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## A Flexible Dynamic Inverse Demand System for Meat Products in U.S.

By T. Kesavan and Brian Buhr<sup>1</sup>

Recently, food consumption trends in the United States have gone through a number of changes, particularly within the meat products category. In addition to prices and income, the demand for meat is influenced by information about nutrition and health; generic advertising of product characteristics; changes in consumer perception about product quality such as low fat or lean meat resulting from the adoption of biotechnology in animal production; concern over food safety; changing life styles and demographic structure; the effect of household value of time due to increased participation of women in the labor force; and expanded processing of basic commodities towards more convenience foods. The effects of these various factors on the trend of food demand and specific changes of consumer demand in the market place are well documented in Raunika and Huang; Senauer, Asp and Kinsey; Capps and Schmitz; and Caswell among others.

An integral part of the economic evaluation of the above changes is the estimation of market demand systems. In most empirical applications, the meat demand analysis are confined to the traditional meat groups based on animal origin such as beef, pork and chicken (See Smallwood et al. for a review). Only a few studies have attempted to focus on the disaggregated meat products in analyzing market demand. For instance, Eales and Unnevehr (1988) separated beef into hamburger and table-cut beef products. Such an orientation facilitated their study to identify the sources of changes in meat demand structure in terms of the cross substitution effect between whole chicken and hamburger. Recently, Brester and Wohlgenant also conducted an analysis focusing on disaggregated beef products, and showed that considerable differences in demand elasticities are observed in ground beef and table-cut beef depending upon the source of data<sup>1</sup>.

Furthermore, in as much as the commodity market analysis relies on the retail demand for the price determination in markets, it is essential to specify the retail demand relationships in "inverse" (price dependent) form. This is usually justified on the basis that supply is rather fixed in the short run and the market cleared is by the retail demand. Given this premise, it will be important to construct inverse demand models that are consistent with economic theory and the observed phenomenon in data.

With respect to theory, recent studies have shown that distance functions can be used to derive inverse demand systems in the same manner as the cost functions are applied to develop direct (quantity dependent) demand systems. While the properties of the inverse demand functions have long been established (See Anderson, Deaton), empirical investigations using this approach have been few and have emerged only very recently (See Huang; Eales and Unnevehr, 1991; Moschini and Vissa). However, none of these studies used data with shorter time intervals which may be more appropriate for inverse demand specifications.

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It is commonly observed that lag adjustments are present in the consumer decision making process. Again, this is much more relevant in the case of shorter time period data. Among the various adjustment processes, state adjustment or partial adjustment schemes are commonly used to incorporate dynamics in demand analysis (See Philips; Johnson et al., and Bewley, 1986 for details). Anderson and Blundell (1982,1983) point out that such representations of dynamic adjustments are restrictive and it may be best to represent dynamics in a more general framework (also see Kesavan et al.).

The purpose of this study is to estimate a flexible dynamic inverse demand system with particular focus on disaggregated meat commodities based on a new set of monthly disappearance data. Following Moschini and Vissa (also see Eales and Unnevehr, 1991), a linear approximate inverse demand system was adopted as the basic model for food demand. A general dynamic model that combined both the long-run and short-run effects together was developed and applied to the monthly meat demand data. The approach merged the data generation properties with the long-run steady state relationship in a systematic manner much like in the error correction model (see Hendry et al. among others). Such an approach satisfied the need to develop models that are consistent with the observed phenomenon in meat demand, namely the dynamics and the necessity to maintain the axioms of microfoundations, namely the Slutsky restrictions within a unified estimation framework.

### Conceptual Framework

Based on consumer theory, marshallian demand functions<sup>2</sup> are expressed as a function of prices and expenditures. Theoretically, the inverse of this function can be expressed in terms of normalized prices (with respect to expenditures) as a function of quantities (see Deaton). Market equilibrium in general can be achieved either through quantity or price adjustments. Since price and quantity variations are exactly proportional to each other under perfect-market conditions, theoretically, both inverse and direct demand functions are equivalent (see Barten and Bettendorf). However, from an estimation point of view, they are not the same. If consumers are price takers and the quantity variable is the one adjusting towards the market equilibrium conditions, then a "direct" demand function is appropriate. On the other hand, for many agricultural commodities supply is rather inelastic in the short run, compelling producers to be price takers and causing the market equilibrium to be determined by the retail demand. The monthly meat demand data used in this study reflects a shorter time period where the assumption of predetermined quantities is justified. Thus, inverse demand functions are appropriate for the meat demand system.

### Linear "Approximate" Inverse Demand System (LAIDS)

The inverse representation of the direct utility function is the distance function which provides the theoretical framework for deriving inverse demand systems and their properties (see Anderson; Deaton; and Huang). Briefly, the distance function can be defined as the proportion by which the quantities consumed must be changed in order to achieve the particular utility level. By duality theory, every direct utility function has its dual representation of the distance function. Unfortunately for most popular demand

systems, analytical (closed-form) solutions for the dual representations of the cost functions do not exist. In any case, given the aggregate nature of data and the inherent problems associated with applying individual theory exactly over the group of consumers, it may be best to extend demand systems as approximate demand systems. This study takes this pragmatic approach in modelling the inverse demand functions. Accordingly, the inverse demand functions in budget share form are expressed as functions of quantities and an aggregate quantity index (known as the scale index),

$$w_i = a_i + \sum_{j=1}^n a_{ij} \log(q_j) - b_i \log(Q), \quad (1)$$

where  $w$  represents budget share of commodity  $i$ ,  $q$  represents the quantity demanded, and  $Q$  is the quantity scale index.

Both Moschini and Vissa, and Eales and Unnevehr (1991) have shown that a nonlinear system can be derived from a distance function<sup>3</sup> that resembles the PIGLOG cost specification of the AIDS system in which case  $\log Q$  becomes,

$$\log Q = a_0^* + \sum_{i=1}^n a_i \log q_i + \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n a_{ij} \log q_i \log q_j. \quad (2)$$

Since the PIGLOG specification is not self-dual in nature, the above representation does not ensure consistency in aggregation and consequently, there is nothing "ideal" about the specification in equation 2 (see Moschini and Vissa). From an estimation point of view, the quadratic specification in (2) forces the system of inverse demand in (1) to be nonlinear. For simplicity and computational ease, therefore, this study assumes a geometric quantity index (stone quantity index) for the scale quantity,

$\log Q = \sum_{i=1}^n w_i \log q_i$ . Since this index, referred to as stone quantity index, is

predetermined before estimation, the inverse system specified in (1) is linear in parameters. This linearity is particularly appealing in the case of dynamic analysis. Moreover, it has been shown that the geometric quantity index provides a good approximation to the quadratic expression specified in (2) (Moschini and Vissa; Eales and Unnevehr, 1991).

Equation (1) is extended as an approximate system in the sense that it provides a first-order local approximation to any arbitrary inverse demand system. Therefore, it is termed the linear approximate inverse demand system (LAIDS). This function is also flexible in the sense that it does not impose any a priori restriction on the substitution possibilities.

The theoretical restrictions for this demand system are given by,

$$\begin{aligned}\sum_{j=1}^n a_j &= 0 && \text{(homogeneity)} \\ a_{ij} &= a_{ji} && \text{(symmetry)} \\ \sum_{i=1}^n b_i &= 0 && \text{(adding-up).}\end{aligned}\tag{3}$$

The quantity and scale elasticities (flexibilities) formulae for LAIDS model are computed as,

$$\begin{aligned}\epsilon_{ij} &= \frac{a_{ij}}{w_i} - b_i \frac{w_j}{w_i} - \delta_{ij}, \\ \epsilon_{is} &= \frac{b_i}{w_i} + 1,\end{aligned}\tag{4}$$

where  $\epsilon_{ij}$  refer to the quantity elasticities;  $\epsilon_{is}$  refers to the scale elasticity and  $\delta$  is the kronecker delta. The LAIDS provides the basic framework for investigating dynamics in monthly meat demand data in the subsequent empirical analysis.

### Dynamics

Dynamics in meat demand analysis has been established in the context of the direct demand systems (see Wohlgenant and Hahn; Capps and Nayga). Lag adjustments may be present in an inverse demand system as well because consumers cannot adjust instantaneously to changes in quantity. Frequently a first difference specification is used in demand systems estimation as a parsimonious representation to incorporate dynamics. However, such arbitrary differencing results in loss of long-run information (see Harvey; Engle and Weiss) that may of interest in policy applications. Also, differencing is often motivated by the nonstationarity in the series and introduces further complications in econometric modeling of commodity markets due to the differences in the interpretation of the disturbance term between levels and difference specifications.

Alternatively, dynamic adjustments can be introduced based on an assumed lag distribution structure in the model. The difficulty here is the identification of parameters and the problem of model misspecification due to misspecification in the lag structure particularly in estimating the long-run parameters. In this respect, it has suggested that dynamic specifications should be tested against alternative specifications as part of model validation (see Hendry et al., and Mizon and Hendry).

Taking the above factors into consideration, this study adopts a linear transformation procedure to derive a general dynamic framework in levels form which provides a way of moving from the simple static structure to a more general dynamic

representation dictated by the statistical criteria (or data). For this purpose, the LAIDS is first extended as an autoregressive distributed lag model as,

$$W = \sum_{l=1}^L A_l W_l + \sum_{m=0}^M B_m X_m + V, \quad (5)$$

where  $W$  is the vector of budget shares,  $X$  represents the matrix of independent variables (quantities and the aggregate stone quantity index) and  $L$  and  $M$  indicates the order of lags considered in dependent and independent variables. Noting that the steady state relationship between the independent ( $X$ ) and dependent variable ( $W$ ) is given by,

$$W = \frac{\sum_{m=0}^M B_m}{I - \sum_{l=1}^L A_l} X \quad (6)$$

the original autoregressive distributed lag model in (5) is transformed into a general dynamic model as,

$$W = D_L \Delta_L W + C_M \Delta_M X + G X, \quad (7)$$

where  $\Delta$  is the difference operator, and  $C$ ,  $D$ , and  $G$  are the matrix of parameters to be estimated. This transformation, known as a Bewley transformation, has been recently discussed in the context of the error correction model and estimation of long-run parameters (see Wickens and Breusch; Banaerjee et al.). In particular,  $G$  represents the long-run parameters consistent with equation (6), thus the standard errors for the long-run coefficients can be derived directly.

Although a number of transformations are available we prefer this one because of: (i) the resulting dynamic model is linear in parameters and easy to estimate; (ii) the long-run parameters are identified directly providing flexibility in imposing theoretical restrictions only on the long-run parameters if desired; (iii) the long-run and short-run effects are merged together in a systematic way; (iv) the relative ease of performing misspecifications tests on lag structure or short-run dynamics; and (v) the various other popular forms such as the static and partial adjustment models are nested within.

Of course, the static model is nested within the general model (7) when all the short-run dynamics parameters are set equal to zero i.e.  $C=D=0$ . The lag adjustments of the dependent variable denoted by matrix  $D$  may contain the cross commodity effects as well as the multiple lag effects for the same commodity. Accordingly, if the matrix  $A$  is full with non-zero cross diagonal elements, the model is referred to as the generalized partial adjustment model; and if  $D$  is merely diagonal, the model becomes the traditional partial adjustment type model where only own commodity lags are included. Thus, the general dynamic model provides a way of discriminating against the traditional hypothesis of partial and generalized partial adjustment processes, in addition to the static model.

## Data Development

Retail price series for selected cuts are available from the Bureau of Labor Statistics (BLS) and published periodically by the USDA (Livestock and Meat Situation). The impediment to analyzing disaggregated meat products has been the inability to determine appropriate quantities of meat products corresponding to these price series collected by BLS. Brester and Wohlgenant (1991) and Eales and Unnevehr (1988) provide the initial steps toward the disaggregation of beef. However, both studies were done in the context of annual data and ignored disaggregation of pork.

For the development of meat products data, monthly supply and use data obtained from the USDA provided the starting point of calculating meat quantities. The supply and use data are in standard aggregate form based on animal origin; namely beef, pork, and chicken. Assuming that types of meat products obtained from differing animal classes also differ, it was necessary to disaggregate the commercial livestock production data by classes of animal. Disaggregated commercial production was obtained by multiplying monthly slaughter of each class of animal by the monthly average carcass weight of each class of animal. The accounting identity that the commercial production by class of animal within each meat group be equal to the total commercial production for that particular meat group was satisfied by a correction factor.

The second stage of the quantity disaggregation procedure was to determine the proportions of ground and table-cut meat product for each class of commercial production. The assumptions for beef and pork follow.

Brester and Wohlgenant used information obtained from the Western Livestock Marketing Information Project (WLMIP) to determine the proportion of beef animals which was converted to their respective components of ground beef and table cuts. The same proportions were applied to the monthly commercial production data. The following proportions of ground beef were assumed to be obtained from each class of beef animal: cows, 90%; bulls, 100%; fed cattle, 25%; non-fed cattle, 45%; imports, 80%; and exports, 20%. These proportions were assumed to remain constant over time. This seems more practical in a monthly framework since the length of time period is reduced. Ending stocks were assumed to be comprised of the same proportion of meat products as the same periods commercial production of cuts. Applying supply identities to these quantities yielded total supply, and application of the USDA's carcass-retail conversion factor provided an estimate of the retail disappearance of ground beef and beef table cuts desired.

The data for pork meat were disaggregated in a similar fashion. To identify the pork meat products, it was necessary to break commercial production into commercial production of barrows and gilts, sows, and boars. The proportion of ground pork provided by each animal class was obtained from the American Meat Institute's (AMI) *Meat Facts* publication. AMI reported that 20% of a 175 pound hog carcass was processed into ground pork and sausages. This proportion was applied to commercial production by barrows and gilts. Similar information was not available for commercial sow production. However, the inverse of the relationship used for barrows and gilts was assumed for sows i.e. 80% of commercial sow production was ground pork. Further, it was assumed that 100% of commercial boar production went to ground pork or pork sausage. Imports and exports were assumed to follow the 20% ground pork assumption

similar to production, in the absence of better information. As with beef, ending stock proportions of ground pork were assumed to be the same as the relative proportions in current commercial production. Retail disappearance of ground pork and table cuts were obtained by applying the USDA carcass-retail conversion factor.

Chicken supply and use data was not separated into component products. This was primarily due to inconsistencies in the reported monthly data, as well as the dramatic changes over time in the proportions of breasts, further processed chicken, and whole birds within chicken production. Thus, the assumption of constant proportion was deemed to be inappropriate. Therefore, the total chicken disappearance is simply the total retail disappearance reported by the USDA. The quantity index for other food was derived by deflating the personal consumption expenditure for food less the meat products (nominal terms) by food price index less meat.

Monthly retail prices were obtained from the monthly BLS series reported by the USDA. Because the level of disaggregation of the meat products considered in this study were not identical to the level of the available price series, it was necessary to aggregate the retail price series. For beef table cuts, the simple average of the six primal cut beef prices were used as the beef table-cut price. The six cuts included sirloin steak, T-bone steak, porterhouse steak, round steak, round roast, and rib roast and constituted the major share of the retail cuts in beef. The price for ground beef was available as such and used directly. For pork, the average of the three available cut prices namely hams, pork chops, and sirloin roast were used as the price of pork table-cuts. The price information for ground pork was not available. Instead, the retail price of pork sausage was used as a proxy for the price of ground pork. For chicken, the average of retail breast and leg price was employed as the price of chicken<sup>4</sup>.

### Estimation Results

The meat product system consists of six commodities - ground beef, table cut beef, ground pork, table cut pork, chicken and other food. Therefore, a two step budgeting process between food and nonfood is implied here. The estimation period was set from January 1981 to December 1989, with the data for the year 1990 retained for post-sample predictive evaluation. Instead of monthly dummies, seasonality is represented by a more flexible fourier representation. This also helps to conserve the valuable degrees of freedom as the second order harmonic variables were deemed sufficient to represent seasonality in the data<sup>5</sup>. The harmonic variables are incorporated into the inverse demand system by translating the intercept as,

$$a_i = sd_{i0} + \sum_{r=1}^2 sd_{ir} \sin(2\pi r t/K) + \sum_{r=1}^2 sd_{ir+2} \cos(2\pi r t/K), \quad (8)$$

where  $sd$  are parameters to be estimated;  $r$  is the order of the harmonic variables;  $t$  is the time trend; and  $k=12$  for the monthly data (Doran and Quilkey). A maximum likelihood procedure was applied after deleting the other food equation to maintain the adding-up restriction. In all estimation, the symmetry and homogeneity restrictions were imposed except in the case of the general dynamic model where the restrictions were

imposed only on the long-run terms.

### Static and Differenced Models

The data was first applied to the static and two versions of the differenced specifications (first and twelfth differences). The estimated flexibilities for these models are reported in Table 1. The first differenced model included seasonal harmonic variables and the intercept, whereas the twelfth differenced specification did not include any of these variables. The results indicate that the estimated quantity and scale elasticities vary across the static and differenced specifications. In particular, the magnitude and sign of the cross flexibilities vary widely across the models. Considering that the cross commodity effects are important in policy evaluation perverse cross quantity effects are somewhat troublesome. In general, the own quantity flexibility of the differenced specifications are higher (in absolute terms) than that of the values derived from the static version. To counteract the absence of dynamics, the static model produced higher scale flexibility (in absolute terms) for beef and pork products compared to the differenced specifications.

Misspecification in econometric models are often understood through tests of properties of residuals. In this regard, the Q statistics indicate the randomness among disturbances. Although the use of Q statistics for individual equations are not appropriate within the multi-equation system, it provides an informal test for model misspecification. All Q statistics are significant for the static and the twelfth differenced models indicating that the assumption of white noise disturbance may be violated which in turn suggests that there may be misspecifications in the model. For the first difference model, the Q statistics are significant only for beef and pork products equations. These results merely suggest that the disturbances are not white noise in the static model and differenced specifications do not entirely overcome the omission of dynamics in the specifications<sup>6</sup>.

Specifically, one may also conclude that the significant Q statistics for the twelfth difference specification suggests that a 12 month lag adjustment may be too long for consumers to adjust in the case of meat products, whereas, the one month lag adjustment may be too short a time period for consumers to adjust. This observation further underscores the importance of evaluating dynamics within a general framework that allows for a more transparent way of including or excluding of short-run dynamics as part of misspecification tests. Such a task is achieved by applying the general dynamic model formulated in (7).

### The General Dynamic Model

A systematic approach was taken to successively go from the static model towards a more general dynamic framework dictated by the data. Accordingly, the data was applied to different dynamic models with different lag structures. The estimated models and the statistical results of comparisons are reported in Figure 1. In the first attempt, the static model was extended to a simple partial adjustment model by including lagged differences of the dependent variables alone. The log-likelihood ratio test indicated that this simple partial adjustment model was preferred over the static model. However, to

satisfy the invariance property of arbitrary deletion of one equation within a share system, it is required that the lag adjustment coefficients be equal across equations (see Anderson and Blundell, 1982; Bewley, 1986). Therefore in subsequent analysis, this restriction was always imposed. The final model that resulted after the statistical comparisons of the various nested models included lags up to fourth order of the differenced dependent variable and the first differences of the exogenous variables. This model, termed the general dynamic LAIDS (GD/LAIDS), is given by,

$$\begin{aligned}
 w_{it} = & sd_{i0} + sd_{i1} * \sin\left(\frac{2\pi t}{12}\right) + sd_{i2} * \cos\left(\frac{2\pi t}{12}\right) \\
 & + sd_{i3} * \sin\left(\frac{2\pi 2t}{12}\right) + sd_{i4} * \cos\left(\frac{2\pi 2t}{12}\right) \\
 & + \sum_{l=1}^4 d_{il} * \Delta_l w_t + \sum_{j=1}^{n+1} c_{ij} \Delta X_{jt} + \sum_{j=1}^{n+1} g_{ij} X_{jt} + v_{it}
 \end{aligned} \tag{9}$$

Intuitively, this model states that the inverse demand system is a function of both levels and differences of quantity and aggregate quantity index variables. The coefficients ( $g_{ij}$ ) attached to the current exogenous variables represent the long-run coefficients, hence the estimated flexibilities based on these coefficients are long-run in nature. Thus the more general dynamic model merged the long-run information with the short-run dynamics that are commonly observed in the meat demand data.

The estimated coefficients of the final model, referred to as the general dynamic LAIDS (GD/LAIDS), is presented in Table 2. Note that the lag coefficients of the dependent variables are constrained to be equal across the equations for maintaining the invariance property of the adding-up restriction. Except for the first order coefficient, they were all significant suggesting the importance of short-run dynamic adjustments in the meat demand data. The R-square values of the individual equations were fairly high. The significant coefficients for the harmonic variables indicate the importance of seasonality in the monthly data.

The average of the long-run flexibilities computed over the whole sample period are reported in Table 3. As expected, all own quantity and scale elasticities are negative. It is interesting to note that the flexibility of the ground cuts are smaller than their table cut counterpart in both beef and pork. This suggests that the price of table cuts are more elastic to changes its own quantities than the ground variety in both beef and pork. On the other hand, the scale elasticities were higher for ground variety than the table cuts indicating that the price of the ground meat variety will be more sensitive to changes in the aggregate food consumption than the table cuts for both beef and pork. However, the magnitude of the scale elasticities for ground beef seem to be somewhat larger. While the flexibilities for the disaggregated commodities are expected to be larger in the long run, further investigation is needed to substantiate this scale effect. Out of the 30 cross quantity flexibilities, only seven flexibilities exhibited a positive sign. The negative (positive) sign of the cross flexibilities indicates that commodities are substitutes (complements). For the most part, the perverse cross effects that were observed in the static and differenced models (Table 1) have been rectified by the

adoption of general dynamic model.

In order to validate the model further, the model was simulated with the additional year of data for 1990. The results of the dynamic simulations for the static and the general dynamic model are presented in Table 4. As expected, the general dynamic model produced a lower root mean square percent error when compared to the static model. The Theil statistics also indicated lower bias for the dynamic model. These results together with the reasonable estimates reported in table 3 indicate that the dynamic model is valid and could be effectively used in forecasting and policy applications.

### Final Remarks

In this study, a new data set was created for meat products based on the supply and disappearance data and applied to estimation of a dynamic inverse demand system. A linear approximate inverse demand system was used as the basis of investigating dynamics in the inverse meat products demand system. The linear approximate inverse demand system resembled in characteristics and met the minimum flexibility criteria of the functional form. The extension of the model to include dynamics was amenable because of the linearity of the model as well as the linear transformation of the general distributed lag model. This flexible dynamic model is general in the sense that it allowed for merging the short and long-run effects together and provided a way of testing against the partial adjustment and static representations.

The results suggest that dynamics and seasonality are important in meat products demand and it is best to represent the dynamics within a general framework. Statistical comparisons of various specifications indicate that a more general dynamic model that includes lagged differences of dependent variables, levels, and differences of the independent variables is preferred over the partial adjustment or static representations. Historical and post sample simulation results validate the general dynamic model in terms of small root mean square percent error and low Theil statistics. The estimates derived from the flexible inverse dynamic demand system produce reasonable flexibilities and eliminated many of the perverse cross commodity effects that are observed either in the static or differenced models. Thus, the model can be effectively used in monitoring the changes in the meat demand due to alternative trade strategies, product promotion, product development, and technological improvements in animal and meat production.

The results of this study suggest a number of future research opportunities. Although the data development could be extended to disaggregate the table cuts, the assumption about using fixed proportions may be too severe to compute a valid data series. Therefore, it will be important to gather additional information on the conversion factors or find alternative sources of data to analyze food products at the disaggregated product level. One alternative is to extract the information for disaggregated products based on the estimated flexibilities of the aggregate food groups. In terms of model development, while the linear approximate inverse demand system is a convenient and flexible representation for estimation of inverse demand systems, much needs to be done in terms of evaluating the approximation properties of this system. An initial attempt in this area has already been performed by Moschini and Vissa. In this regard, the relative

performance of this system with other approximate systems such as inverse rotterdam demand, quadratic, or inverse linear logit system should be evaluated. Both the rotterdam and linear logit model have the same number of free parameters and hence are as flexible as the linear approximate demand system. Also, it will be important to understand the approximation characteristics of LAIDS, in terms of curvature or global properties of flexible functional forms.

### End notes

1. While scanner and household expenditure survey data perhaps offer the best sources of information in terms of per capita consumption of (disaggregated) meat products analysis, they have limited potential for deriving market demand parameters. A detailed explanation on the relative merits and demerits of alternative sources of data to demand analysis is beyond the scope of this study, however, please see Buse for a discussion on this.

2. Throughout this paper, the quantity dependent functions where prices and expenditures are treated as independent variables are termed as direct demand functions, whereas the price dependent form where the quantities are taken as independent variables are referred to as inverse demand function.

3. The logarithmic generalized linearity specification of the distance function can be specified as,

$$\log D(u, q) = (1-u) \log a(q) + u \log b(q),$$

where  $D$  denotes the distance function,  $u$  indicates utility and  $a(q)$  and  $b(q)$  are homogenous functions.

4. Although the retail price for whole birds were available, it is not considered to be representative of the actual product available at the retail level and hence, not used in the calculation of the retail price for chicken.

5. The log-likelihood test statistics with the static model (equation 1) indicated that second-order harmonic variables are sufficient for the data to represent seasonality.

6. Following Deaton and Muellbauer, the presence of autocorrelation is taken for omission of dynamics.

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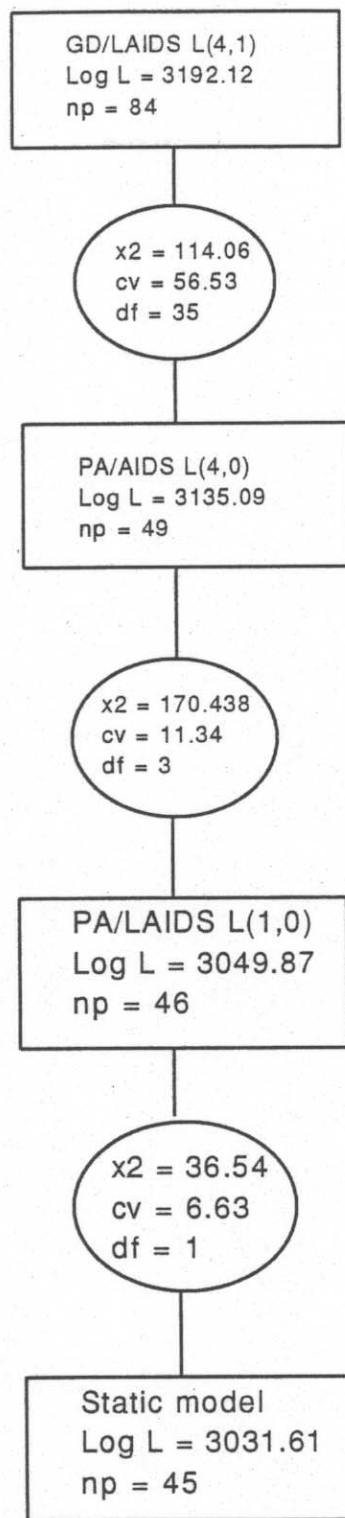


Figure 1. Tests of alternative dynamic models.

Notes: The values within L( ) indicate the order of lags for dependent and independent variables; CV indicates the critical values for chi-square statistics at 1% level of significance; and np denotes the number of parameters estimated.

Table 1. Estimated uncompensated flexibilities and scale elasticities for meat products from various models.

with respect to quantity of								Q stat. Q(12)	Log-I	no. of param.
Model/ commodity	gr. beef	tb. beef	gr. pork	tb. pork	chicken	ot. food	Scale			
A. Static/LAIDS (with seasonal harmonic variables + intercept)								3031.605		45
gr. beef	-0.2907	-0.2868	-0.0015	0.0127	-0.1362	-3.1394	-3.8418	210.81		
tb. beef	-0.0557	-0.3643	0.0037	-0.0005	-0.0068	-1.8644	-2.2879	122.03		
gr. pork	0.0197	0.0048	-0.0906	-0.6970	0.0022	-1.9135	-2.5645	194.47		
tb. pork	0.0371	0.0117	-0.2004	-0.3452	-0.0350	-1.5471	-2.0789	284.43		
chicken	-0.0137	0.0840	0.0537	0.0123	-0.1643	-0.7148	-0.7428	228.81		
ot. food	-0.0121	-0.0445	-0.0053	-0.0199	-0.0312	-0.6763	-0.7895			
B. First difference/LAIDS (with seasonal harmonic variables + intercept)								3332.03		45
gr. beef	-0.9759	0.0232	0.0032	0.0140	0.0125	0.3122	-0.6109	33.67		
tb. beef	0.0028	-0.9327	0.0021	0.0030	0.0067	0.1124	-0.8058	41.82		
gr. pork	-0.0066	-0.0193	-0.9924	-0.0114	-0.0112	-0.2718	-1.3128	11.58		
tb. pork	0.0058	0.0154	0.0031	-0.9548	0.0103	0.2338	-0.6864	8.75		
chicken	-0.0071	-0.0198	-0.0036	-0.0122	-0.9791	-0.2938	-1.3156	19.00		
ot. food	-0.0148	-0.0517	-0.0097	-0.0298	-0.0302	-0.8827	-1.0190			

Table 1. Cont.

with respect to quantity of										
Model/ commodity	gr. beef	tb. beef	gr. pork	tb. pork	chicken	ot. food	Scale	Q stat. Q(12)	Log-I	no. of param.
C. 12th difference/LAIDS (no intercept or seasonal variables)										
gr. beef	-0.9927	-0.0361	-0.0053	-0.0165	-0.0229	-0.4864	-1.5598	369.5	2851.595	20
tb. beef	-0.0048	-0.9578	0.0015	-0.0051	-0.0061	-0.1998	-1.1722	222.64		
gr. pork	-0.0168	-0.0562	-1.0006	-0.0436	-0.0315	-0.8140	-1.9626	169.96		
tb. pork	-0.0004	-0.0126	-0.0114	-0.9835	-0.0066	-0.2066	-1.2211	256.08		
chicken	0.0018	0.0170	0.0053	0.0111	-0.9679	0.2063	-0.7264	358.67		
ot. food	-0.0160	-0.0533	-0.0065	-0.0200	-0.0216	-0.8479	-0.9651			

Notes: The abbreviation gr. denotes ground; tb. denotes table cuts; and ot. denotes other.

The mean budget shares for the period from Jan. 1981 through Dec. 1988 are 0.0183, 0.0620, 0.0107, 0.0362, 0.03504, and 0.8372 respectively for gr. beef, tb. beef, gr. pork, tb. pork, chicken, and ot. food. The average values of flexibilities for the whole sample are reported in the table.

Table 2. Maximum likelihood estimates for the general dynamic LAIDS for meat product

	Share of gr.beef	Share of Tb.beef	Share of gr. pork	Share of tb.pork	Share of chicken
Intercept	0.0180* (0.73x10 <sup>-4</sup> ) <sup>d</sup>	0.0634* (0.0001)	0.0193* (0.51x 10 <sup>-4</sup> )	0.0366* (0.0001)	0.0349* (0.0002)
gr.beef	0.0082* (0.0014)	0.18 <sup>a</sup> x 10 <sup>-4</sup> (0.0016)	0.0001 <sup>a</sup> (0.0008)	0.0002 <sup>a</sup> (0.0013)	-0.0028* <sup>a</sup> (0.0012)
tb.beef	0.18 x 10 <sup>-4</sup> (0.0016)	0.0229* (0.0026)	0.0023 <sup>a</sup> (0.0010)	0.0052 <sup>a</sup> (0.0018)	-0.0069* <sup>a</sup> (0.0019)
gr.pork	0.0001 (0.0008)	0.0023* (0.0010)	0.0073* (0.0011)	-0.0085* <sup>a</sup> (0.0015)	0.0015 <sup>a</sup> (0.0008)
tb.pork	0.0002 (0.0013)	0.0052* (0.0018)	-0.0085* (0.0015)	0.0142* (0.0026)	0.0010 <sup>a</sup> (0.0018)
chicken	-0.0028* (0.0012)	-0.0069* (0.0019)	0.0015 (0.0008)	0.0010 (0.0018)	0.0218* (0.0034)
scale	-0.0602* (0.0043)	-0.0958* (0.0056)	-0.0223* (0.0029)	-0.0565* (0.0069)	-0.0039 (0.0080)
$\Delta_1$ gr.beef	-0.0022 (0.0026)	-0.0023 (0.0029)	-0.0004 (0.0016)	-0.0015 (0.0040)	-0.0010 (0.0047)
$\Delta_1$ tb.beef	0.0004 (0.0048)	-0.0007 (0.0078)	-0.0033 (0.0033)	-0.0072 (0.0081)	0.0053 (0.0107)
$\Delta_1$ gr.pork	-0.0001 (0.0036)	-0.0018 (0.0046)	-0.0012 (0.0025)	0.0055 (0.0061)	-0.0009 (0.0066)
$\Delta_1$ tb.pork	-0.0002 (0.0043)	-0.0047 (0.0058)	0.0036 (0.0029)	0.0009 (0.0078)	-0.0002 (0.0085)
$\Delta_1$ chicken	0.0006 (0.0027)	-0.0005 (0.0041)	-0.0026 (0.0021)	-0.0042 (0.0050)	-0.0004 (0.0067)
$\Delta_1$ ot.food	-0.0171 (0.0526)	-0.0456 (0.0804)	-0.0248 (0.0386)	-0.0486 (0.0955)	0.0297 (0.1236)
$\Delta_1$ scale	0.0458 (0.0621)	0.1079 (0.0946)	0.0377 (0.0457)	0.0736 (0.1126)	-0.0473 (0.1467)

Table 2. Contd.

$\Delta_2 w$	0.1527* (0.0229)	0.1527* (0.0229)	0.1527* (0.0229)	0.1527* (0.0229)	0.1527* (0.0229)
$\Delta_3 w$	0.1578* (0.0221)	0.1578* (0.0221)	0.1578* (0.0221)	0.1578* (0.0221)	0.1578* (0.0221)
$\Delta_4 w$	0.1214* (0.0211)	0.1214* (0.0211)	0.1214* (0.0211)	0.1214* (0.0211)	0.1214* (0.0211)
$\sin 1^c$	$0.91 \times 10^{-4}$ (0.0001)	$-0.0021^*$ (0.0002)	$0.0004^*$ (0.0001)	$0.0008^*$ (0.0003)	$-0.0013^*$ (0.0003)
$\cos 1^c$	$0.0004^*$ (0.0001)	$-0.84 \times 10^{-4}$ (0.0003)	$0.0006^*$ (0.0001)	$0.0011^*$ (0.0003)	$0.54 \times 10^{-4}$ (0.0004)
$\sin 2^c$	$-0.60 \times 10^{-4}$ (0.0001)	$-0.10 \times 10^{-4}$ (0.0002)	$-0.0002^*$ (0.0001)	$0.0003$ (0.0003)	$0.0001$ (0.0003)
$\cos 2^c$	$0.60 \times 10^{-4}$ (0.0002)	$0.0001$ (0.0002)	$0.0002^*$ (0.0001)	$0.0004$ (0.0003)	$-0.86 \times 10^{-4}$ (0.0003)
$R^2$	0.9412	0.9735	0.8891	0.8788	0.7903
RMPSE	4.433	2.1797	4.2192	3.5510	4.2145

<sup>a</sup> Parameters derived based on symmetry conditions.

<sup>b</sup> w indicates dependent variables. The cross-equation lag coefficients are restricted to be equal.

<sup>c</sup>  $\sin 1$ ,  $\cos 1$ ,  $\sin 2$ ,  $\cos 2$  are sine and cosine functions of  $\frac{(2\pi t)}{12}$ ,  $\frac{(2\pi t)}{12}$ ,  $\frac{(2\pi 2t)}{12}$ , and  $\frac{(2\pi 2t)}{12}$ , respectively.

<sup>d</sup> The figures within parantheses indicate standard errors.

\* indicates statistically significant at 5 % level.

Table 3. Estimated flexibilities and scale elasticities for meat products based on the general dynamic LAIDS

commodity	with respect to quantity of						Mean share
	gr. beef	tb. beef	gr. pork	tb. pork	chicken	ot. food	
gr. beef	-0.5973	-0.2068	-0.0288	-0.1074	-0.2779	-3.1711	0.0183
tb. beef	-0.0277	-0.7236	0.0210	0.0285	-0.1672	-1.6869	0.0624
gr. pork	-0.0264	0.0877	-0.3291	-0.8779	0.0714	-2.0364	0.0107
tb. pork	-0.0216	0.0473	-0.2535	-0.6607	-0.0282	-1.6572	0.0362
chicken	-0.0832	-0.2068	0.0431	0.0238	-0.3775	-0.5133	0.0350
ot. food	-0.0017	-0.0102	-0.0003	-0.0042	-0.0073	-0.6909	0.8372

Table 4. Simulation statistics for meat products from various models

A. General Dynamic/LAIDS									
	Mean Error	Mean % Error	Mean		Mean Abs. % Error	RMS Error	RMS % Error		
			Abs. Error	Abs. % Error					
Gr. beef	0.000208	1.4762	0.000664	3.48865	0.000894	4.4335			
Tb. beef	0.000689	1.1980	0.001121	1.85067	0.001300	2.1797			
Gr. pork	0.000077	0.8554	0.000378	3.54137	0.000452	4.2192			
Tb. pork	0.000163	0.5995	0.001084	3.02776	0.001264	3.5510			
Chicken	-0.000280	-0.6977	0.001225	3.44287	0.001514	4.2145			
B. Static/LAIDS									
	Mean Error	Mean % Error	Mean		Mean Abs. % Error	RMS Error	RMS % Error		
			Abs. Error	Abs. % Error					
Gr. beef	0.000142	1.1970	0.000813	4.19222	0.001148	5.5021			
Tb. beef	0.000521	0.9718	0.001537	2.45470	0.001945	3.0333			
Gr. pork	0.000077	0.9399	0.000485	4.50266	0.000580	5.3248			
Tb. pork	0.000179	0.6880	0.001219	3.38660	0.001486	4.1264			
Chicken	-0.000350	-0.8389	0.001425	3.98964	0.001789	4.9239			