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Crop Yield Futures and Revenue Distributions

Viswanath Tirupattur, Robert J. Hauser and Nabil M. Chaherli[1]

The use of impending crop yield futures contracts to hedge expected net revenue is examined. The expectation being modeled here reflects that of an Illinois corn and soybean producer in March of the revenue realized after harvest. The effects of using price and yield contracts are measured by comparing the resulting expected distribution to the expected distribution found under five general alternatives: (1) a revenue hedge using just price futures, (2) a revenue hedge using just yield futures, (3) a no-hedge scenario where revenue is determined by realized price and yield, (4) a no-hedge scenario where revenue is determined by the market and by participating in the current deficiency-payment program, and (5) a no-hedge scenario where revenue is determined by the market and by participating in a proposed revenue-assurance program. Three major conclusions are drawn. First, hedging effectiveness using the new crop yield contract depends critically on yield basis risk which presumably can be reduced considerably by covering large geographical areas. Second, crop yield futures can be used in conjunction with price futures to derive risk management benefits significantly higher than using either of the two alone. Third, hedging with price and crop yield futures can potentially offer benefits that are large relative to the revenue assurance program analyzed. However, the robustness of the findings depends largely on whether yield basis risk varies significantly across regions.

Background

Crop producers face both price risk and yield risk. Producers use futures and options markets directly and indirectly through elevators for price risk management. However, similar private-sector instruments for managing output risk have not been available. On the other hand, federal agricultural support programs such as deficiency and non-recourse loan programs as well as subsidized crop yield insurance programs have provided risk management mechanisms. A private-market alternative for production and income stabilization will soon be available in the form of new crop yield futures and options.

Corn yield futures and options will begin trading at the Chicago Board of Trade (CBOT) in June 1995. Yield futures for soybeans, winter wheat, and spring wheat have also been

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proposed by the CBOT. The CBOT yield futures contract is based on the USDA reported estimate of an average state yield. For corn, the Iowa yield per acre will be used, and the value of the contract is the traded yield (in bushels) times \$100. There will be two expiration months -- September and January -- when the contract is cash settled based on the USDA September and January corn yield reports. Current proposals call for state average yields of Illinois, North Dakota and Kansas to be used to settle the yield futures for soybeans, spring wheat and winter wheat.

The use of yield contracts for hedging production is often discussed in one of two contexts. The first context involves the direct use of the contract by the producer. The second context involves the indirect use by the producer through either, for example, elevators offering a forward contract or through insurance companies offering revenue or production insurance. Indeed, the yield contract is often referred to as a "yield insurance contract".

The general purpose of the present analysis is to provide insight into the potential effects of using the yield futures contract in conjunction with the price futures contract on the expected-revenue distribution facing the producer. The model reflects the expectation of revenue to be realized by an Illinois corn and soybean producer making planting decisions in March. The effects of using price and yield contracts are measured by comparing the resulting expected distribution to the expected distribution found under five general alternatives: (1) a revenue hedge using just price futures, (2) a revenue hedge using just yield futures, (3) a no-hedge scenario where revenue is determined by realized price and yield, (4) a no-hedge scenario where revenue is determined by the market and by participating in the current deficiency-payment program, and (5) a no-hedge scenario where revenue is determined by the market and by participating in a proposed revenue-assurance program.

Data and Methods

We analyze the revenue distributions resulting from the use of price and yield futures and from participation in government support programs by simulating the revenue functions in each case. A general description of the approach is as follows. Prices and yields are assumed to follow a lognormal distribution. A vector **V**, consisting of cash prices and yields of corn and soybeans is generated by using a linear transformation of i.i.d. univariate standard normal variates based on a variance-covariance matrix estimated from central Illinois county level data for corn and soybeans. Futures prices and yields are then generated, conditional on the corresponding cash prices and yields. Thus each pair of cash and futures is assumed to follow a bi-variate lognormal distribution, resulting in another vector **FV**, consisting of futures prices and yields. Revenue distributions are then found from the two vectors, **V** and **FV**.

More specifically, we first generate $\mathbf{V}= (p_c, y_c, p_s, y_s)$, where p_c, y_c, p_s, y_s represent cash prices and yields of corn and soybeans with mean vector $\boldsymbol{\mu}$ and a variance-covariance matrix Σ. Note that $\boldsymbol{\mu}$ and Σ are defined in terms of changes in natural logs, implying lognormality of prices and yields in levels and allowing the use of Choleski decomposition for generating the vector **V** with the required variance-covariance matrix. Recall that for every positive definite square matrix, e.g., Σ, there exists a unique lower triangular matrix **T** such that $\mathbf{TT}'=\Sigma$. This result is known as the Choleski decomposition. If $\mathbf{X} \sim N(0,1)$ and **T** is the matrix from Choleski decomposition, then $\mathbf{W}=\mathbf{TX}+\boldsymbol{\mu}$ is distributed as $N(\boldsymbol{\mu},\Sigma)$. We use a matrix of four i.i.d univariate standard normal random variates with a sample size of 10,000 draws each to obtain $\mathbf{W}$[2]. Exponentiating $\mathbf{W}$ yields the desired vector $\mathbf{V}$. A variance-covariance matrix was estimated using sample data on cash prices and yields for Champaign county, Illinois, for the period 1972-93. Yield data were obtained from various issues of the Illinois Agricultural Statistics (Illinois Cooperative Crop Reporting Service) and price data were obtained Illinois Agricultural Marketing Service. The estimation was done using log changes in cash prices and yields. The estimated variance-covariance matrix and correlation matrix are reported in Tables 1 and 2.

Futures prices and yields corresponding to cash prices and yields are generated using a procedure suggested by Hull. The procedure is similar to that used for generating the vector V, differing only in the sense that, instead of Σ, only pairwise correlation coefficients (ρ_i) are required. The pairwise correlation coefficients reflect basis risk. When ρ_i is one, there is no basis risk and futures and cash processes are identical. As ρ_i decreases, basis risk increases.

Using vectors **V** and **FV**, revenue realizations can be computed for any given set of expected prices and yields and policy parameters. Revenue from using just cash markets, mr_T, is computed as:

$$mr_T = \sum_i w_i [p_{i,T} \cdot y_{i,T}] \tag{1}$$

where w_i is the proportion of ith crop (I=1,2) on the farm and T is the terminal time period. Revenue from hedging using price and yield futures, $hr_{P\text{-}Y,T}$, is found by:

$$hr_{P-Y,T} = \sum_i w_i [p_{iT} y_{iT} + (hr_{p,i})(P_{i,t} - P_{i,T}) E_t(y_{i,T}) + (hr_{y,i})(Y_{i,t} - Y_{i,T}) E_t(p_{i,T})] \tag{2}$$

where $hr_{p,i}$ and $hr_{y,i}$ are price and yield hedge ratios, $E_t(y_{i,T})$ and $E_t(p_{i,T})$ are expectations made at time t about terminal yields and prices, $P_{i,t}$ is the new-crop futures price for crop I at time t, and $Y_{i,t}$ is the yield futures for crop I at time t. The second and third terms in (2) describe the income generated in the price and crop yield futures markets. For example, assume price hedge ratio to be one. The hedge is placed by establishing a short position in the price futures market equal to $E_t(y_{i,T})*P_{i,t}$. The hedge is maintained until contract expiration when the futures position is offset at the value equal to $E_t(y_{i,T})*P_{i,T}$. Likewise, assume the yield hedge ratio is one. A short position is established in the yield futures market equal to $E_t(p_{i,T})*Y_{i,t}$, which is offset at $E_t(p_{i,T})*Y_{i,T}$. In this illustration, where the two hedge ratios are equal to one, a "full hedge" is described because the quantity established in the price hedge is the expected yield and the price established in the yield hedge is the expected price. A "partial hedge" is described by setting $0<hr_{p,i}<1$ and /or $0<hr_{y,i}<1$. Note further that setting $hr_{p,i}$ equal to zero results in a "pure" yield hedge and setting $hr_{y,i}$ equal to zero results in a "pure" price hedge.

Revenue from participation in the existing government support programs, rdl_T, is given by the following:

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[2]See Tong for further details on this procedure.

$$rdl_T = \sum_i w_i [Max(p_{i,T}, LR_i) y_{i,T} + (PgmY_i)(1 - (ARP + Flex)) Max(TP_i - Max(p_{i,T}, LR_i))] \tag{3}$$

where *LR* is the loan rate, $PgmY_i$ is the program yield, *ARP* and *Flex* are the percentages of setaside acres and flex acres and *TP* is the target price. The first term describes the revenue payouts from the non-recourse loan program and the second term describes revenue from deficiency payments. There are no deficiency payments for soybeans.

Revenue from the proposed revenue assurance program, ra_T, is given by the following.

$$ra_T = \sum_i w_i [Max((p_{i,T} y_{i,T}), \theta Z_i)] \tag{4}$$

where θ is the coverage level (proportion) assured under the revenue assurance program and Z is the target gross revenue. Note that the target gross revenue for each crop is considered separately as opposed to a revenue assurance for the farm.

Results

Gross revenue realizations are computed for each of the marketing strategies described above. A fixed level of costs representing all production costs except land costs is subtracted from each gross revenue realization to compute net revenue realizations. The parameter values used for the simulation analysis are described in Table 3. The resulting distributions are analyzed within two contexts -- hedging effectiveness (HE) and the frequency distribution of net revenue realizations. HE indicates the level of variance reduction achieved through the use of a risk management mechanism and and is measured here in a way that requires explicit incorporation of basis risk. HE is computed as: *[1- (VAR(HR)/VAR(UHR))]* where VAR is the variance operator, HR is the hedged revenue and UHR is the unhedged revenue[3].

We first illustrate the importance of yield basis risk. Recall that basis risk is reflected in the simulations through ρ_{cp}, ρ_{cy}, ρ_{sp}, and ρ_{sy}; i.e., the correlation coefficients between the intra-year changes in the Wiener processes associated with the cash and futures processes of corn prices and yields and soybeans prices and yields. It is expected that the largest source of basis uncertainty for a Champaign county cash grain farm pertains to corn yield basis, since the corn yield contract will be settled based on the Iowa state average yield. We compute revenue realizations following equation (2) using a range of values for ρ_{cy} (0.2 to 1.0) but holding the values of ρ_{cp}, ρ_{sp} and ρ_{sy} constant at 0.973, 0.995 and 0.876. The frequency distributions of the resulting distributions along with corresponding HE measures are reported in Table 4. As ρ_{cy} increases the resulting revenue distribution tightens. Correspondingly, HE increases from 0.23 to 0.92 as ρ_{cy} increases from 0.2 to 1.0 indicating that hedging effectiveness for a producer using crop yield futures depends critically on the yield basis risk. In other words, the higher is the

[3]See Hauser, Garcia and Tumblin for a detailed discussion on HE.

correlation between farm level corn yield and Iowa state average corn yield, the more effective the yield hedge is. It is important to emphasize in this context that unlike cash and futures prices which tend to be highly correlated, farm yields are not necessarily highly correlated with a state average yield level (Iowa for corn and Illinois for soybeans). This implies that even though price basis risk does not vary widely across the Midwest, yield basis risk may vary substantially and thus the effectiveness of the yield hedge for individual producers may vary by location even within the Midwest. The ability to widen the geographical area to reduce basis risk may prove particularly useful when using yield futures. For example, large grain companies or reinsurers may be able to reduce basis risk considerably by covering large areas, and then offer secondary contracts to producers that reflect this decreased basis risk. In the subsequent analysis, ρ_{cy} is fixed at 0.621 which is the estimated correlation coefficient between the changes in corn yields in Champaign county yield and Iowa state averages.

Above, the hedge ratios for both price and yield contracts are assumed to be one, implying a full hedge. We determine "optimal hedge ratios" for the price and yield contracts by parametrically varying the hedge ratios associated with price and yield for corn and soybeans separately from 0.0 to 1.0 in discrete intervals of 0.1. Values of HE under alternatives parametric assumptions of hedge ratios are presented in Tables 5 and 6. The first column in both tables represents hedging effectiveness using a pure price hedge, and the first row represents hedging effectiveness using a pure yield hedge. For corn, the "optimal" hedge ratios for pure price and yield hedges are 0.6 and 0.4 respectively, resulting in a HE of only 28 percent and 11 percent respectively. For soybeans, the "optimal" hedge ratios for pure price and yield hedges are 0.7 and 0.4 respectively, resulting in a HE of 53 percent and 10 percent respectively. However, if both crop yield and price futures are used, HE increases considerably. In case of corn, HE increases up to 50 percent using a combination of price (0.7 hedge ratio) and crop yield (0.5 hedge ratio) futures contracts. Similarly, for soybeans, HE increases up to 86 percent using a combination of price (0.9 hedge ratio) and crop yield (0.8 hedge ratio) futures contracts. Thus these results suggest that price and crop yield futures can be used together to achieve significant improvements in risk management benefits.

Expected net revenue distributions from cash marketing and various hedging strategies using "optimal hedge ratios" are compared to those resulting from government programs in Table 7 in terms of discrete probability densities. The probabilities associated with the scenario where revenue is determined by just realized price and realized yield are presented in the NMR column. NHR1, NHR2 and NHR3 represent hedging using both price and yield futures, a pure price hedge and a pure yield hedge respectively. NRDL and NRA represent the expected distribution associated with a deficiency and loan program and with a revenue assurance program respectively.

When no hedging strategies are used (NMR), the probability of receiving a net revenue of \$45 to \$70 is 7.5%. When hedging with both price and yield contracts, the probability falls to 0.1%. Examination of Table 7 provides perspective on how the use of price and yield contracts causes the market revenue distribution to collapse. The mean remains at about \$134 while, as expected, the distribution becomes progressively tighter with the use of yield contracts (NHR3), price contracts (NHR2), and then yield and price contracts (NHR1).

In a safety-first context where, say, \$95 is the threshold level, the probability of receiving less than the threshold level is 24.2% in the no-hedge scenario, NMR. Hedging with the yield contract reduces the probability to 22.3%. The use of just price contracts reduces it to 17.7%, and the use of both contracts reduces it to 8%.

Under 70% revenue assurance, the mean increases slightly from about $134 to $135.5 and the probability of revenue at lower end of the distribution goes to zero. The probability of receiving revenue less than the $95 threshold is quite high, as much as 24.2%. The overall risk-reduction effect seems minimal. Note that the expected average gross revenue is about $262 per acre and thus the 70% revenue assurance level is about $183. After accounting for non-land costs, the assured net revenue is about $60. Consequently, because of the relatively low threshold levels and because of the offsetting effects of corn and soybeans, the truncating effect on the net revenue distribution does not appear large.

However, the effects of the present analysis ignores any market price level effect of a program. It is often argued that a revenue-assurance program would cause commodity prices in general to increase because replacing the current program with a revenue assurance program would presumably lead to a decrease in production and an increase in price.

The expected distribution associated with participation in the deficiency-payment program (NRDL) is scaled considerably higher than the others, resulting in a mean of about $170. The probability of falling below $95 is 2.3%.

An important point when comparing the free market distributions to either of the distributions involving government programs involves the "stability" of the results across regions. The underlying basis risk of price hedges and particularly yield hedges may vary considerably from region to region, presumably causing the comparative results between non-program and program distributions to be sensitive to location.

Conclusions

We draw three major conclusions from the results. First, hedging effectiveness using the new crop yield contract depends critically on yield basis risk which presumably can be reduced considerably by covering large geographical areas. Second, crop yield futures can be used in conjunction with price futures to derive risk management benefits significantly higher than using either of the two alone. Third, hedging using price and crop yield futures has a potential to offer benefits larger than those from the proposed revenue assurance program. However, the robustness of the findings depends largely on whether yield basis risk varies significantly across regions.

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Table 1. Sample Variance-Covariance Matrix Used to Estimate the Cash Prices and Yields

	Δp_C	Δy_c	Δp_s	Δy_s
Δp_C	0.047357			
Δy_C	-0.01915	0.047691		
Δp_s	0.035028	-0.01527	0.037954	
Δy_s	-0.01369	0.023965	-0.01025	0.019965

Table 2. Implied Sample Correlation Coefficient Matrix

	Δp_C	Δy_c	Δp_s	Δy_s
Δp_C	1.000			
Δy_C	-0.403	1.000		
Δp_s	0.826	-0.359	1.000	
Δy_s	-0.445	0.777	-0.372	1.000

Table 3. Parameter Values Used in the Simulations

	Corn	Soybeans
Expected Price ($/Bu):	2.10	5.79
Expected Yields (Bu/Acre)	131.08	42.16
Cash-Futures Correlations:		
- price	0.973	0.995
- yield	0.621	0.876
Proportion of acreage in the farm	0.58	0.42
Target price ($/Bu)	2.75	-
Loan rate ($/Bu)	2.00	5.00
ARP (%)	10	-
Flex (%)	15	-
Revenue assurance level	0.70	0.70
Costs per acre ($) (Excluding land rents)	155.20	81.04

Table 4. Effect of Yield Basis Risk on Net Revenue Probability Density Functions
(Hedging using price and yield futures)

Net Revenue	ρ_{cy} (0.2)	ρ_{cy} (0.4)	ρ_{cy} (0.621)	ρ_{cy} (0.8)	ρ_{cy} (1.0)
< 45	3.4	2.2	0.8	0.1	0.0
45-70	5.3	3.8	2.7	1.0	0.1
70- 95	10.4	10.5	8.6	5.9	1.3
95-120	17.1	18.1	20.1	21.0	13.2
120-145	22.4	25.3	30.1	37.7	63.6
145-170	19.4	21.0	24.0	26.4	21.2
170-195	13.1	12.8	10.6	6.8	0.6
195-220	6.2	4.7	2.6	1.0	0.0
220-245	2.0	1.1	0.5	0.1	0.0
>245	0.7	0.3	0.1	0.0	0.0
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	100%	100%	100%	100%	100%
Mean ($)	134.17	134.19	134.20	134.19	134.15
Variance	2199	1696	1144	702	218
HE	0.229	0.406	0.599	0.754	0.923

ρ_{cp}, ρ_{sp} and ρ_{sy} are held constant at 0.973, 0.995 and 0.876 respectively.

Table 5. Corn Hedging Effectiveness Estimates using Price and Yield Futures

	HRy										
HRp	0.00	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90	1.00
0.00	0.000	0.053	0.088	0.107	0.109	0.095	0.063	0.015	-0.050	-0.131	-0.230
0.10	0.089	0.145	0.185	0.208	0.214	0.204	0.176	0.132	0.071	-0.007	-0.102
0.20	0.161	0.221	0.265	0.292	0.302	0.295	0.272	0.231	0.174	0.100	0.010
0.30	0.216	0.280	0.328	0.359	0.373	0.370	0.350	0.314	0.261	0.191	0.104
0.40	0.254	0.322	0.374	0.408	0.426	0.427	0.412	0.379	0.330	0.264	0.181
0.50	0.275	0.347	0.402	0.441	0.463	0.468	0.456	0.428	0.382	0.320	0.241
0.60	0.279	0.355	0.414	0.457	0.483	0.491	0.484	0.459	0.418	0.360	0.285
0.70	0.266	0.346	0.409	0.455	0.484	0.498	0.494	0.473	0.436	0.382	0.311
0.80	0.236	0.320	0.387	0.437	0.471	0.488	0.487	0.471	0.437	0.387	0.320
0.90	0.188	0.276	0.347	0.402	0.439	0.460	0.464	0.451	0.422	0.375	0.312
1.00	0.124	0.216	0.291	0.349	0.391	0.415	0.423	0.414	0.389	0.346	0.287

HRp and HRy are hedge ratios for price and yield futures contracts respectively.

Table 6. Soybeans Hedging Effectiveness Estimates using Price and Yield Futures

	HRy										
HRp	0.00	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90	1.00
0.00	0.000	0.000	0.073	0.093	0.103	0.102	0.091	0.068	-0.867	-0.008	-0.063
0.10	0.137	0.183	0.218	0.243	0.257	0.261	0.254	0.236	0.207	0.168	0.118
0.20	0.253	0.304	0.344	0.373	0.392	0.400	0.397	0.383	0.359	0.325	0.279
0.30	0.349	0.404	0.449	0.483	0.506	0.518	0.520	0.511	0.491	0.461	0.420
0.40	0.425	0.485	0.534	0.572	0.600	0.616	0.623	0.618	0.603	0.577	0.540
0.50	0.481	0.545	0.599	0.641	0.673	0.695	0.705	0.705	0.694	0.670	0.641
0.60	0.517	0.585	0.643	0.690	0.727	0.753	0.768	0.772	0.809	0.749	0.721
0.70	0.533	0.606	0.668	0.719	0.760	0.790	0.810	0.819	0.817	0.804	0.781
0.80	0.528	0.605	0.672	0.728	0.773	0.808	0.832	0.845	0.848	0.840	0.821
0.90	0.503	0.585	0.656	0.717	0.766	0.806	0.834	0.852	0.859	0.855	0.841
1.00	0.458	0.545	0.620	0.685	0.739	0.783	0.816	0.838	0.849	0.850	0.840

HRp and HRy are hedge ratios for price and yield futures contracts respectively.

Table 7. Probability Density Function of Net Revenue Under Alternative Risk Management Mechanisms

Net Revenue	NMR	NHR1	NHR2	NHR3	NRDL	NRA
< 45	2.2	0.1	1.0	1.8	0.0	0.0
45-70	7.5	1.0	4.0	6.2	0.2	7.7
70-95	14.5	6.9	12.7	14.3	2.1	16.5
95-120	18.9	25.1	21.2	20.1	9.1	19.0
120-145	18.6	34.2	24.4	20.3	18.9	18.6
145-170	15.0	21.4	17.5	15.3	23.8	15.0
170-195	10.7	8.2	10.9	10.7	20.3	10.7
195-220	6.0	2.4	4.9	5.8	13.3	6.0
220-245	3.4	0.6	2.0	3.0	7.2	3.4
>245	3.2	0.3	1.3	2.5	5.1	3.2
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	100%	100%	100%	100%	100%	100%
Mean($)	134.14	134.16	134.15	134.16	169.53	135.50
Variance	2854	913	1835	2528	1882	2639

A FLEXIBLE DYNAMIC INVERSE DEMAND SYSTEM: AN APPLICATION TO U.S. MEAT DEMAND

Matthew T. Holt and Barry K. Goodwin*

In recent years there has been considerable interest in systems of inverse demand equations for agricultural commodities. Prior studies have, however, tended to give dynamic considerations short shrift, working instead with either first-difference or first-order autoregressive models. This study addresses squarely this issue by developing a general vector time-series model for expenditure shares in the context of an inverse demand system. Importantly, minimal constraints are placed on the model's short-run structure; consistent theoretical behavior is, however, incorporated in the model's long-run structure by using an Inverse AIDS (IAIDS) demand system. The resulting framework is used to model consumer meat expenditure decisions in the U.S. with favorable results. The model is then used to test for several more restrictive specifications such as autoregressive and partial adjustment models. In each case these more commonly used models are rejected. Also, the general model is superior in several regards to a first-difference specification.

1. INTRODUCTION

In recent years there has been renewed interest in systems of inverse demand equations for food and agricultural products (Chambers and McConnell; Barten and Bettendorf; Huang). In such systems prices are defined as dependent variables, while quantities consumed are treated as exogenous or right-hand-side variables (Anderson; Weymark). Interest in inverse demand systems stems from the fact that many food products, unlike most manufactured goods and services, involve relatively long production lags so that quantities available in the short run are essentially fixed. Furthermore, many food items are highly perishable, and therefore storable for only brief periods of time.

In light of this emerging interest in inverse demand models, several authors have explored ways in which estimable models can be specified that maintain essential elements of the theory. Christensen, Jorgenson, and Lau, for example, develop an Inverse Translog (ITL) demand system, which was subsequently employed by Christensen and Manser to estimate of a system of inverse meat demand equations. Alternatively, Chambers and McConnell and Barten and Bettendorf developed an inverse differential demand system analogous to the Rotterdam demand model. Recent advances in modelling inverse demand systems, however, utilize the distance function (Deaton), and include the Inverse Almost Ideal Demand System (IADS) of Moschini and Vissa, and Eales and Unnevehr (1994), and the Inverse Lewbel Demand System (ILDS) of Eales. In general, results show that inverse demand systems can provide reasonable estimates of short-run demand flexibilities for food items, and in particular for meats in the U.S.

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While considerable progress has been made in the application of inverse demand systems, further work is required. Importantly, models estimated to date have largely ignored the potential for market and price dynamics to influence consumption decisions. This is in spite of the fact that dynamic adjustments in consumer demands for meats are well documented (Wohlgenant and Hahn, Kesavan et al.). Factors such as short-run inventory adjustments, habit persistence, and sticky prices can all result in significant dynamic behavior in short-run consumer demand and price formation. The result is that consumers are likely unable to adjust to equilibrium every time period. Previous studies have tended to either ignore the potential for dynamic adjustments in demand and persisted in working with static models, or have otherwise attempted to capture their effects in relatively restrictive ways.

The objective of this paper is to combine recent advances in modelling systems of inverse demand equations with dynamic demand specifications. Specifically, the framework advanced originally by Anderson and Blundell (1982, 1983) is used to estimate a flexible dynamic inverse demand system for quarterly U.S. meat demands. The Anderson-Blundell (A-B) approach has considerable appeal because it places minimal restrictions on dynamic adjustments that can occur in short and intermediate runs, while at the same time allowing for a fully specified inverse demand system (specifically, the IAIDS) to be embedded in the model's long-run structure. A further advantage of their approach is that restrictions implied by theory can be imposed on the model's long-run structure, where, if anything, we expect such restrictions to hold (Paris, Caputo, and Holloway). Finally, the A-B dynamic model nests within it several popular but more restrictive dynamic specifications, including autoregressive and partial adjustment models, as well as a static specification. Further, these specifications can be tested against the more general alternative.

In recent years there have been numerous meat demand studies, including Moschini and Meilke; Eales and Unnevehr (1988, 1993, 1994); Eales; Alston and Chalfant (1991, 1993); Brester and Wohlgenant; and Kesavan et al. Of these, only Kesavan et al. develop a dynamic model similar in spirit to the one presented here. Moreover, to our knowledge the A-B approach, although well established in the general economics literature, has not been used previously to estimate a dynamic demand system (either direct or indirect) for a set of agricultural commodities. We report here the first known attempt to do so.

The specification of the IAIDS model used to characterize long-run demand behavior is given in the next section. In section 3 we turn to modelling short-run dynamics in the context of an error correction model, where error correction terms are identified by IAIDS demand equations. The approach is then applied to a model of quarterly U.S. meat demand for the period 1960-93 in section 4. To facilitate comparison, the general dynamic model is contrasted with a model specified on first differences of the data, a common but potentially restrictive approach to capturing short-run dynamics in meat demand estimation (e.g., Moschini and Meilke; Eales and Unnevehr (1988, 1993); Alston and Chalfant (1991, 1993); Brester and Wohlgenant). Finally, results are summarized and conclusions are presented in section 5.

2. THE IAIDS MODEL AND LONG RUN PREFERENCES

As noted in the introduction, the modelling strategy pursued here assumes the long-run structure of a dynamic model of meat expenditures is consistent with economic theory. We consider this structure first. Anderson and Blundell (1983) assumed that consumer expenditures could, in the long run, be characterized by a direct AIDS demand system. Our approach follows A-B's general setup, but with the caveat that long-run preferences are now specified according to the IAIDS demand system.

Let $\underline{\mathbf{w}}$ denote a $\underline{n}$ x 1 vector of budget shares on $\underline{n}$ goods, $\underline{\mathbf{q}}$ a $\underline{n}$ x 1 vector of quantities, and Q a measure of scale effects. In general, the long-run inverse demand structure may be written as:

$$\underline{\mathbf{w}} = f(\underline{\mathbf{q}}, Q, \underline{\boldsymbol{\theta}}), \tag{1}$$

where $\underline{\boldsymbol{\theta}}$ is a vector of underlying parameters that characterizes consumer preferences. By using the IAIDS demand system of Moschini and Vissa and Eales and Unnevehr (1994) to describe (1) yields:

$$\underline{\mathbf{w}} = \Pi(\underline{\boldsymbol{\theta}})\underline{\mathbf{x}}, \tag{2}$$

where $\underline{\mathbf{x}}$ = is a $\underline{l}$ x 1 vector of (transformed) quantities and scale effects, and Π is an appropriately dimensioned matrix function of the parameters, $\underline{\boldsymbol{\theta}}$. Specifically, a single equation from (2), representing the i-th budget share, is given by:

$$w_i = \alpha_i + \Sigma_j \gamma_{ij} \ln q_j + \beta_i \ln Q, \tag{3}$$

where $w_i = \pi_i q_i$, π_i being the normalized price of the i-th good (nominal price p_i normalized by total outlay); q_j denoting the per capita quantity of the j-th good consumed; and lnQ a suitable *per capita* quantity aggregator index. The specification of lnQ, derived from the consumer's underlying distance function representation, is:

$$\ln Q = \alpha_0 + \Sigma_j \alpha_j \ln q_j + \tfrac{1}{2} \Sigma_i \Sigma_j \gamma_{ij} \ln q_i \ln q_j, \tag{4}$$

which can be interpreted as a translog quantity aggregator index.

The long-run IAIDS structure is therefore given by (3) and (4), $i = 1,\ldots,\underline{n}$, which includes nonlinear cross-equation parameter restrictions. This structure conforms to the description of long-run preferences in (2), where $\underline{x}$ consists of an intercept, log quantity terms, and transformed log quantity terms. The vector of underlying preference parameters can be obtained by placing suitable nonlinear restrictions on Π. Furthermore, in any fully integrable inverse demand system the usual properties of adding up, homogeneity, and symmetry apply. For the long-run IAIDS model these restrictions imply: $\Sigma_i \alpha_i = 1$, $\Sigma_i \gamma_{ij} = 0$, $\Sigma_i \beta_i = 0$ (adding up); $\Sigma_i \gamma_{ij} = 0$ (homogeneity); $\gamma_{ij} = \gamma_{ji}$ (symmetry). See Eales and Unnevehr (1994) for further details on the derivation and properties of the IAIDS model.

3. A FLEXIBLE DYNAMIC MODEL OF CONSUMER EXPENDITURES

In recent years there has been considerable interest in estimating error correction models, where short-run dynamics are modeled simultaneously with the model's implied long-run structure (Engle and Granger; Hoffman and Rasche). The flexible dynamic framework used here to model consumer expenditures on meat has its foundation in the error correction paradigm. The main difference is, of course, that we embed a theoretically consistent specification of consumer behavior in the long-run structure, the IAIDS model.

For illustrative purposes, consider a general first order dynamic model of the form:

$$\Delta\underline{\mathbf{w}}_{\underline{t}} = A^{*}\Delta\underline{\mathbf{x}}_{\underline{t}} - B^{*}(\underline{\mathbf{w}}_{\underline{t}-1} - \Pi(\underline{\boldsymbol{\theta}})\underline{\mathbf{x}}_{\underline{t}-1}) + \underline{\boldsymbol{\epsilon}}_{\underline{t}}, \tag{5}$$

where Δ is a first difference operator such that $\Delta z_t = z_t - z_{t-1}$, A^* is a conformable short-run coefficient matrix, B^* is an appropriately dimensioned speed-of-adjustment or *error correction* matrix, $\underline{\epsilon}_t$ is a $\underline{n} \times 1$ vector of independently and identically distributed mean-zero random error terms, and $\underline{t}$ is a time index, $t = 1,\ldots,T$. Define the parameter matrices in (5) such that $B^* = (I - C_1)$, $A^* = A_1$, and $\Pi(\boldsymbol{\theta}) = B^{*-1}(A_1 + A_2)$. It then follows that an equivalent representation of (5) is:

$$\mathbf{w}_t = A_1\mathbf{x}_t + A_2\mathbf{x}_{t-1} + C_1\mathbf{w}_{t-1} + \boldsymbol{\epsilon}_t. \qquad (6)$$

The two dynamics specifications, (5) and (6), are observationally equivalent. While (6) may be the more familiar specification of a dynamic model, the relative advantage of (5), however, is that the model's long-run parameters--in this case, the parameters of the IAIDS model--are specified directly. In other words, model (5) facilitates directly imposing behavior consistent with theory on the long run structure.

Without further restrictions, neither (5) or (6) are estimable. This is because: (1) an intercept term is included in both $\mathbf{x}_t$ and $\mathbf{x}_{t-1}$; and (2) because adding up implies $\boldsymbol{\iota}'\mathbf{w}_t = 1$ for all t, where $\boldsymbol{\iota}$ is a conformable vector with all elements equal to one. To derive an estimable form of (5), let $\tilde{\mathbf{x}}_t$ denote $\mathbf{x}_t$, only with the constant term deleted, and let superscript n denote the operator that deletes the n-th row of any matrix or vector. It then follows that an estimable form of (5) is given by:

$$\Delta\mathbf{w}_t = A\Delta\tilde{\mathbf{x}}_t - B(\mathbf{w}^n_{t-1} - \Pi^n(\boldsymbol{\theta})\mathbf{x}_{t-1}) + \boldsymbol{\epsilon}_t. \qquad (7)$$

As Anderson and Blundell (1983) note, there is a loss of identification in the error correction matrix, B. Specifically, they show that the $n \times (n - 1)$ elements of B are related to the n^2 elements of B by

$$b_{ij} = b^*_{ij} - b^*_{in}, \qquad i = 1,\ldots,n, \text{ and } j = 1,\ldots,n - 1.$$

Without additional information pertaining to the error correction parameters, the b^*_{ij}s cannot be recovered from estimated b_{ij} parameters. In any event, the adding up restriction does, however, imply no loss of information regarding the model's long run structure; all elements in $\boldsymbol{\theta}$ can be recovered by applying appropriate restrictions on Π^n. Finally, adding up restrictions on the complete model in (7) implies $\boldsymbol{\iota}'\Delta\mathbf{w}_t = 0$. As Anderson and Blundell (1982) demonstrate, this identity results in additional restrictions on elements of A and B. The column sums of these matrices must all be zero.

Model (7) is a flexible specification of dynamics in consumer expenditures. Nested within this specification are several commonly used dynamic setups, including autoregressive and partial adjustment models. A purely static model is also nested within dynamic system (7). Specifically, a first-order autoregressive model of the type estimated by, for example, Eales and Unnevehr (1994) and Eales, can be obtained by imposing the restrictions:

$$a_{ij} = \Pi_{ij+1}(\underline{\boldsymbol{\theta}}), \qquad i = 1,\ldots,\underline{n} - 1,\ j = 1,\ldots,\underline{k} - 1, \tag{8}$$

on (7), where a_{ij} and $\Pi_{ij+1}(\underline{\boldsymbol{\theta}})$ are, respectively, the ij-th elements of A and $\Pi^{\underline{n}}$. Likewise, a partial adjustment model can be deduced from (7) by imposing the restrictions:

$$a_{ij} = \Sigma_{\underline{k}}\, b_{i\underline{k}}\Pi_{\underline{k}j+1}(\underline{\boldsymbol{\theta}}), \quad i = 1,\ldots,\ \underline{n} - 1,\quad j = 1,\ldots,\ \underline{k} - 1, \tag{9}$$

where a_{ij} and $\Pi_{ij+1}(\underline{\boldsymbol{\theta}})$ are as defined in (8). Finally, a purely static model, where adjustments to equilibrium occur instantaneously every period, can be derived from (7) by combining the restrictions in (8) with restrictions on B. Specifically, a static model can be obtained by enforcing:

$$a_{ij} = \Pi_{ij+1}(\underline{\boldsymbol{\theta}}), \qquad i = 1,\ldots,\underline{n} - 1,\ j = 1,\ldots,\underline{k} - 1,$$

$$b_{ij} = 1\ i = j,\quad b_{ij} = 0,\ i \neq j,\ \text{and}\ b_{\underline{n}j} = -1, \quad j = 1,\ldots,\underline{n} - 1. \tag{10}$$

The restrictions implied in (8)-(10) provide a basis for conducting statistical tests of the dynamic structure of a system of expenditure equations. Of the above specifications, the autoregressive model is most frequently employed in meat demand studies (e.g., Eales and Unnevehr (1984), and Eales). Importantly, as illustrated by the restrictions in (8), autoregressive models constrain short-run and long-run effects to be identical. This is a strong assumption, and moreover, such restrictions are typically imposed without the benefit of formal statistical support. Lastly, it is possible to impose restrictions on (7) to obtain a share equation system specified entirely in first-difference form.[1/] But as Anderson and Blundell (1982) indicate, likelihood ratio or other asymptotically equivalent tests are invalid in this situation so that formal tests for a first-difference alternative are not available.

4. AN APPLICATION TO MEAT EXPENDITURE DECISIONS IN THE U.S.

The data used in the application are quarterly time-series data on consumers' expenditure on four meat items in the U.S. for the period 1960-1993.[2/] Specifically, the four meats included are beef, pork, chicken, and turkey. The data were obtained from standard USDA sources, and all quantities are expressed in per capita terms. Prior to estimation, all data were deseasonalized by regressing each price and quantity series on a set of three trigonometric seasonal indices, a fifth-order polynomial trend, and interaction terms between trend and seasonal indices to allow for gradual shifts in seasonality.[3/] The resulting deseasonalized data, used in all subsequent estimations, are summarized in figures 1 and 2 and table 1.

First, augmented Dickey-Fuller (ADF) test statistics reported in table 1 indicate that the null hypothesis that all meat expenditure share and quantity data contain a unit root cannot be rejected at any reasonable levels.[4/] This result has implications for subsequent model specification, and among other tings, suggests that modelling short-run behavior by using data in levels is inappropriate.

Turning to the data themselves, as figure 1 illustrates, the most dramatic change in meat consumption over the past 30 years has been for chicken, with per capita consumption in 1960 at about 5.5 pounds (on a quarterly basis) but increasing to slightly under 20 pounds by 1993. Moreover, per capita chicken consumption surpassed pork in 1986 and beef in 1990. At the same time, beef consumption increased from slightly over 15 pounds per capita in 1960 to a maximum of 24 pounds in the first quarter of 1976 (table 1), and has since returned to early 1960s levels. At the same time, pork consumption has neither grown nor declined dramatically (table 1), although consumption did drop significantly in the mid 1980s. Lastly, per capita turkey consumption remains low, but has experienced some growth in recent years.

Alternatively, figure 2 and table 1 show that expenditure shares on these meats have remained relatively more stable than have quantities consumed. For example, beef's share of total meat expenditures has hovered between 50 and 59 percent, reaching its absolute peak in 1975. Likewise, expenditures on pork have declined gradually over the sample period from approximately 35 percent in the early 1960s to 27 percent in the mid-1990s. The opposite pattern is observed for chicken, with its share of total meat expenditures growing from around 10 percent in the early 1960s to just over 18 percent in recent years. Lastly, turkey's share of total meat expenditures has remained rather constant at around 3 percent, although modest growth has been noted in recent years. The stability of expenditure shares may suggest that much of the shifts in quantities consumed are largely offset by relative price changes.

As the preceding discussion suggests, considerable changes have occurred in meat expenditures in the U.S. over the past thirty years. What implications do these changes have for modelling meat demands, and might meat expenditure equations be better characterized in dynamic context? To address these and related questions, we estimate a general dynamic flexible model similar to that outlined in the previous section. Specifically, we estimate dynamic share equations that include fourth-order error correction terms of the type:[5/]

$$\Delta \underline{\mathbf{w}}_t = A\Delta\underline{\mathbf{x}}_t - \sum_{k=1}^{4} B_k(\underline{\mathbf{w}}^n_{t-k} - \Pi^n(\underline{\boldsymbol{\theta}})\underline{\mathbf{x}}_{t-k}) + \underline{\epsilon}_t, \qquad (11)$$

where

$$\underline{\Pi}^n_i(\underline{\boldsymbol{\theta}})\underline{\mathbf{x}}_{t-k} = \alpha_i + \Sigma_j\, \gamma_{ij} \ln q_{jt-k} + \beta_i \ln Q_{t-k}, \quad i,j = 1,\ldots,3, \quad k = 1,\ldots,4, \qquad (12)$$

and

$$\ln Q_{t-k} = \Sigma_j\, \alpha_j \ln q_{jt-k} + \tfrac{1}{2}\Sigma_i \Sigma_j\, \gamma_{ij} \ln q_{it-k} \ln q_{jt-k}, \quad i,j = 1,\ldots,3, \quad k = 1,\ldots,4. \qquad (13)$$

In the dynamic system specified in (11)-(13) $\underline{\mathbf{x}}_t = (1, \ln q_{1t}, \ln q_{2t}, \ln q_{3t}, \ln q_{4t}, \ln Q_t)'$, where $q_{1t} = BFQ_t$, $q_{2t} = PKQ_t$, $q_{3t} = CKQ_t$, $q_{4t} = TKQ_t$; $t = 5,\ldots,136$; $\underline{\Pi}^n_i(\underline{\boldsymbol{\theta}})$ denotes the i-th row of the long-run IAIDS parameter matrix, $\Pi^n(\underline{\boldsymbol{\theta}})$; and $\underline{\epsilon}_t$ is a mean-zero, joint normally distributed error vector, Ω denoting the contemporaneous covariance matrix of $\underline{\epsilon}_t$.

Adding up, homogeneity, and symmetry restrictions imposed on parameters in $\Pi^n(\underline{\boldsymbol{\theta}})$ in (11) and (12) are as defined previously. With these restrictions in place, there are 60 free parameters to be estimated in model (11). Because $\iota'\Delta w_t$ = 0 for all t, it follows that $\iota'\Omega = 0$ for all t. That is, the contemporaneous covariance matrix is singular. To avoid this problem the equation for turkey was omitted during estimation (both in the short-run structure, as well as in the long-run IAIDS model). Full information maximum likelihood estimates of the parameters implied in the flexible dynamic meat expenditure model in (11)—with all restrictions implied by theory imposed—were obtained by using the Davidon-Fletcher-Powell algorithm as implemented in the FORTRAN-based program GQOPT. The estimates, along with asymptotic standard errors, are reported in table 2.

In terms of the estimated long-run IAIDS demand structure, 18 of the 24 estimated parameters reported in table 2 are more than twice their asymptotic standard errors. Regarding the estimate of the short-run coefficient matrix A, eight of 16 estimated a_{ij} parameters exceed their asymptotic standard errors by more than two. Alternatively, only five of the 48 estimated parameters in the B_k matrices reported in table 2 are more than twice their asymptotic standard errors. This result is likely due to multicollinearity because a likelihood ratio (LR) test of the restrictions implied by $B_2 = B_3 = B_4 = 0$ yielded a test statistic of 59.293, which is extreme in the asymptotic $\chi^2(33)$ distribution.

As outlined in equations (8), (9), and (10), the flexible dynamic model has nested within its structure, respectively: (1) a fourth-order autoregressive model; (2) a first-order partial adjustment model; and (3) a static IAIDS model. The LR test statistic for restrictions implied by a fourth-order autoregressive model equals 247.812, the value of an asymptotic $\chi^2(39)$ distribution under the null hypothesis, strongly rejecting the fourth-order autoregressive model. Likewise, the LR test statistic for the first-order partial adjustment model is 224.723, an extreme value in the asymptotic $\chi^2(36)$ distribution. The first-order partial adjustment model is also rejected in favor of the general dynamic specification. Finally, the LR test statistic for a static IAIDS model is 896.460, which for all practical purposes has a <u>p-value</u> of zero in the asymptotic $\chi^2(48)$ distribution. Of these three specifications, the fourth-order autoregressive model is most similar to the types of IAIDS models estimated previously for meat demands (e.g., Eales and Unnevehr (1994), and Eales).[6/] Importantly, our results show that the autoregressive approach to dealing with dynamics in meat demand estimation may well be too restrictive.

Although the first-difference model cannot be tested statistically against the general dynamic model, it is possible to compare estimation results. Estimates of a first-difference model—obtained for the same sample period—are recorded in table 3. Compared with the long-run IAIDS structure in table 2, the biggest discrepancies seem to occur for estimates of β_i scale parameters. The first-difference model implies larger β_i estimates (in absolute terms) for pork and turkey and smaller β_i estimates for beef and chicken (again, in absolute terms) than does the flexible dynamic model. This outcome is consistent with Anderson and Blundell's (1982), who found large divergences in estimated expenditure effects between a general dynamic AIDS model and a more restrictive static AIDS model. In addition to scale effects, there is also considerable variation in estimates of cross-quantity effects between the two models.

Further comparisons between the two models can be made by examining the estimated residuals. Several diagnostic measures are reported in table 4. For the dynamic model, Box-Pierce Q(12) statistics indicate only the pork share equation has any remaining significant autocorrelation. Likewise, for the first-difference model, only the chicken equation has significant autocorrelation. Importantly, $\bar{R}^2$s for share equations in the dynamic model are, in every case, larger than their counterparts in the first-difference model (table 4). In fact, $\bar{R}^2$s for beef, pork, and chicken equations in the dynamic model are more than twice those estimated for their counterparts in the first-difference model. Of course residual root mean squared-errors exhibit a parallel pattern, being lower for all equations in the dynamic model than in the first-difference model. On balance, the flexible dynamic model does a good job of explaining the data, and provides a better fit than does a first-difference specification.

Additional insights can be obtained by examining own-price, cross-price, and scale flexibilities for both models. These estimates, along with asymptotic standard errors, are recorded in table 5.[7/] To start, all own-price flexibilities for the dynamic model are negative and are less than one in absolute terms, suggesting that meat demands are <u>flexible</u> (i.e., own-price flexibilities are between zero and minus one). Furthermore, the magnitudes, at least for beef, pork, and chicken, are comparable to those reported by Eales and Unnevehr (1994) and Eales. Interestingly, long-run cross-price flexibilities computed with the dynamic model suggest that pork and beef, and chicken and turkey are gross <u>q</u>-substitutes. Perhaps of greater interest, however, is that no beef cross-price flexibilities is significantly different from zero (table 5), a result that stands in contrast to that reported by Eales. Scale flexibilities computed for the dynamic model are all negative and in each case are significant. In general, scale flexibility for beef is larger than previous estimates and scale flexibilities for pork and chicken are smaller than prior estimates.

Cross-price and scale flexibilities for the first-difference model reported in table 5 are generally in closer agreement with those reported by Eales and Unnevehr (1994) and Eales, at least with respect to beef, pork, and chicken. When compared with the estimates of the dynamic model, with the exception of turkey there is not much discrepancy in own-price estimates. Estimated cross-price flexibilities are, however, generally larger in absolute terms than those for the flexible dynamic model. Likewise, there is a noticeable difference in scale beef flexibilities for beef implied by the two models. Interestingly, own- and cross-price flexibilities for turkey are mostly insignificant in the first-difference model, and the associated scale flexibility is implausibly large and positive (albeit significantly different from zero). Flexibilities obtained under the general dynamic specification generally appear more acceptable.

As a final comparison of the two approaches to modelling meat demand, eigenvalues of the Antonelli substitution matrix, along with associated standard errors, were computed at the means of the sample data.[8/] To assure existence of a well-defined distance function, not only must estimated share equations satisfy homogeneity and symmetry, but the estimated Antonelli substitution matrix must be negative semi-definite as well.[9/]

The negativity results, reported in table 6, are striking. In neither case is the dominate eigenvalue, λ_1, significantly different from zero. For the dynamic model, however, the remaining three eigenvalues are significantly less than zero, while for the first-difference model only the final value, λ_4, is significantly less than zero. Moreover, in 10,000 draws on the parameter vector, the long-run IAIDS specification embedded in the general dynamic model did not fail the negativity requirement on the estimated Antonelli matrix once, as indicated by Prob = 1.0 for the dynamic model in table 6. Alternatively, in the same number of draws, Prob = 0.18 for the first-difference model, implying the negativity condition is satisfied only 18 percent of the time. On the basis of these results alone, it appears the long-run IAIDS structure associated with the general dynamic model provides a more satisfactory representation of consumer preferences than does the first-difference model.[10/]

5. CONCLUSIONS

In recent years there has been renewed interest in estimating inverse demand systems for meat and other agricultural commodities. While progress has been made, dynamic considerations in most prior applications of inverse demand systems have been largely overlooked. This paper has addressed this issue by specifying and estimating a flexible dynamic model of consumers' meat expenditures in an inverse demand context. This was accomplished by adopting Anderson and Blundell's (1982, 1983) approach, which allows modelling of short-run expenditure dynamics in a fully flexible manner, while at the same time maintaining a theoretically consistent structure in the model's long-run response. Specifically, long-run demands were specified according to the Inverse Almost Ideal Demand System (IAIDS) advanced recently by Eales and Unnevehr (1993, 1994) and Moschini and Vissa. Importantly, the specified model had nested within its framework several commonly used specifications for demand dynamics, including autoregressive and partial adjustment setups.

A fourth-order general dynamic model was estimated by using quarterly time-series data on meat expenditures and quantities in the U.S. The estimated model fit the data well, appeared to do an adequate job of capturing dynamics in meat expenditure decisions, and yielded reasonable parameter and flexibility estimates. Of interest is that more restrictive specifications associated with: (1) an autoregressive model; (2) a partial adjustment model; and (3) a static model all were rejected in favor of the general specification. Inasmuch as these models, and in particular the autoregressive model, are among the most frequently employed dynamic demand specifications, results here suggest that future work should pay much more attention to the nature of underlying market dynamics.

Finally, the general dynamic model was compared with a first-difference model, a specification which has been employed frequently in studies that use time-series data. The general dynamic model was found to be superior in a several regards to the first-difference model, including model fit, flexibility estimates, and, perhaps most importantly, in its ability to satisfy negativity conditions arising from consumer theory. Given that these conditions are often the most difficult to impose in empirical applications, results reported here suggest that the dynamic specification could also be a useful vehicle for conducting policy and welfare analysis.

ENDNOTES

1/ In particular, a first difference model can be obtained from (7) by imposing:

$$a_{ij} = \Pi_{ij+1}(\underline{\theta}), \qquad i = 1,\dots,\underline{n} - 1,\ j = 1,\dots,\underline{k} - 1,$$

$$b_{ij} = 0, \qquad i,j = 1,\dots,\underline{n} - 1.$$

2/ In the empirical application the first four observations are used to initialize the model's dynamic lag structure.

3/ Specifically, the seasonal indices are given by $\cos(2\pi t/2)$, $\sin(2\pi t/4)$, and $\cos(2\pi t/4)$, $t = 1,\dots,136$.

4/ Indeed, the same general results regarding unit roots hold for the log quantity data as well. ADF test statistics for a unit root in the log quantity terms are, respectively, -1.89 (ln QBF), -2.68 (ln QPK), -1.81 (ln QCK), -2.05 (ln QTK), all of which are less than, in absolute terms, the critical value of -3.13 at the 10 percent level.

5/ The fourth-order specification in (11) was determined largely on the basis of preliminary testing; the specification makes sense, however, because previous studies involving quarterly time-series data often find significant autocorrelation at annual frequencies (e.g., Kesavan et al.).

6/ Specifically, models estimated by Eales and Unnevehr (1994) and Eales employ a first-order autoregressive model with the autocorrelation terms constrained to be the same across equations (this is done to ensure invariance with respect to the equation omitted; see, e.g., Berndt and Savin). When this specification was tested against the general dynamic model, an LR test statistic of 249.284 was obtained, a value which also is extreme in the asymptotic $\chi^2(47)$ distribution.

7/ Flexibilities were obtained by using the formulae reported in Eales and Unnevehr (1994), evaluated at the means of the sample data. Standard errors were obtained by employing the Monte Carlo simulation techniques introduced by Geweke and employed in a demand systems context by Chalfant, Gray, and White. Specifically, the estimated parameter covariance matrix was used to obtain 10,000 draws on the $\underline{\theta}$ parameter vector. Flexibilities were then computed after each draw. Resulting sample standard deviations were used as estimates of asymptotic standard errors.

8/ The same Monte Carlo method used to compute standard errors for flexibilities was used to compute standard errors for eigenvalues, as well as the associated probability the Antonelli substitution matrix is quasi-concave.

9/ Due to adding up, the Antonelli matrix can never be of full rank, and hence can never be strictly concave. The implication is the dominate eigenvalue of the Antonelli matrix will—within acceptable roundoff error—equal zero.

10/ Of course all results regarding eigenvalues of the Antonelli matrix are conditional on symmetry and homogeneity being imposed.

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TABLE 1

<u>Descriptive Statistics for IAIDS Meat Demand Variables: Variations in Quantities and Budget Shares (sample 1961-93, N = 132)</u>

Augmented Dickey-Fuller regression equation for a unit root:

$$\Delta y_{t} = \alpha + \delta t + \rho y_{t-1} + \sum_{i=1}^{8} \zeta_{i} \Delta y_{t-i} + \varepsilon_{t}, \quad t = 1, \ldots, 136.$$

Variable	Sample Average	Standard Error	Min	Max	ADF[a]
<u>Quantities</u>:					
Beef Quantity (BFQ):	19.29	2.00	15.39	24.04	-1.91
Pork Quantity (PKQ):	14.44	1.40	11.71	17.82	-2.66
Chicken Quantity (CKQ):	11.29	3.81	5.58	19.69	-0.07
Turkey Quantity (TKQ):	2.41	0.98	4.52	1.22	-1.63
<u>Budget Shares</u>:					
Beef Budget Share (WBF):	0.55	0.02	0.50	0.59	-1.07
Pork Budget Share (WPK):	0.30	0.02	0.26	0.35	-2.32
Chicken Budget Share (WCK):	0.12	0.03	0.09	0.18	-0.27
Turkey Budget Share (WTK):	0.03	0.01	0.02	0.05	-1.38

Note: Quantities are in pounds <u>per capita</u>, budget shares are in percent. Min denotes minimum value in the sample data and Max denotes the corresponding maximum value. Likewise, ADF denotes the augmented Dickey-Fuller unit root test statistic on ρ.

a. Critical value at the $\alpha = 0.10$ level is -3.13.