expenditure elasticities for the GD/AIDS are found to be greater than unity for both beef and chicken, but the value for pork is only 0.719. Within the meat group, the cross-price elasticities indicate beef and chicken to be substitutes to pork, whereas pork and chicken are complements to beef.

The estimated conditional demand elasticities reported in Table 3 vary slightly among the different models, particularly with respect to cross-price elasticities. The long-run, own-price and expenditure elasticities for various dynamic models (GD/AIDS, AR/AIDS, PA/AIDS) are generally similar, except for chicken. The own-price elasticity for chicken from the GD/AIDS specification is similar to PA/AIDS, but higher than the estimate from the AR/AIDS or ST/AIDS. The expenditure elasticity of chicken from GD/AIDS is higher than the estimates from any of the other models. A comparison of cross-price elasticities derived from the static to PA/AIDS to GD/AIDS specifications indicates that the more dynamic structures provide slightly higher cross-price elasticities in the case of pork.

For policy analysis, the total or unconditional demand elasticities are preferred. Furthermore, conditional demand elasticities are difficult to compare with the results of other studies. To compute total elasticities, the first-stage meat expenditure allocation model specified in Eq. 6 is estimated with the homogeneity condition imposed. The long-run group expenditure elasticities based on the GD/AIDS are used to derive the second group price index, GP_2.

The results of the estimated meat group expenditure allocation, Eq. 6, are provided in Table 4. Apart from the prices and total expenditure variables, a trend variable is included to capture the effect of other, omitted variables. The estimated model is reasonable in terms of explanatory power and magnitude of the coefficients. The diagnostic checks indicate some serial correlation, but no attempt is made here to correct this.[14]

The first meat group price index, GP_1, is statistically significant, indicating that the substitution effect due to relative price changes within the group is an important determinant of meat expenditure. However, the within-group expenditure effect reflected through GP_2 is not statistically significant.

The meat group elasticity with respect to other food prices, obtained directly from the coefficients reported in Table 4 since this is a log-linear specification, is negative, indicating complementarity. Similarly, meat is observed to be a substitute with nonfood goods, with a cross-price elasticity of 0.54. The total expenditure elasticity for the meat group is 0.52.

Based on the long-run conditional or group elasticities of the GD/AIDS (Table 3) and the results of first-stage allocation (Table 4), the "total" or unconditional price and expenditure elasticities are calculated using the formulae:

$$\eta_{iM}^{T} = \eta_{iM}^{G}\,E_y$$

$$\eta_{ij}^{T} = \eta_{ij}^{G} + \eta_{iM}^{G}\,(E_1\,\hat{W}_j + E_2\,\hat{W}_j\,\eta_{jM}^{G})$$

Table 4. Estimated parameters for the meat expenditure model

Variable	Estimated coefficient	Standard error	t-ratio
Seasonal dummies			
April–June	0.0260	0.0089	2.93
July–Sept	−0.0130	0.0083	−1.23
Oct–Dec	−0.0290	0.0079	−1.72
Log of:			
GP_1	0.6800	0.3311	2.05
GP_2	0.1623	0.3395	0.478
Food less meat	−0.7887	0.1611	−4.90
Nonfood	0.5377	0.1628	3.30
Per-capita total expenditure	0.5172	0.1550	2.93
Trend	−0.0040	0.0021	−1.89
Constant	1.3523	0.7885	1.72
Adjusted R^2	0.997		
Log likelihood	230.3		
$Q(12)$[a]	38.29		
Durbin–Watson statistic	1.02		

[a]The Q statistics indicate the Box-Pierce statistics for serial correlation of residuals. The critical value at 5% level of significance is 21.03 for 12 degrees of freedom.

Table 5. Estimated unconditional elasticities for meat commodities based on the GD/AIDS

	Uncompensated price elasticities with respect to price of:			
Commodity	Beef	Pork	Chicken	Total expenditure
Beef	−0.554	0.254	0.138	0.535
Pork	0.478	−0.810	0.219	0.372
Chicken	0.421	0.397	−1.051	0.767

where superscript $T =$ "total" (or unconditional) elasticities.

The estimated total price and expenditure elasticities are reported in Table 5. Since GD/AIDS is preferred over other models based on the likelihood ratio tests, the total elasticities based on the GD/AIDS alone are reported. The results show that chicken is more own-price responsive than beef or pork. The total expenditure elasticities are 0.54, 0.37 and 0.77, respectively, for beef, pork and chicken. The positive cross-price elasticities indicate that meat commodities are gross substitutes to one another within the total expenditure allocation. The total demand elasticities are reasonable and conform to theory.

CONCLUDING REMARKS

Dynamic specification of meat demand has been a subject of constant inquiry in demand analysis. However, most studies have emphasized dynamics with the more narrow focus of capturing short-run dynamics. The long-run coefficients are usually deduced from short-run and lag adjustment parameters. The emphasis of this study is to identify the long-run structure together with the short-run dynamics in demand for meat. For this purpose, a flexible, linear model in levels form is specified based on a transformation suggested in the error correction literature and applied to quarterly meat data. The resulting model nests the commonly used partial adjustment and autoregressive processes and thus provides a way of choosing a dynamic specification that is consistent with the data.

The empirical results illustrate the potential for dynamic misspecification error when an instantaneous or restricted adjustment process is assumed. Dynamic specification error may lead to biased statistical inference when hypothesis testing is involved. This implies that dynamic specifications should be tested rather than arbitrarily imposed, as is often the case in current practice. In this respect, results of this study suggest caution when using restricted dynamic specifications for hypothesis testing (e.g., evaluations of structural change). Better would be first testing the model specification against alternatives, particularly when shorter time period data are involved.

The model presented here provides a viable method for specifying a general dynamic framework. The linearity and the levels form of the specification should provide an easy and convenient way for estimating dynamic models applied to commodity markets. Since the dynamic specification is data-based, it should also provide superior forecasting power, which is essential in market analysis. Often, models for the purpose of forecasting produce results that are inconsistent with theory. The general dynamic model adopted here merges the long-run, steady-state theory with short-run time-series properties of data, and produces elasticities that are robust for policy applications.

The study carries out dynamic misspecification tests by assuming the AIDS as the basic model for meat consumption behavior. The problem of distinguishing incorrect functional form and dynamic misspecification is an important issue and requires further consideration. In addition, changes in demographics may be important determinants of observed dynamic behavior. These should be evaluated in future analysis. Also, the error correction method adopted here implicitly assumes a linear steady-state structure. More complex data-based models are also a subject for future study. Finally, the time-series-based dynamic models (such as the one specified here) should be compared with other explicit adjustment models such as state-adjustment or quadratic-cost adjustment models.

NOTES

[1]Econometric studies have addressed the problem of identifying the presence of autocorrelated structures versus lagged dependent variables in the past. The discussion here merely provides an expository note about what may be an underlying motivation for dynamics in demand analysis. It is not designed to argue for or against autoregressive or partial adjustment processes. Interested readers should refer to Harvey (1981) or Fomby, Hill and Johnson (1984).

[2]This kind of treatment is the same as is implied in tests for model specification using Durbin-Watson statistics. For instance, Deaton and Muellbauer (1980) point out that the presence of autocorrelation in demand systems may be due to misspecification, particularly lack of dynamics.

[3]Alternatively, one can also derive dynamic models using a multiperiod quadratic loss function (see Nickell 1985). Because the objective of this study is to incorporate dynamics in meat demand in a general sense, it is sufficient to start with an autoregressive distributed lag model (see Hendry, Pagan and Sargan 1984).

[4]Another alternative form can be derived by subtracting W_{t-m} from both sides of Eq. 3 and manipulating algebraically to obtain a different dynamic specification. This is similar to the model specified by Anderson and Blundell (1982; 1983). The transformation used for Eq. 5 provides a convenient alternative form for directly estimating

short- and long-run effects, the associated speed of adjustment, and their standard errors. However, a number of alternative transformations are available (see Banerjee, Galbraith and Dolado 1990).

[5]Houthakker and Taylor's (1970) state adjustment (SA) model (see Phlips 1983) deserves some mention here. Like any other dynamic process, the psychological stock process implied in the SA model is *ad hoc* and generally applied only in a single equation. The estimated form of the SA model is somewhat similar to GD/AIDS (Eq. 5) in the sense that the right-hand side variables consist of actual levels and first differences of the exogenous variables. However, the parameters in SA models are short-run in nature and are uniquely identified only under certain nonlinear restrictions on the parameters. This makes the SA model difficult to work with in system-wide applications. Furthermore, the long-run estimates depend on the ratio of regression coefficients, which also involves the depreciation parameter in the psychological stock adjustment process. Therefore, the SA model cannot be nested within the GD/AIDS model.

[6]In empirical meat demand analysis, several researchers have obtained satisfactory results by accepting homogeneity and symmetry conditions through a parsimonious dynamic representation, particularly in the form of first-differenced models (for example, Moschini and Meilke 1989; Blanciforti, Green and King 1986; Eales and Unnevehr 1988). Tests of theory based on conditional demand systems are not very useful. On the other hand, parsimonious representations such as first-difference models result in loss of long-run information that may be of economic interest. Since identification of the long-run structure is also important, this study proposes a flexible, general dynamic framework by following the error correction method.

[7]LaFrance (1991) has considered the complexity of the estimation problem with endogenous group expenditures in separable demand models. The first-stage specification and inclusion of two group price indexes is in the spirit of estimating a separable model consistently across two stages, although our focus is limited to deriving total and group elasticities for meat commodities under consideration.

[8]The lag structure of the general model is also tested using GD/AIDS in Eq. 5, by using log-likelihood ratio tests. The results confirm the first- and fourth-order lag specification of GD/AIDS.

[9]In model selection, it may be important to carry out the test procedures without any restrictions imposed, because the rejection of the model is not independent of the implied restrictions (homogeneity and symmetry) in the model. The minimum restriction needed to identify the system is to impose the adding-up restriction. Likelihood ratio tests without homogeneity and symmetry restrictions also produce similar inference.

[10]Generalized partial adjustment models consist of lags from other commodities as well, as opposed to only own-commodity lag structure in partial adjustment models. Imbedded in Anderson and Blundell's model is the generalized partial adjustment model, which requires no additional restrictions for satisfying the adding-up restriction. The log-likelihood ratio test statistics for GD/AIDS and PA/AIDS indicate a χ^2 value of 6.14, which is lower than the critical value of 6.25 (at 0.01 probability) with 3 degrees of freedom.

[11]Sequential Wald tests are generally suggested for common factor models such as the one adapted here. The log-likelihood tests performed are asymptotically equivalent to Wald test statistics (see Mizon and Hendry 1980).

[12]For dynamic stability the roots of the polynomial equation $1-\alpha_1 Z-\alpha_2 Z^4$ must be greater than one in absolute level. The computed real and imaginary roots for GD/AIDS satisfy this criterion, indicating that the system is dynamically stable.

[13]As discussed in Green and Alston (1991), these formulae are applicable only when the budget shares in the Stone price index are treated exogenously. In our study, the previous budget shares are used in calculating the Stone price index, which overcomes the problem of simultaneity. The LA/AIDS is extended here as an approximate demand system to the original nonlinear AIDS where the deflated (by the Stone price index) meat expenditure variable is used directly in the estimation. In this case, the formulae hold and work as well as the complicated formulae in practice (Foster, Green and Alston 1990).

[14]As discussed earlier, presence of autocorrelation may be due to inappropriate model specification (log-linear case here) or lack of dynamics. Because the focus of the study is to develop a general dynamic framework for meat demand, detailed analysis of meat expenditure allocation is not pursued. However, the analysis helps to demonstrate the distinction between group and total demand elasticities.

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