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EMPIRICAL ANALYSIS OF AGRICULTURAL COMMODITY PRICES:

A VIEWPOINT

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by

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Abstract

Numerous models of price-demand-supply behavior in agricultural markets have been proposed and estimated. The literature contains valuable contributions, but the cumulative effect is somewhat disappointing. This paper appraises the status of the price analysis literature and makes suggestions for improving the quality of empirical results. Both structural and time-series models are appraised.

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"...There are no formulas or models for scientific discovery." (Heckman, p. 883)

Introduction

The pioneers of agricultural price analysis hoped to estimate econometric relationships which could be used for forecasting and policy analysis, hence for decision-making (e.g., Waugh 1964, pp. 1-10). It has become clear, however, that the optimism of the past must be tempered by the reality of the present. Empirical results are sensitive to (often arbitrary) specification decisions, and pretesting can result in highly misleading results (Wallace). Variables treated as exogenous and stationary perhaps are not. Models are sometimes estimated by inappropriate methods. Moreover, evidence is growing that published empirical results can not be confirmed (Tomek 1992).

Consequently, we believe that the quality of many empirical price analyses is in doubt. Nonetheless, numerous innovative and insightful results have been obtained. Thus, this paper tries to provide a balanced progress report on the current state of the field. We do this by organizing the paper into two sections: one on structural models and one on time-series models emphasizing time-series properties of agricultural prices. This categorization covers many, but not all of the approaches to commodity price analysis.

The paper also provides a viewpoint on how to begin the task of improving the quality of empirical results. One paper cannot provide a blueprint for solving all of the problems of empirical price analysis, particularly when different kinds of solutions are called for in different situations. Hence, we concentrate on providing constructive criticisms and syntheses. Our general point is that high quality empirical research requires depth and scholarship beyond current levels and that such research is extremely difficult to do.

Structural Models

This section of the paper reviews traditional structural models of agricultural product markets, emphasizing supply and demand specifications. Brief surveys of models of product characteristics, marketing margins, and storage are also included. Most of this section deals with structural models of time-series observations and thereby complements the review of time-series methods covered in the next major section.

Modeling the Price Determination Process

Agricultural product markets are commonly assumed to be competitive and in equilibrium. Moreover, given the biological lags

between decisions to produce and the realization of output, models of these markets are often recursive (e.g., Gallagher, et al.; Spriggs; Stillman). To facilitate discussion, it is useful to write a linear structural model as

$$By_t = Cx_t + Au_t$$

where A and B are GxG matrices of parameters, C is a GxK matrix of parameters, y_t is a Gx1 vector representing the tth observation on each of G current endogenous variables, x_t is a Kx1 vector representing the tth observation on each of K predetermined variables, including lagged values of y_t, and u_t is a Gx1 vector with identity covariance matrix representing the tth error term for each of the G equations.

In a recursive system, the one-way causality in y_t means that B is lower triangular with ones on the main diagonal, and A is diagonal (the contemporaneous covariances of the residuals among equations are zero). Hence, the relationship among equations is assumed to arise from the logical flow of causality in y_t through time. The variables in the x_t vector are assumed stationary, and since the error terms are also assumed stationary, the implication is that the variables in y_t are stationary as well. Under these assumptions, each structural equation is identified, and OLS is a consistent and asymptotically efficient estimator for the parameters of each structural equation.[1]

Within a recursive framework, alternative hypotheses about the formation of price expectations can exist, including the rational expectations hypothesis (Fisher). The empirical definition of expected prices inevitably influences the dynamic behavior of the model. In addition, inventory behavior, adjustment costs, habit formation, and perhaps other factors influence the dynamics of prices and quantities. Unfortunately, "the" correct way to model the dynamics of the endogenous variables in a structural framework is almost never clear, and different specifications are often broadly consistent with the observed behavior of the variables.

In a few instances, agricultural markets have been modeled as being in disequilibrium (Baumes and Womack; Ziemer and White). While little appears to be gained from disequilibrium specifications of agricultural markets (Ferguson), prices in some markets are influenced by government programs from time to time. Price support programs can, for example, hold prices above equilibrium levels. Such markets may be modeled as

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[1] Alternative specifications are, of course, possible. Endogenous variables may have a simultaneous rather than recursive relationship; the contemporaneous covariances may not be zero; a nonlinear specification may be preferred; etc. Many of these modifications are discussed. We omit discussion of nonparametric models.

having two regimes, one when government programs are influential and one when they are not (e.g., Liu, et al.).

Disequilibrium models may yet prove to be useful in other applications that involve "sticky" prices. A more common approach to modeling agricultural markets is to use distributed lag specifications to reflect costs of adjustment. In this view, changes in endogenous variables are not instantaneous, because a variety of impediments (costs) to change exist (Nerlove). The adjustment process is treated as a series of short-run equilibria, and the long-run level is assumed to be unobservable.

Current production and beginning inventories of agricultural products are arguably predetermined, but prices and allocations of these quantities to alternate end-uses may be simultaneously determined. For example, the apple crop each year is fixed, but some flexibility exists in allocating production among fresh, frozen, canned, juice and other uses. If prices are observed for the sales to alternate end-uses, then allocation and demand equations form a simultaneous system (e.g., French and Willett's application to asparagus). In this case, the B matrix (above) is not triangular, and A is probably not diagonal.

Model specifications are taking account of the increasing complexity of agricultural product markets. An international trade component is essential for many commodities (e.g., Gallagher, et al. or Spriggs). Depending on the research problem and commodity, the model also may need to accommodate joint product relationships, farm-wholesale-retail market level relationships, quality or variety differences (as in wool or cotton markets), and the effects of government programs. A recent model of the beekeeping industry, for example, has 27 current endogenous variables, 11 lagged endogenous variables, 17 exogenous variables, and 13 behavioral equations (Willett and French).

Prices of agricultural products are often related, resulting in multi-market partial equilibrium models, e.g., models of the feed grain-livestock complex. The "ultimate" model may involve the entire agricultural sector of a country, or it may be a computable general equilibrium model (see Hertel for a contrast of a multi-commodity partial equilibrium with a general equilibrium framework).

Structural models have the potential to provide useful information, but they have nonetheless been subjected to growing criticisms. Basically, the maintained hypotheses--the information that can be treated as unquestionably correct--are in fact questionable. Yet, overidentifying restrictions are rarely tested (Sims 1980), though they have long been in doubt (Liu). Likewise, the exogeneity of the "exogenous" variables is almost never tested (for an exception see Thurman), and as discussed in the time-series section, the stationarity assumptions about the variables

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may not be true. Also, simultaneous systems often have a large number of predetermined variables relative to the number of observations, and consequently one or two observations may have a large influence on the estimates. This is particularly serious in light of the pretesting that normally occurs in model specification.

Thus, large structural models are subject to important limitations, and one might question whether the quality of the information obtained from these models exceeds the costs of building them. Funders of research must see value in results from such models, but the profession faces a major challenge in improving structural econometric models.

In subsequent sections, we look more closely at what has been learned from modeling the supply, demand, and other components of agricultural markets and at the associated specification and estimation problems. It seems fair to argue, however, that the analyses of supply and demand for particular commodities tend to ignore the larger structural systems in which these equations are implicitly embedded and vice versa. Thus, estimates of demand systems usually do not consider the possible simultaneity or recursiveness of prices and quantities, while models of markets ignore restrictions implied by demand theory.

Supply Analysis

The analysis of agricultural supply is firmly rooted in microeconomic theory: farm managers are assumed to maximize expected discounted profits (or utility of profits) subject to various constraints. Agricultural economists have made major contributions to developing, adapting, and applying theoretical concepts to specific agricultural commodities, but a vast gulf still exists between theory and empirical analyses of supply (for a summary and critique, see Just 1992).

Supply models have some features in common. Namely, since a lag exists between the time a decision to produce is made and the time production is realized and sold, expected profits are often assumed to be a function of expected output prices and expected yields; input prices are assumed known and exogenous at the initial decision time. Consequently, product price risk and yield risk may be arguments in the supply function. But, supply functions for specific farm commodities differ markedly, because of the differing characteristics of the commodities themselves, differing competitive uses for resources across commodities, varying importance of government programs, as well as differences in how analysts address specific modeling issues.

Livestock and livestock products' supply can be differentiated from crop supply. The output of livestock and livestock products is constrained in the short run by the size of the breeding flock or herd. The flock

produces both young and cull animals, and joint products, such as lamb and wool, are sometimes important. If expected profit rises, young animals will be added to the breeding herd rather than sold for slaughter, and consequently the short-run supply response, as measured by quantity slaughtered, can be negative. Since, however, other adjustments such as feeding animals to heavier weights may be feasible, the net response may still be positive (Jarvis; Chavas and Klemme; Wipple and Menkhaus). The flexibility to respond to a price change varies with the stage of the production cycle (Chavas and Johnson).

The output response to price increases may differ from those for price decreases (Cochrane). When prices increase, farmers make investments and adopt new technologies that are not abandoned when prices decline. Thus, analysts have specified "irreversible functions" and have found evidence consistent with the hypothesis (e.g., Houck; Traill). For livestock, the biological constraints which exist for supply expansion do not exist for culling the breeding herd, and the speed of adjustment probably differs between price increases and decreases, implying that the length of the long-run adjustment differs depending on the direction of price change.

Perennial crops present similar modeling challenges. In any given year, production is limited by bearing acreage; producers may leave production unharvested and cull trees in response to low prices, but little can be done to increase output. Indeed, an appropriate measure of expected, discounted profit is a critical issue because years pass before new tree stock bears fruit. Although agricultural economists have been ingenious in extracting information from limited data sets, a full analysis of tree crop supply requires data on plantings, removals, age composition of orchards, and yields by age (French, King and Minami).

Among farm commodities, annually produced crops perhaps are the simplest to model. Farmers make annual decisions about the area to plant and about cultural practices to use (hence, about yields). Thus, supply response can be measured via acreage planted and yield equations. However, even supply analysis of annual crops is not easy. Many of the major crops, such as wheat, corn, soybeans, rice, and cotton, are influenced by government programs. Hence, considerable effort has been devoted to estimating supply response in the presence of government programs. Broadly speaking, two approaches have been taken. In one, variables that take account of farm programs (e.g., measures of effective price supports) are included in the model (e.g., Houck, et al.). This type specification typically results in a fairly parsimonious model, but assumes that model parameters are constant over alternative program regimes.

The second approach attempts to model the free market and farm program time periods as separate regimes, thereby permitting parameters to differ in the two periods (e.g., Lee and Helmberger). This alternative has the potential to provide more information and avoid the possible bias of assuming constant parameters over the entire sample period, but this advantage is obtained at the cost of estimating more parameters. Lee and Helmberger use pooled time-series and cross-section (states) observations. The bounded price variation model provides an alternative specification of two regimes, one with equilibrium prices and one when prices decline to the support level (e.g., Holt). Price supports generally provide a lower limit on prices, but market prices can decline below the support level, depending on program provisions and farmer participation in the program. Still another specification of a switching procedure is found in Chen and Ito.

The specifications of acreage planted equations can be remarkably different. For example, the specifications of soybean supply by Gardner 1976, by Houck, et al., and by Lee and Helmberger are compared in Table 1. These analysts believe that expected soybean and corn prices are important and that soybean acreage has dynamic properties. But they do not agree on how expectations should be measured, including how government programs should be modeled, nor do they agree on how the dynamic behavior of acreage should be specified. None of their soybean models consider price or yield risks. The different specifications, however, explain acreage response about equally well.

The problem of measuring expectations arises in every model of agricultural supply, either implicitly or explicitly. Alternative empirical measures are explicitly compared for the supply of fed beef in a paper by Antonovitz and Green. They consider naïve expectations (simple lag of cash prices), futures prices, ARIMA forecasts (sometimes called quasi-rational expectations, see Nerlove, Grether and Carvalho, p. 307), adaptive expectations, and rational expectations. Students of futures markets would argue that futures prices are the market's rational measure of expected price, but the futures and rational expectations specifications of Antonovitz and Green give quite different empirical results. In contrast, under some specifications, rational and adaptive expectations models result in identical or similar empirical models (Eckstein). For annually produced, continuous inventory commodities, inventories link prices through time; hence, current observations on cash, nearby, and distant futures prices are highly correlated (Tomek and Gray).

Supply analysts have increasingly considered measures of risk in their models (Just 1974; Traill). As noted, alternative measures of expected price exist, implying at least an equal number of alternative measures of risk. Actually, the number of measures of risk is larger, as the differences between expected and realized outcomes can be treated in

Table 1. Alternative Soybean Acreage Response Functions

Equation	Explanatory Variables						R^2
	FPS_t	FPC_t	A_{t-1}	TRD			
(1)[a]	7.2	-10.2	0.55	0.59			.98
	(3.6)[c]	(2.0)	(2.4)	(1.3)			
	PS/PC_{t-1}	PSS_t	PFC_t	DPC_t	A_{t-1}		
(2)[a]	5.6	2.4	-3.9	-9.7	0.87		.99
	(3.0)	(1.3)	(2.0)	(1.1)	(16.5)		
	PCX_{t-1}	PSX_{t-1}	TRD	FPP_t	ADV_t	ρ	
(3a)[b]	-0.23	0.34	0.13	-	-	.50	-
	(4.4)	(6.9)	(7.9)				
(3b)[b]	-0.46	0.02	0.63	.11	-.08	.50	-
	(6.6)	(0.2)	(10.1)	(3.5)	(3.9)		

[a] Dependent variable in equations (1) and (2) is acres of soybeans planted in millions, sample period 1950-74; A_{t-1} is lagged dependent variable. FPS and FPC are planting time prices of post-harvest futures contracts, soybeans and corn, respectively; PS/PC is ratio of soybean to corn prices received by farmers; PSS is effective support price for soybeans; PFC is effective support price for corn; DPC is effective division payment rate for corn; TRD is trend (see Gardner; Houck, et al.)

[b] Equations (3a) and (3b) are linear in logarithms, representing two regimes depending on effectiveness of price supports, 1948-80 sample for four states, with intercept varying by state. Dependent variable is acres of soybeans planted in thousands (in logarithms). PCX and PSX are farm prices of corn and soybeans, respectively, deflated by an index of input prices; FPP is expected feed gain program payments available to farmers; ADV is maximum acreage diversion or set aside; ρ is autocorrelation coefficient (Illinois value shown).

[c] t-ratios in parentheses

different ways. The specific risk measure may be based on squared or absolute deviations, and symmetric (both positive and negative) or only unfavorable differences (negative differences for product prices) may be used (Tronstad and McNeill).

Notwithstanding the many different empirical implementations of price risk measures, research results suggest that risk has a negative effect on supply and that the exclusion of risk from the model biases the own-price elasticity of supply downward. Risk variables are often statistically important, clearly improving the fit of the model.

For many farm commodities, improved technology is the single most important factor determining the level of supply, but typically the effects of technical change are modeled in an *ad hoc* fashion. The most common specification is to include a linear trend in the model and thus to assume that the parameters of the model are constant over the sample period, net of the trend variable. In contrast, as noted in the next section, analysts have spent much effort trying to determine whether changes in consumer preferences have resulted in structural change in the demand for farm products. The problem on the supply side is that technological change is so pervasive and continuous that it is difficult to measure. Thus, it may be impossible to address the effects of technological change in a fully satisfactory way (for a nonparametric approach, however, see Chavas and Cox).

Another type of contribution relates to obtaining supply estimates on a more disaggregated basis. Supply response can vary by region since climate, land quality and other factors may vary geographically, by variety of the commodity which may be highly correlated with region (say, spring versus winter wheat), by size and type of farm (say, full and part-time), and perhaps by age or other attributes of the farm manager. When data are available, it is possible to obtain additional insights into the nature of supply response at more disaggregated levels. These results cannot be characterized in the space available, but a few are illustrated in Table 2. Such results remind us of the difficulties of talking about "the" price elasticity of supply or of making comparisons of elasticities without careful qualification.

Although models which consider the dynamics of supply and the effects of risk appear to find more price elastic supply than other specifications, it is difficult to generalize from the diversity of empirical results. Rather, given the diversity, it appears that no one modeling approach is suitable for all commodities or research problems, and moreover we seem to know little more about the "true" structure generating the data for any particular farm commodity than when empirical supply analyses first started. The reason is that most price analysts impose a structure on the data and, in general, do not test whether the assumed

Table 2. Estimated Own-Price Elasticities of Supply

Commodity	Elasticity	Citation
Milk Production, US		Chavas-Klemme
short run	0.11	
long run	5.03 to 6.69	
Milk, NE, short run		Adelaja
small frms	0.52	
medium frms	0.27	
large frms	0.23	
Sheep breeding flock		Whipple-Menkhaus
w.r.t. lamb price		
short run	0.87	
long run	11.53	
w.r.t. wool price		
short run	0.32	
long run	4.36	
Wheat Acreage		Morzuck-Weaver-
corn belt states	0.61 to 0.95	Helmberger, Tbl 1 1
other winter wheat		
states	0.22 to 0.46[a]	
Dakotas	0.71 to 0.99[a]	

[a]   Excludes Montana

structure is correct (except for some rather superficial appeals to t-values, signs, etc.). Thus, we are doubtful about the benefits of imposing an even more rigid theoretical structure on the data as seems to be implied by Just (1992). Empirical results must be data consistent as well as theory consistent (Hendry and Richard), and at a minimum, analysts have a responsibility to demonstrate how their results improve upon previous results. We have more to say about improving models in the last section of the paper.

Demand Analysis

Empirical demand models can be broadly classified as *ad hoc* or partial specifications and demand-systems specifications, which impose restrictions from demand theory on the system. Both categories, in turn, have many specific alternatives. No single approach to model specification has surfaced as "the best." As in supply analysis, specifications vary with the problem under study, and demand analyses for foods and fibers have been stimulated by a variety of research problems.

There is perhaps a predisposition among economists, however, to estimate "theory consistent" demand systems. Initially, empirical analyses and judgment were combined to construct matrices of demand elasticities for individual foods which are consistent with theory (Brandow). This approach has been continued and refined (e.g., Huang). A potential benefit is the large number of estimated parameters, but the estimates are based on relatively few sample points. (Huang obtains 1,640 parameter estimates from 35 annual observations.) Clearly the estimates require a number of assumptions, approximations, and judgments, which are collectively of unknown quality.

A second approach uses a specific functional form for the demand equations, aggregates over individual commodities to form a relatively small number of commodity groups, and estimates the resulting system subject to theoretical restrictions. Functional forms are selected to strike a balance between mathematical and statistical convenience (simplicity) and realism.[2]

Various linear expenditure systems (for a summary, see Johnson, Hassan and Green) have been fitted for foods. Aggregation into groups, such as meats and cereals, has largely been a matter of judgment, and a linear system can place unrealistic restrictions on elasticity estimates (King). Further, systems specifications often ignore dynamics, possible simultaneity, and variables which may influence the level of demand. It is, therefore, perhaps not surprising that statistical tests often reject the

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[2] Alston and Chalfant (1992) review the nonparametric approach to demand analysis.

constraints on the system implied by demand theory (see Johnson, et al. in Capps and Senauer, Table 1).

Since its introduction, the Almost Ideal Demand System (AIDS) has become especially popular in agricultural economics. It uses a semilogarithmic form which has some theoretical and practical advantages (Deaton and Muellbauer; Blanciforti and Green). The ith equation in the system may be written

$$w_i = \alpha_i + \sum_j \gamma_{ij} \ln p_j + \beta_i \ln(y/P)$$

where $w_i = p_i\, q_i/y$,

$p_j =$ prices,

$i, j = 1, 2, ..., n$ commodities and equations,

$P =$ price index defined by

$$\ln P = \alpha_0 + \sum_i \alpha_i \ln p_i + 1/2 \sum_i \sum_j \gamma_{ij} \ln p_i \ln p_j$$

and $y = \sum_{i=1}^{n} p_i q_i$.

To make the model linear in the parameters, it is common to replace P with P^*, a known price index assumed to be highly correlated with P (Deaton and Muellbauer, p. 316). Potential disadvantages of AIDS include the larger number of parameters to be estimated than with a linear expenditure system and collinearity in the regressors. In addition, the right-hand-side prices and total expenditures are simultaneously determined with the w_i (as in other demand system specifications).

In agricultural economics, the system consists of food groups (meats, fruits and vegetables, etc.) or aggregate commodities within, say, the meat group such as beef, pork, and chicken. Such groupings require assumptions about the separability of utility and budgeting stages of consumers, and the appropriate groupings may be unclear. One analysis suggests, for example, that consumers do not allocate expenditures first to aggregates like chicken and beef and then to products within the aggregate. Rather, allocations may be made between high and low quality goods, where whole chickens and hamburger are examples of relatively close substitutes (Eales and Unnevehr 1988).

Agricultural economists have considered inverse demand specifications, which may be more consistent with the price determination process in agriculture (Eales and Unnevehr 1991), allowed for dynamic behavior in the model by using first differences or by using the lagged dependent variable (Eales and Unnevehr 1988; Moschini and Meilke), and used AIDS to consider specific issues such as structural change in meat demand (Moschini and Meilke). At present, formal systems typically give elasticity estimates for aggregate commodities, which have few practical applications (on computing elasticities, see Green and Alston). To the extent that a systems approach can be used with relatively disaggregated commodities (as in Eales and Unnevehr 1988), the empirical results may have increasing value.

AIDS-style (i.e., expenditure shares in a semilogarthmic form) equations also have been fitted to cross-section observations, usually with prices omitted, but a variety of functional forms have been considered in cross-section analysis. In the absence of price variability, the general form of an Engel (consumption) function is $c_{ij} = f_i(y_j, S_j, X_j)$, where $c_{ij} = $ consumption of the ith good by the jth household, $y_j = $ income of jth household, $S_j = $ household's size or scale, and $X_j = $ other variables which define the household's characteristics. Consumption can be measured as a physical quantity, as an expenditure, or as in AIDS, an expenditure share.

A surprising number of consumption functions have been specified as linear in the variables; the semilogarithmic specification is also popular. When fitted to household data with zero observations on consumption, both forms permit the prediction of negative consumption at positive levels of income. The logit or multi-nomial logit, in the case of a system, is an alternate approach (Tyrrell and Mount). The dependent variable, $\ln[w_{ij}/(1-w_{ij})]$, still cannot be zero; a common practice has been to replace the zero expenditure with an arbitrarily small positive constant; but in this model predictions cannot be negative.

A Tobit model also is a plausible specification. A two-part decision process is assumed: whether or not to purchase and then if a purchase is made, the amount purchased. This approach can explain why consumers make purchases as well as the level of purchases. It is also possible that the survey period is shorter than the purchase cycle, and hence non-purchase is not equivalent to zero consumption (Gould).

A key concept in modeling household data is the life cycle of the household, specifically the number, sex, and age of the household members. Generally, models of household behavior represent age and gender in one of two ways. One approach involves the construction of "adult equivalent scales" for members of the household and then aggregating to obtain a "household equivalent scale" (for alternative approaches to computing adult equivalent scales, see Tedford, Capps and

Havlicek). An alternative is to include size, age, and gender variables as separate regressors, but this implies a large number of parameters. Thus, the trade-off in the two specifications is between the reduced flexibility, but greater simplicity, of scale variables and the greater flexibility, but increased complexity, of having numerous gender/age variables in the model. Tyrrell and Mount use a Lagrangian interpolation polynomial of age, analogous to an Almon lag specification, to limit the number of parameters.

In addition to income and life cycle effects, many other variables can significantly influence food consumption behavior, and these variables may interact with income or each other. Further, the number of (zero-one) categories required to define qualitative concepts adequately is a matter of judgment. The practical question is to have sufficient categories to capture important nonlinearities in the relationship while having as parsimonious a model as possible. Clearly many difficult modeling decisions exist.

Given the large number of specification choices, alternative empirical models differ substantially (e.g., Buse and Salathe; Tedford, Capps and Havlicek). Levedahl (Table 1) summarizes the widely varying marginal propensities to spend on food estimated by various analysts. Analogous to the situation for supply analysis, agreement exists on major concepts that should be included in consumption models--income and life cycle effects--but much disagreement exists on the best way to measure the concepts.

Demand analyses using *ad hoc* specifications with secondary, time-series observations remain important. These models may be single equations or a part of a system to model a particular market or markets. Recent studies usually relate to a specific research issue. For example, Brown and Schrader develop a "cholesterol information index" using the number of articles published on cholesterol and human health. This index is then used in a demand equation for eggs to estimate the "cholesterol effect".

Two areas of food demand research have received much attention in the past 15 years. One is structural change in the demand for meats. Coefficients representing the demand structure for meats appear not to be stable *given* the model specifications and data sets used. The literature is filled with conflicting results about whether structural change has occurred and, if so, when (for a summary of studies see Buse, and for a critique of structural change studies see Alston and Chalfant 1991).

A second area of note in the past 15 years is the study of the effects of advertising on the demand for generic commodities. These studies emphasize the distributed lag relationship between changes in advertising and changes in demand (e.g., Liu and Forker and see the annotated

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bibliography in Hurst and Forker). The results suggest that advertising generally increases demand and that the optimum advertising level is sometimes larger than the existing level. Such results are, however, subject to the same econometric pitfalls as other price analyses. Possible collinearity between advertising expenditures and other trending (but possibly omitted) variables is a particular concern. Competitive effects of generic advertising, say, the effect of advertising pork on the demand for beef, are rarely examined.

In sum, demand studies in agricultural economics are numerous, covering a wide range of topics and issues. We have the sense that the cumulative contribution to knowledge is modest in light of the total research effort. One cannot say, for example, whether or not the demand structure for beef has changed in the past 20 years, and if so, when and why. But, given the dynamic character of the sectors under study, this may be an unfair criticism.

Characteristics Models

Classical theory of utility maximization, based on the consumption and production of a bundle of goods, is implicit or explicit in most of the analyses discussed in the structural models section. Becker noted, however, that goods have utility as inputs into household production, and Lancaster argued that goods are purchased for the utility provided by their characteristics. Price analysts have long been interested in product quality and the influence of quality on prices (Waugh 1929). Quality, of course, is defined by the commodity's characteristics, and these attributes play an important role in the determination of commodity prices. Thus, agricultural economists have contributed to the literature on characteristics models (e.g., Ladd and Suvannunt) and have estimated the demand for nutrients or other characteristics (e.g., Adrian and Daniel).

Attributes, such as pesticide contamination, can have negative effects on prices, and information about attributes can be uncertain and possibly asymmetric (i.e., markets for defective goods, so-called "lemons"). A related question is the costs and benefits of measuring characteristics; for example, can relatively simple measures improve the pricing of hog carcasses (Hayenga, et al.)? Research on food safety falls in this area. The effects of component pricing in marketing orders is another research area (e.g., fat content is a determinant of milk prices), and Bockstael shows that discarding low quality produce generally lowers welfare. Analysts also have estimated the implicit prices of characteristics or services embodied in a commodity (e.g., Carl, Kilmer and Kenny), and in particular, since federal grades are assumed to improve market information, price analysts are interested in the relationship between grade levels and prices (e.g., Brorsen, Grant and Rister). Clearly, the effects of commodity

characteristics is an important area of research, but the topic is sufficiently novel and extensive that an in-depth discussion is not attempted here.

Marketing Margins

Substantial research has been conducted on questions related to price differences between farmers and consumers. Among the questions addressed are the following: What explains the level of margins and their changes? Are increases in farm prices transmitted to consumers more rapidly than decreases? That is, how efficient are markets? In keeping with the basic thrust of these questions, research on marketing margins has concentrated on two areas: the conceptual base for explaining margin behavior and empirical analyses of the transmission of price information across market levels.

A common practice is to think of retail products as having two inputs: those originating on farms and those originating in the manufacturing-distribution (marketing) system. In the simplest model, the two inputs are assumed to be used in fixed proportions over varying levels of quantities marketed, and the supply of marketing inputs is assumed to be perfectly elastic. Thus, the farm-level, derived demand is obtained by subtracting the per unit marketing costs from the retail demand function, and if the retail demand is a linear function, then farm-level demand is a parallel line below the retail function. The quantities at the two levels are merely adjusted for the assumed fixed proportions (e.g., 2.4 pounds of beef at the farm equals one pound of beef at retail). Margins change because per unit marketing costs change (for a review and summary of concepts see Wohlgenant and Haidacher 1989; for an annotated bibliography see Wohlgenant and Haidacher 1991).

The fixed proportions argument is perhaps plausible for food products, since it is not immediately obvious that food manufacturers can substitute between the two broad categories of inputs. Indeed, many of the retail consumption series published by the USDA are based on balance sheets that use fixed coefficients (i.e., assume fixed proportions) to transform farm-level quantities to retail disappearance (consumption). Nonetheless, as Wohlgenant and Haidacher (1989) point out, the fixed proportions and perfectly elastic nonfarm input supply assumptions may be unrealistic. They develop a conceptual and empirical framework emphasizing the retail-level supply and farm-level demand functions of production theory, but assuming that farm-level supply is predetermined. Thus, unrestricted reduced-form equations make retail and farm prices (hence, margins) a function of farm output, marketing costs, retail demand shifters, and trend, all of which are assumed predetermined. These two functions, for eight food groups, are also fitted with symmetry and constant returns to scale restrictions. Using annual data, Wohlgenant and

Haidacher (1989, p. 33) conclude that "food marketing behavior can be characterized as competitive with constant returns to scale."

It is possible that since buyers of farm commodities potentially face input price risk, changes in the level of risk influence the size of margins. Brorsen et al. find that marketing margins for wheat consumed domestically as food in the U.S. are positively related to price risk, net of a cost variable and of a quantity of wheat variable. This result is a bit puzzling given the active use of futures markets by most flour millers. Thompson and Dziura, using data for individual Illinois grain elevators, find, among other things, that the larger the percent of cash grain purchases hedged in futures, the lower the merchandising margins of elevators. The Brorsen et al. result perhaps is explained by variation in risk net of the risk shifted by hedging (even though their risk measure is based on the absolute value of price changes).

With weekly, monthly, or quarterly data, the dynamics of margin behavior are important, and the effects of market imperfections may be clearer with shorter units of observation. Heien assumes that in the short run the fixed proportions assumption is appropriate, markets are not in equilibrium, and store managers apply a markup-over-costs rule to arrive at retail prices. Also, inventory adjustments play a key role in his model. Thus, for instance, an unexpected increase in retail demand reduces current inventories, which then requires an increase in retail supply in the next period. The increase in retail supply results in an increase in farm-level demand (relative to farm-level supply). Consequently, farm and wholesale prices change, since it is assumed that they are determined in competitive markets. Then, retail prices are treated as a markup over wholesale prices. (Other exogenous changes can, of course, be traced through the system in an analogous way.)

In Heien's empirical model, retail price is a function of current and lagged wholesale prices, unit labor costs for retail food stores, and the unemployment rate. Monthly data are used, and tests are conducted for unidirectional "causality" from the wholesale to retail level. In the majority but not all of the 22 foods tested, unidirectional causality was found. (The limitations of causality tests are discussed in the time-series section.) The estimated equations suggest lags of up to four months between wholesale and retail price changes.

Labor and other nonfarm input markets are exogenous in the foregoing (and most other) models of marketing margins. In particular, wages are treated as exogenous in the typical marketing margin model. Lee explicitly models labor supply and demand for the food sector as well as wholesale and retail food prices as simultaneously determined. The implementation of his model uses quarterly observations for food in the aggregate. In this context, Lee concludes that simultaneity is important

and that "wage changes are not only important direct determinants of food price changes but also a principal avenue through which macroeconomic changes influence the food system (p. 101)." Lags are still important and may continue for two or three years beyond the initial shock "when the complete cycle of inflationary effects, wage determination processes and feedbacks into food prices is considered (Lee, p. 101)." Thus, in this view, lags do not necessarily reflect imperfections in particular food manufacturing industries or markup pricing so much as they reflect dynamic adjustments to food price and wage rate changes.

A common hypothesis in the price transmission literature is that farm price increases are transmitted more rapidly than price decreases; presumably middlemen have the market power to pass through cost increases and to temporarily retain the benefits of lower input prices. Most of this literature has assumed that causality runs from the farm to the wholesale to the retail level. Early results were mixed, with the majority finding little if any asymmetry; Ward even found that retail prices for fresh vegetables responded more rapidly to decreases than to increases in wholesale prices. Recent results have more consistently found asymmetric price responses (e.g., Kinnucan and Forker).

Hahn (p. 21) argues for a "Generalized Switching Model" which is "roughly equivalent of a set of unrestricted reduced-form equations for a general set of endogenous switching regressions relating farm, wholesale, and retail prices of a [in this study] meat." Basically, current changes in retail, wholesale, and farm prices are related to lagged price variables (with a specification that permits different responses to increases than decreases), CPI, and trend. Weekly observations are used, where the monthly CPI is distributed over weeks. Hahn's results suggest that asymmetry is especially important in retail price adjustments. However, he found evidence of asymmetry at all market levels.

Price transmission studies are highly empirical. For example, Hahn's model might be characterized as vector autoregressions (see time-series section) with two regimes. By themselves, empirical models do not explain the source of asymmetry. Indeed, the models do not explain why any lags exist, and it is unclear why weeks, even months, are required for prices for fresh meats or produce to adjust to new information even in the case of price increases. In futures markets for agricultural commodities, new information is incorporated into prices certainly within days, perhaps within minutes. Moreover, information is transmitted from futures to cash markets quickly (e.g., Brorsen, Oellermann, and Farris). Thus, a conflict appears to exist between the empirical results which relate cash and futures prices and those which relate farm, wholesale, and retail prices, particularly those studies which suggest lags in farm price adjustments. Perhaps the observations on prices used in price transmission studies are not relevant to the question. Or, perhaps, the macroeconomic feedback effects identified

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by Lee help explain the observed lags. And, firms with some monopoly power may delay price adjustments at the wholesale or retail levels either because of costs of adjustment or because of lack of competition.

In sum, much interesting and valuable research has been conducted on marketing margins and the transmission of information in markets. But, a number of puzzles remain, and it is unclear whether existing models and data are capable of answering these questions.

Storage and Price Behavior

Since seasonality and yield uncertainty are prominent features of farm output, price analysts are interested in the seasonality of price and inventory behavior as well as in the incentives to carry inventories from year to year. But, inventory behavior received modest attention relative to other areas of research in price analysis until the last 15 years. (Gustafson's monograph on optimal carryover of grains and Working's (1949) conceptualization of the supply of storage are notable exceptions.)

Most early models involved tractable special cases of intrayear seasonality or of two-period, interyear inventory behavior. Emphasis was placed on annually produced crops, either with continuous (non-perishable) or discontinuous (semi-perishable) inventories. Clearly, demand also can be seasonal, and stocks are carried for continuously produced commodities. But, these topics have received less attention in the agricultural economics literature.

Since futures markets are important pricing institutions for many farm commodities in the United States, observations exist on a constellation of prices representing the cash market, nearby and more distant futures contracts. Working (1949), in his influential paper, pointed out (1) that the difference between the price of a distant maturity and the price of the nearby maturity (or the cash price) define a price of storage and (2) that a relationship should exist between this price and the level of inventories. He called the relationship the supply of storage; given the time period analyzed, the supply function was relatively stable and shifts in the demand for storage identified the supply function. Working's simple model has implications both for intrayear and interyear behavior of prices (e.g., Tomek and Gray).

Current models can be seen as extensions of Working's and Gustafson's initial efforts. Inventories must be nonnegative and stocks cannot be borrowed from the future, though an active futures market permits buying for future delivery based on future production. Thus, if stocks are small relative to current demand, the current cash price may be high relative to the price for future delivery; the price of storage is negative. Positive, though small, inventories exist at these negative prices.

On the other hand, when stocks are relatively large, arbitrage prevents the futures price from being above the current cash price by more than marginal cost of storing the physical good until contract maturity. Thus, an important nonlinearity exists in the behavior of the price of storage and inventories, which must be understood and correctly modeled.

The willingness of warehouse owners to carry stocks when the price of storage is negative is attributed to "convenience yield." The precise meaning of this term has been the subject of debate. Wright and Williams (1989) summarize and extend this literature. Another issue is whether the expected value of the current futures price equals the expected spot price at contract maturity; it may not, if a risk premium (or other source of bias) exists. Empirical estimates of risk premia have provided mixed evidence on their existence, but if they exist, they apparently are tiny (for a review of this topic and others in the futures literature see Kamara).

With the increased variability of interest rates in the past 20 years, the supply of storage function is less stable than it once was. Moreover, variability in production implies variability in the demand for storage. Paul further points out that grains and oil seeds (e.g., corn and soybeans) compete for the same binspace, and this competition should not be ignored in empirical models of the supply and demand for storage. Actual empirical estimates of the supply and demand for storage are sparse; a modest number of *ad hoc*, single equation models exist to explain the variability of the basis (e.g., Kahl and Curtis).

It is feasible to analyze multiperiod problems using dynamic optimization methods (sometimes based on judgmental rather than econometric estimates of model parameters). Such models have been applied to a variety of policy issues related to buffer stocks, private storage, and price behavior (e.g., Gardner 1979; Glauber, Helmberger and Miranda; Helmberger and Akinyosoye; Knapp; and Wright and Williams, 1982). Williams and Wright summarize and extend this work in their recent book. Among other things, they argue that the stylized facts of annual commodity price behavior are explainable in terms of models that include storage behavior. Further, according to Williams and Wright, models which assume rational forward-looking private storage generate biased prices that are poor forecasters of maturity month prices. Thus, rational expectations models of price behavior, that include storage, may generate observations that, in effect, cast doubt on the rational expectations hypothesis.

It must be noted that other structural models also are consistent with observed price behavior. Indeed, alternative models, some of which rely on the failure of private markets, have received the most attention historically. Further, Williams' and Wright's contributions can be criticized

for underemphasizing the role of demand shocks in price behavior, but their contributions (and those of others) to the analytics and empirics of storage models are important precisely because they call attention to the potentially important role of inventories (relative to other variables) in explaining price behavior.

A different strand of the literature emphasizes optimal hedges for individual decision-makers, using portfolio principles. This literature usually assumes simple objective functions with a number of simplifying assumptions underlying parameter estimates. It is not possible to characterize this research here (for our views see Myers and Thompson; Tomek 1988).

Time-Series Models

In this part of the paper, we evaluate the role of time-series models in commodity price analysis, first by examining the time-series properties which most commodity price series seem to share, and then by considering applications and implications of the results.

Time-Series Properties of Commodity Prices

Looking at graphs of commodity price movements over time, one is immediately struck by the high degree of positive autocorrelation in price levels. Another feature of price movements is that they have occasional spikes. These may be associated with small stocks relative to demand or perhaps are associated with a major regime shift in the underlying market. For commodities subject to government support programs, prices sometimes bounce around the price floor, indicating a truncation in the underlying price distribution.

Dynamic structural models imply autocorrelation, though not necessarily spikes in commodity prices, and some structural models deal explicitly with the truncation of price distributions. Advances in time-series methods are, however, providing new insights into the behavior of commodity prices (and associated variables) and casting doubt on some assumptions made in traditional models. But it should be noted at the outset that modern time-series methods are commonly applied to data observed at high frequencies (e.g., daily or weekly) while structural models are commonly applied to data observed at lower frequencies (e.g., quarterly or annually).

Stochastic Trends. Early attempts to model the autocorrelation in commodity prices with a time-series approach involved fitting deterministic linear trends. However, it soon became apparent that predictions from such simple models were inaccurate, prompting a search for better models. One way to generalize the deterministic trend model is to assume a

stochastic trend, which increases (or decreases) by a given amount on average, but in any particular period the amount of increase (or decrease) deviates from the average by some unpredictable amount (Stock and Watson). Formally, the notion of a stochastic trend can be modeled as a random walk with drift

$$w_t - w_{t-1} = \mu + \epsilon_t$$

where the drift parameter μ is the average predictable change in w_t each period, and ϵ_t is a serially uncorrelated random shock to the trend. When a commodity price p_t contains a stochastic trend, then the price can be written as the sum of a random walk component and a stationary component

$$p_t = w_t + z_t$$

where z_t has finite variances and autocovariances and a distribution which does not depend on time. In this case, w_t represents the stochastic trend and z_t represents stationary deviations or cyclical swings away from trend.

The existence of stochastic trends in commodity prices is consistent with the use of ARIMA models, popularized by Box and Jenkins, to characterize commodity price data. Beveridge and Nelson have shown that any variable which can be modeled as an ARIMA process with order of integration one (i.e., requires first differencing to induce stationarity) can be represented as the sum of a random walk component and a stationary component. Thus, research, which has found that once-integrated ARIMA models provide a useful representation of many commodity price series (e.g., Baillie and Myers), is consistent with the idea that these prices are made up of a stochastic trend and stationary deviations around trend. The ARIMA representation also explains why stochastic trends are sometimes called *unit roots* because the autoregressive polynomial in the lag operator representation of once-integrated ARIMA models has a root that is equal to one.

Space limitations preclude a detailed discussion of the literature on testing for stochastic trends. Interested readers are referred to Perron; Phillips; Phillips and Perron; and Kwiatkowski, et al. Many of these tests have been applied to commodity price data (Ardeni; Baillie and Myers; Goodwin), and high frequency commodity price data typically show evidence of stochastic trends. The evidence is far less clear with annual data. The explanation for this discrepancy may lie in the smaller number of annual observations typically available and/or in the low power of unit root tests.[3] Deaton and Laroque argue that commodity prices sampled at

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[3] Unit root tests have low power against the alternative that the series is stationary, but with a root that is close to unity. For the Dickey-Fuller and Phillips-Perron tests, a stochastic trend is the null hypothesis. Consequently, a stochastic trend is accepted unless

annual frequencies should be stationary for theoretical reasons, although as they admit, this is difficult to discover empirically because of the small number of annual observations typically available.

Stochastic trend models are not the only way to capture the autocorrelation in commodity prices. In particular, fractionally integrated stochastic processes (Granger and Joyeux; Diebold and Rudebusch) and the Markov switching model (Hamilton) are both capable of generating strong autocorrelation and long swings in data series without relying on a pure stochastic trend. Another alternative is to model commodity price movements using nonlinear dynamics and results from chaos theory (Benhabib). It remains to be seen whether these alternative methods can lead to improved models of the behavior of commodity prices.

Comovements in Commodity Price Series. Different commodity prices exhibit, at least during some time periods, a tendency to move together. This comovement in prices is a feature shared by many apparently unrelated commodities and has three main explanations (Pindyck and Rotemberg). First, supply and demand shocks in one commodity market may spill over into other markets. While this is a logical explanation for commodities which are related to one another either in production or consumption (e.g., wheat and rice), it cannot explain comovements between largely unrelated commodities (e.g., cattle and copper). Second, macroeconomic shocks, say to interest rates, may affect all prices together. But such shocks explain only a small fraction of the actual comovement in commodity prices (Pindyck and Rotemberg). A third possibility is that speculators overreact to new information, and this causes spillovers between commodity markets. In this interpretation, "excess comovement" among prices leads to volatility that is greater than it "ought to be." This argument also is not fully satisfactory because it does not account for the possibility of errors of underadjustment.

The idea of comovements in commodity prices can be formalized by using the theory of *cointegration*. If two commodity prices each have stochastic trends, and can therefore be represented as the sum of a random walk component and a stationary component, then they are cointegrated if they share the same random walk

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[3](...continued)
strong evidence exists against it. In response, Kwiatkowski, et al. developed a test where the null hypothesis is stationarity of the series. This test can be used as a consistency check on standard unit root tests. DeJong, et al. argue, however, that in many cases neither test (unit root against the trend-stationary alternative and trend-stationary against the unit root alternative) will reject.

$$p_{1t} = w_t + z_{1t}$$

$$p_{2t} = \delta w_t + z_{2t}$$

where p_{it} is commodity price i; z_{it} is the stationary component of i; and δ is a parameter representing the long-run equilibrium relationship between the two prices. Rearranging the two equations,

$$p_{2t} = \delta p_{1t} + z_t$$

where $z_t = z_{2t} - \delta z_{1t}$. This characterizes the long-run equilibrium relationship between the two prices with z_t representing stationary deviations away from the long-run equilibrium.

The foregoing long-run equilibrium can be estimated consistently by ordinary least squares (OLS), even when z_t is autocorrelated, heteroscedastic, and contemporaneously correlated with p_{1t}. This is because any other linear combination of p_{1t} and p_{2t}, besides that represented by the long-run equilibrium relationship, has an infinite variance. Thus, OLS converges rapidly to the true value for δ. Nevertheless, the OLS estimate generally follows a nonstandard distribution theory, even asymptotically, so pitfalls exist in hypothesis testing in such cointegrating regressions (Engle and Granger; Phillips and Ouliaris). Tests for cointegration typically involve estimating the hypothesized long-run equilibrium relationship (as above) and testing the residuals for a stochastic trend. If the null hypothesis of a stochastic trend in the errors can be rejected, then the conclusion is that prices are cointegrated. The idea of cointegration extends to the multivariate case (Engle and Granger; Johansen).

Empirical tests for cointegration among commodity prices have provided mixed results. Goodwin and Schroeder find some evidence of cointegration among regional U.S. cattle prices and Goodwin, using Johansen's multivariate testing framework, supports the hypothesis of one cointegrating vector among five international wheat prices (after adjusting for transportation cost differentials). However, Ardeni investigates several commodity prices, including wheat, at different regional locations and concludes that the evidence for cointegration is weak, even when considering prices for the same commodity at different locations. Furthermore, unpublished research conducted at the World Bank suggests that cointegration among different commodity prices is the exception rather than the rule.

It is important to recognize that cointegration is not the only explanation for comovement in commodity prices. Two prices may be driven by distinct stochastic trends, but the trends may still be highly correlated. In the very long run these prices would diverge and become unrelated, but they could show considerable comovement in finite data series. Alternatively, the stochastic trends driving two prices could be

distinct and uncorrelated, but strong correlations may exist between the stationary components of the series. Prices correlated in this way would also move together in the short run. The problem, of course, is that it can be extremely difficult to distinguish between these alternative situations given limited data and the low power of unit root tests.

Time-Varying Volatility and Excess Kurtosis. Another stochastic property of many commodity price series is a tendency to move between volatile periods, where relatively large price changes are the norm, and tranquil periods where price movements are much more subdued. This time-varying volatility in commodity prices is especially obvious in data sampled at daily, weekly and monthly intervals, but seems less of a concern in quarterly and annual data. Time-varying volatility is consistent with the existence of a stochastic trend in commodity prices. In fact, most research on time-varying volatility in commodity prices focuses on price changes, implying that the stochastic trend in the series has been removed by first differencing. The differences usually exhibit little residual autocorrelation, but the variance of the changes is not necessarily a constant.

Two common ways of accounting for time-varying volatility in commodity prices are the autoregressive conditional heteroscedastic (ARCH) model developed by Engle and the generalized ARCH (GARCH) model of Bollerslev. A simple GARCH model of commodity price changes can be represented

$$p_t - p_{t-1} = \mu + e_t$$

$$e_t \,|\, \Omega_{t-1} \sim D(0, h_t)$$

$$h_t = \omega + \alpha e_{t-1}^2 + \beta h_{t-1}$$

where D is some probability distribution with mean zero and variance h_t and Ω_{t-1} is a set of information available at time t-1. This model allows the conditional variance of price changes to change over time in a systematic fashion, and is therefore capable of capturing time-varying volatility in commodity prices. Multivariate versions of the GARCH model have also been developed, although these are plagued by over-parameterization as the number of parameters expands rapidly with the order of the model (Bollerslev, Engle and Wooldridge; Holt and Aradhyula; Myers 1991).

A simple test for conditional heteroscedasticity has been developed by Engle and applied to several commodity prices by Baillie and Myers. High frequency data generally display strong evidence of time-varying volatility. Furthermore, the GARCH model seems to be effective at capturing this time-varying volatility in commodity prices. Yang and Brorsen compare the ability of GARCH models, mixed diffusion-jump processes, and deterministic chaos, to best represent the stochastic

properties of commodity prices. Using daily data, they conclude that the GARCH model performs best out of these three alternatives.

Another question about the stochastic properties of commodity prices is, can the unpredictable component of price movements best be modeled as a draw from a normal distribution, or is some other distributional assumption more appropriate? The tails of empirical commodity price distributions are typically fatter than the normal, indicating excess kurtosis in the distributions (Gordon). Early attempts to deal with this problem used more general distributional assumptions, such as the stable Paretian family.

More recently, however, it has become apparent that ARCH and GARCH models provide a partial solution to the excess kurtosis problem. The reason is that even if the conditional distribution of price changes is assumed normal in an ARCH or GARCH model, the unconditional distribution is not normal and, in fact, has fatter tails than the normal (Engle). Nevertheless, ARCH and GARCH models generally fail to capture all of the excess kurtosis in commodity price distributions, if the assumption of conditional normality is maintained. One solution is to assume that the conditional distribution of price movements follows a t-distribution with degrees of freedom treated as a parameter to be estimated. Both Baillie and Myers, and Yang and Brorsen, conclude that the GARCH model with conditional t-distribution does a good job of modeling the time-varying volatility and excess kurtosis that appear to characterize most commodity price series.

Cash Versus Futures Price Behavior. Most of the foregoing discussion of stochastic properties is equally applicable to cash and futures prices, but the means of the two types of series probably behave differently. A futures price is the expected value of a cash price at a forthcoming maturity date, where the expectation is conditional on current information. Theoretically, the expected price change from the current period until contract maturity can be zero, because the current futures quote anticipates the systematic (expected) change in the cash price. Thus, changes in prices for a futures contract conceivably have no predictable component (Working 1958).

Whether or not futures price changes actually contain predictable components is an unanswered, controversial question. There are at least two reasons why daily futures prices might have predictable components. One is the existence of risk premia, but as noted above, the evidence suggests that such premia are small, if not zero. A second reason for a predictable component in futures price changes is market imperfections (e.g., prices may over- or under-adjust to new information). Academic economists are predisposed to believing that most futures markets are relatively competitive and that market imperfections are small.

Nonetheless, many traders use technical analyses, which assume that price changes are predictable. The seeming success of some technical analyses is at odds with academic research which usually finds small autocorrelations in futures price changes (Rausser and Carter).

The empirical evidence is stronger that distributions of futures price changes have excess kurtosis and time-varying volatility (Gordon; Kenyon, et al.). As an alternative to modeling volatility as an ARCH or GARCH process, Streeter and Tomek take a more structural approach and find that the variance of futures price changes depends on a variety of factors, including time-to-maturity, seasonality, economic conditions, and market structure.

Implications for Structural Models. When estimating structural supply and demand models, like those discussed in the first part of this paper, all variables are usually assumed stationary (no stochastic trends) and the errors normally distributed, homoscedastic, and serially uncorrelated. Consequently, these structural systems are commonly estimated by applying OLS to the reduced form and an instrumental variables (IV) estimator, such as two stage least squares, to the structural form.[4] If the variables are really stationary, then such estimation and inference is justified on the basis of conventional normal asymptotic distribution theory.

If, however, some exogenous variables in the model contain stochastic trends, then both price and quantity variables generally have stochastic trends as well, suggesting two main possibilities (Myers 1992).[5] One is that the linear combinations of stochastically trending variables represented by the supply and demand equations (i.e., the structural error terms) have a stochastic trend. In this case there is no long-run relationship between the variables and the result is a "spurious regression" (Granger and Newbold 1974). Results from OLS or IV estimation of such equations are notoriously unreliable, implying that "statistically significant" relationships exist when in fact they do not.

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[4] The structural form of recursive systems can, of course, be estimated with OLS.

[5] As the reduced form implies, endogenous variables are linear combinations of the exogenous variables in the system. Because a linear combination of stochastically trending variables generally also has a stochastic trend, price and quantity variables will usually have stochastic trends as well. The exception occurs when the stochastically trending exogenous variables are cointegrated, with a long-run equilibrium relationship which is represented by the parameters in the reduced form. In this case, price and/or quantity variables will be stationary. If endogenous price and quantity variables *are* stationary, then the usual IV approach to estimation and inference is appropriate, even when exogenous variables have stochastic trends (Sims, Stock and Watson). Thus, this case is not very interesting and we make no further comments about it.

The second possibility is that the structural disturbances are stationary and the supply and demand equations, therefore, represent stationary linear combinations of stochastically trending variables. In other words, prices, quantities, and the exogenous supply and demand shift variables are cointegrated with the long-run relationship between the series represented by the parameters of the supply and demand functions.

What are the implications for estimation and inference when structural equations actually represent cointegration relationships? Fortunately, the conventional IV estimator applied to the supply and demand equations remains consistent (Hansen and Phillips; Phillips and Hansen). In fact, the IV estimator applied to a cointegrating regression converges more rapidly to the true parameter values than it would if all of the variables were stationary. The asymptotic distribution of the IV estimator is, however, not based on the conventional normal theory, as it would be with stationary variables. Thus, conventional normal distribution theory cannot be used in hypothesis testing, *even when relying on large sample results*. If price and quantity variables really do contain stochastic trends, then the standard inference procedures typically used in econometric models of commodity markets are flawed.

It turns out that the OLS estimator of cointegrated supply and demand equations is also consistent and converges rapidly to the true parameter values, despite the obvious simultaneity problem. Like the IV estimator, the OLS estimator of cointegrating relationships generally has a non-standard asymptotic distribution. Hansen and Phillips have developed methods for "modifying" OLS (and IV) estimators and standard errors so as to reduce bias and allow conventional asymptotic inference.

Even if the conventional assumption of stationary price and quantity variables is correct, the structural error terms may still display time-varying volatility that might be modeled with ARCH or GARCH specifications. Such volatility has the same general effect on statistical inference as any other form of heteroscedasticity, in that a loss of efficiency occurs and estimated standard errors may be biased (Engle). Excess kurtosis creates problems whenever inference requires a particular distributional assumption on the disturbance terms. This can be a particular problem in maximum likelihood estimation of commodity market models. Time-varying volatility and excess kurtosis can be modeled parametrically using GARCH models and a conditional t-distribution for the innovations. If properly specified, such models should lead to increased efficiency and more accurate standard errors. Some nonparametric methods, which are more robust to specification error, have also been developed (Pagan and Ullah).

Forecasting

Early applications of time-series analysis to agricultural commodity prices involved forecasting with ARIMA models (Brandt and Bessler). Generally ARIMA models perform well relative to alternative methods when forecasting over short time horizons, particularly when the underlying economic fundamentals are fairly stable, but performance deteriorates over longer time horizons. Since ARIMA models rely only on information contained in past values of the series being forecast, it is difficult to incorporate other relevant information which might assist in forecasting, including information on the economic structure of the market in which prices are being determined. Apparently such information is more important for longer-term forecasting. Furthermore, the univariate nature of ARIMA models means that they cannot be used for conditional forecasting, such as forecasting conditional on particular policy or market scenarios (Bessler and Kling).

Multivariate time-series models, typically of the vector autoregression (VAR) form, can help overcome some of the problems with univariate ARIMA forecasting.[6] Multivariate models include information contained in past values of related variables, not just the particular series being forecast. Unfortunately, however, unrestricted VAR models usually have many parameters relative to the number of data points. Thus, prior restrictions are almost always needed to increase degrees of freedom and improve the precision of forecasts (for an exclusion-of-variables approach, see Kaylen). One source of restrictions is price theory, and imposing such identification restrictions is discussed in more detail below. Identification restrictions also facilitate conditional forecasting, to the extent allowed by the particular scheme used to identify the model. Another source of restrictions is unit root Bayesian priors suggested by Litterman. Bayesian VAR models have been shown to forecast better than ARIMA models, and unrestricted VAR models, in some applications.

Another way in which time-series analysis has been used to forecast commodity prices is through composite forecasting. Composite forecasts combine alternative sources of information, such as ARIMA forecasts, VAR forecasts, forecasts from structural models, and expert opinion, using an optimal weighting scheme (Granger and Newbold 1986).[7] Composite forecasts typically perform better than each of the component parts taken

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[6] The vector autoregressive moving average (VARMA) model generalizes VAR models much as univariate autoregressive moving average models generalize autoregressive models. However, VARMA models are highly nonlinear, and therefore difficult to estimate. Reasonably low order VAR models appear capable of representing the correlations in most economic data. Hence, most applied literature has used VAR models.

[7] In practice, simple averages of the components have worked well.

separately, particularly when the individual forecasting methods making up the composite are based on quite disparate sources of information.

Causality Tests

A time-series variable x_t is said to Granger cause another y_t if lagged values of x_t provide information useful for predicting current y_t (Granger). This deceptively simple idea has found its way into many areas of empirical economics, particularly after the important tests conducted on money and income by Sims (1972). Granger's definition of causality is rooted firmly in theoretical statistics and has little to do with the philosophical notion of "cause and effect." But this has not stopped Granger causality tests from becoming a standard tool in the analysis of multivariate time-series models.

Commodity price analysis underwent a flurry of activity in Granger causality testing in the early 1980s. For example, Bessler and Brandt examined bivariate relationships among many different cattle and hog market variables, concluding that causal relationships found were largely consistent with the economic theory of livestock price determination. As noted above, Heien, and also Ward, investigated Granger causality between prices at different levels in the food marketing chain. Both found that causality tends to run up the marketing chain from farm to wholesale to retail prices. In a bivariate study of land rents and land prices Phipps discovered one-way Granger causality from rents to land prices which is consistent with the present value model of land price determination. In a whimsical study, Thurman and Fisher asked, what comes first, the chicken or the egg? The answer, egg prices Granger cause chicken prices.

Despite the many applications of Granger causality tests in commodity prices analysis, it has become clear that there are serious problems with the method (Conway et al.). First, causality findings are not robust to model specifications. A finding of one-way causality between two variables in a bivariate model can be completely reversed with the inclusion of a third relevant variable into the model. Second, standard causality tests only test for *linear* predictive power among variables. But even if one variable has no linear predictive power for another, they may still be nonlinearly related, and therefore have predictive power in a nonlinear model. Third, data transformations, such as simple differencing, are not causality preserving. This is particularly troublesome given the tendency discussed above for many commodity price series to have stochastic trends. Given these and other problems, there is reason to approach empirical studies using Granger causality tests with a healthy degree of caution and skepticism.

Even putting these theoretical problems aside, there is still a question about how useful results are from causality tests. That is, suppose

that Granger causality tests have been undertaken and that the results appear consistent with some theory of price determination, does that mean we can conclude that the theory is valid? The answer is probably no. An estimated, significant causal relationship only provides weak evidence supporting the theory. For example, Phipps' finding of one-way causality from land rents to land prices hardly provides reason to accept the present value model of land prices. As further studies have shown, other stronger implications of the present value model are soundly rejected by the data (Falk). If an expected causal relationship is rejected, however, then it certainly throws a theory in doubt.

Granger causality tests have become less frequent in price analysis in recent years. Given all of the problems, this is probably a good thing.

Hypothesis Generation

Unconstrained VAR models can be viewed as a convenient summary of the historical correlations among a set of related variables. Thus, any valid theory of commodity price determination should be capable of generating price paths which are consistent with these estimated historical correlations. This suggests that unconstrained VARs can be a valuable source of hypotheses about the way commodity markets work (Cooley and Leroy). The process begins with data collection and estimation of the unconstrained VAR. Then, a search is instigated for theories of price determination which are capable of mimicking the estimated VAR. These theories become maintained hypotheses which can be tested and evaluated with further work.

Using VAR models for hypothesis generation is fairly uncontroversial because it avoids many of the difficult issues involved in imposing and testing economic structure using observational data, as opposed to experimental data (Pratt and Schlaifer; Holland). Yet these difficult issues are only postponed, not overcome, because any hypotheses generated by analyzing unconstrained VAR models still have to be formally tested somehow. Thus, while using unconstrained VAR models to generate hypotheses is uncontroversial, it is also inadequate as a means of testing different theories about the way commodity markets work.

Identification in Multivariate Time-Series Models

While unconstrained VAR models may be useful for hypothesis generation and, to a lesser extent, forecasting and causality testing, they do not allow us to answer many of the interesting questions in price analysis. Which of a given set of theories of price determination best fits the historical data? What are the effects of a change in demand on equilibrium prices and quantities? How will the introduction of a prospective policy, for example a buffer stock scheme, affect the path of

future commodity prices? To answer these kinds of questions one needs to go beyond unconstrained VARs and impose some form of identification scheme on the model. This use of VAR models is controversial because the nature and extent of identification restrictions imposed is different than those typically used to identify conventional structural models.

A linear econometric model of a commodity market might be written in general form as

$$By_t = \sum_{i=1}^{n} B_i y_{t-i} + Au_t$$

$$u_t \sim D(0,I)$$

where y_t is a vector of relevant commodity market variables;[8] B, the B_i and A are matrices of unknown parameters; and u_t is a vector of errors with zero mean and an identity covariance matrix. The only restriction placed on the parameter matrices at this stage is that B has ones on the diagonal (a normalization). The reduced form of this system (obtained by premultiplying both sides by B^{-1}) is an unrestricted VAR. At this level of generality the model obviously is underidentified.

The standard structural approach to identification is to use economic theory to place restrictions on the B, B_i and A matrices. Typically y_t is separated into endogenous and exogenous variables, and exclusion restrictions are applied to the model (e.g., exclude supply shifters from the demand equation). Sometimes, theory also suggests cross-parameter restrictions, such as the cross-equation restrictions which typically characterize rational expectations models. This approach works well when little uncertainty surrounds the true structure (theory) generating data. If incorrect theories are imposed during the identification process, however, results may be highly misleading because exclusion restrictions lead to the omission of relevant variables (Sims 1980). This problem is exacerbated by the apparent unwillingness of price analysts to test overidentifying restrictions in commodity market models.

In a time-series approach, minimal identification restrictions are imposed so that results can be consistent with a broader range of theories. This perspective makes most sense when considerable uncertainty exists regarding the true data generating process. Omitting relevant variables can cause serious biases, and it makes statistical sense to specify the model as generally as possible when uncertainty is high. The disadvantage is imprecise estimation when the number of parameters to be estimated is high relative to the number of data points available. Furthermore, minimal

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[8] It is assumed that any deterministic component of y_t (e.g., a mean and/or deterministic trend) has been removed prior to model specification.

identification may not be sufficient to answer the questions which an analyst wants to ask of the model.

Standard VAR identification involves leaving the dynamics of the model (i.e., the B_i matrices) unrestricted, with identification focusing on the contemporaneous interactions between variables in the model (i.e., the A and B matrices). This precludes exogeneity restrictions so that all variables are treated as endogenous. The Cholesky decomposition imposes a recursive structure on the model by restricting B to be lower triangular and A diagonal. The model is then just identified. This approach was popularized by Sims and used by Bessler, and by Orden, to investigate the effects of macroeconomic policies on agriculture.

But what if there is a contemporaneous feedback between variables in the model? It turns out that contemporaneous feedback (simultaneity) among variables is fairly easy to accommodate (Bernanke; Fackler). The dynamics of the process (B_i matrices) remain unrestricted, and the restrictions are still imposed on the A and B matrices. A recursive structure is not required, however, and maximum likelihood methods can be used to estimate the model. This more general approach has been used by Orden and Fackler to investigate the effects of macroeconomic policies on agriculture and by Myers, Piggott and Tomek to decompose wool market variability into components caused by aggregate demand shocks, aggregate supply shocks, and changes in buffer stock operations.

Another way to identify VAR models is to impose long-run restrictions. For example, suppose that y_t contains two variables, one that has a stochastic trend and one that is stationary. Then restrictions can be imposed on the B, B_i and A matrices which identify one element of u_t as a permanent shock which is associated with the stochastic trend, and the other element of u_t as a temporary shock associated with the stationary component of the system. Blanchard and Quah use this approach to identify permanent shocks (which they call aggregate supply shocks) and temporary shocks (which they call aggregate demand shocks) in a macroeconomic model. Notice, this approach to VAR identification restricts the dynamics of the process (the B_i matrices), although all variables are still treated as endogenous.

Structural and VAR models are often contrasted, one as founded on economic theory and the other as largely atheoretical. But both structural and VAR models must be identified before they can address the questions that economists typically want to ask. Furthermore, identification in the two types of model is similar in that theory is used to restrict the A, B_i and/or B matrices in the general linear model. The difference lies in the nature and number of the identification restrictions. Structural models opt for extensive sets of overidentifying restrictions (which are rarely tested) while VARs focus on minimal just identifying restrictions, in order to be

consistent with a broader set of theories about how the market or economy actually works. In between these extremes lies a continuum of alternative identification schemes.

Toward Improved Price Analyses

Price analyses should be appraised relative to their intended uses and the alternatives for accomplishing these aims. The objectives of empirical price analyses can be grouped under four main headings: forecasting, policy analysis, improved understanding of agricultural markets including the stochastic properties of variables, and hypothesis generation. Forecasting and policy analysis seem to be the most frequently mentioned reasons for doing price analyses, but these objectives are the most difficult to accomplish well. Parameter estimates usually are unstable (fragile), changing as the sample and model change. Varying parameter estimates imply poor forecasts and are a questionable basis for policy analysis.

General contributions to knowledge and hypothesis generation are less frequently mentioned objectives, but appear to be what price analysts have done best, at least to date. Innovative contributions to knowledge have been made; modeling the effects of two regimes (with and without price supports) on supply is just one example. Nonetheless, the cumulative effect of such research is, in our judgment, modest, because little has been done to narrow the range of uncertainty about preferred models and to identify robust results.

While interesting ideas have been developed, empirical studies often end with hypotheses that deserve further testing. Authors do not always appreciate that a "final" empirical result, obtained by pretesting, has unknown type I error, nor that alternative models can have similar, about equally good statistical fits, but different interpretations. If many price analyses are hypothesis generating, then other analyses should be hypothesis winnowing. Of course, our data and tools are not always of sufficient quality to reach definitive conclusions about alternative hypotheses. Conflicting results can persist for long periods of time, awaiting data that can help discriminate among them. In any case, research can help define the range of conflict.

The first requirement for improved empirical output is a renewed interest in data quality. The nature of the probability distributions of variables must be appraised, including analysis for stationarity and possible outliers. In structural models, the analyst must address whether observed variables measure the economic concepts postulated by the model. The general question is, are the quality and quantity of the data available adequate to address the research problem? (The answer can be "no.")

Second, we must continue to try to improve models. Unfortunately, supporters of various approaches seem to have divided into contending camps. Bayesians dispute classical econometricians, and multivariate time-series models are presented in stark contrast to structural models. It is our view, however, that no single approach is best. Rather, models should vary with the research problem and available data. For example, if the problem requires analysis of daily observations, time-series methods are probably going to be important. When either a time-series or a structural model can be considered, it is important to appreciate the similarities of the two approaches rather than just focus on the differences. As noted above, both types of models are structural in the sense that they use economic theory and logic to generate identification restrictions.

Since the true model generating the observed data is usually uncertain, the historical predisposition of price analysts to employ highly restricted models is, in our view, often unwarranted, especially if the restrictions are not clearly justified by the research problem. Models inevitably involve simplification and compromise, but to the degree possible, they should be consistent both with theory *and* the data (for a discussion of criteria, see Hendry and Richard). The analyst should demonstrate that the results address the research problem and that they represent an improvement over alternatives. This may require confirmation and replication analyses of the alternatives (Tomek 1992).

Third, models must be fitted by an appropriate estimator, one thought to be consistent with the data generating process. There is perhaps a paradox that agricultural economists place considerable weight on using up-to-date econometric procedures, but seem to have been relatively unconcerned about the potential inference problems associated with nonstationary variables, outliers, and pretesting. One cannot help but wonder about the number of spurious regressions that have been published.

Fourth, empirical results should be subjected to a broad battery of tests of model adequacy (Godfrey). Do the assumptions underlying the model and the estimator appear to be correct? How robust are the results? Are the model restrictions valid? Ultimately, the researcher's judgment is required, but this judgment should be informed by in-depth knowledge of the limitations of the model and of alternative models. Research should include both the innovations of new hypotheses and the appraisal of competing results. As implied above, this winnowing is likely to require confirmation analyses and the use of tests of adequacy.

In sum, we favor a pragmatic and rather empirical approach to price analysis, but we do not favor empirical ad hocery. Price analysis requires in-depth scholarship. Such research must start with a clear problem statement, which in turn, leads to the needed depth of understanding of published research, data, econometric models and logic, estimators, and

tests of adequacy. The scholarship we envision may mean fewer published papers, but those published would be of higher quality. Useful empirical price analysis is exceedingly difficult to do. We must accept this fact and the implication that future research must be held to a higher standard of excellence.

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