# Econometric Developments in Agricultural and Resource Economics: The First 100 Years

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This article reviews the major contributions of agricultural and resource economists in the area of econometrics over the past 100 years. Early on, a number of agricultural economists were in on the ground floor in terms of developing new econometric methods. Over time as the economics profession became more empirically oriented, agricultural and resource economists increasingly assumed the role of "early adopters" of new econometric methods. Even so, agricultural and resource economists continue to make useful modifications to econometric techniques in order to adapt the methods to the unique nature of the problems and applications that we study.

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In the United States, at least, the development of modern econometric methods is often attributed to the unprecedented work of the Cowles Commission during the 1940s and beyond. Even so, and as econometric historians such as Epstein (1989) and Morgan (1990) have noted, econometric techniques in various forms certainly existed prior to this time, with a small but influential number of practitioners pursuing the means with which to systematically quantify economic relationships based on real-world observations. Who were these early econometricians, the forerunners, as it were, to the Cowles Commission? And upon what problems and issues were they focused?

In nearly all instances they were preoccupied with studying and quantifying relationships in what would today be described as agricultural and resource markets. They were quantifying demand relationships for various commodities; exploring observed cycles in the production, pricing, and profitability of producing various agricultural products; studying the impact of government policies or the introduction of new technologies; and forecasting the future. In short, many of the early pioneers in econometrics were, by any other name, agricultural and resource economists.

The agricultural and resource economics profession can lay claim to a long and rich history of fundamental contributions to the literature on econometric and statistical methods and economic measurement. Any list of these early pioneers would, for example, necessarily include Henry Moore, Henry Wallace, Henry Schultz (a student of Moore's), Phillip Wright and his son Sewall, Mordecai Ezekiel, Frederick Waugh, Elmer Working, and his brother Holbrook, Gerhard Tintner, and even Trygve Haavelmo. Each of these individuals made important and elemental contributions to the emerging field of econometrics. These individuals helped pioneer basic linear estimation techniques, including multiple correlation analysis, model identification and instrumental variable (IV) estimation, business cycle analysis, and statistical estimation of systems of demand and supply curves. Relatively more contemporary agricultural and resource economists who have followed in the traditions established by these early pioneers (in many cases, students of the pioneers) include Marc Nerlove, Karl Fox, Zvi Griliches, George Judge, Arnold Zellner, Yair Mundlak,

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Wayne Fuller, William Griffiths, Stan Johnson, and David Dickey, to name but a few. These individuals have, for example, made important basic contributions to panel data analysis, Bayesian econometrics, estimation methods for linear and nonlinear systems of equations, modeling expectations, the generalized method of moments (GMM), and unit root testing.

While the breadth and scope of contributions to econometrics by agricultural and resource economists is impressive, perhaps the relevant observation is that the impacts of the early and more recent pioneers on the nature and direction of research in our profession continue to this day. Indeed, the hallmark of much of our research rests on the incorporation and testing of relevant economic theory via appropriate, typically sophisticated, empirical techniques designed to take advantage of the unique features of the data being explored, the problem being examined, and the subtle but potentially important implications of economic theory. As Wassily Leontief (1971) noted in his 1970 presidential address to the American Economics Association:

> An exceptional example of a healthy balance between theoretical and empirical analysis and of the readiness of professional economists to cooperate with experts in the neighboring disciplines is offered by Agricultural Economics. … They also were the first among economists to make use of the advanced methods of mathematical statistics. (p. 6)

Simply put, we stand on the shoulders of giants; their intellectual legacy continues to this day. To fully comprehend the impact of these pioneers on our profession, one need only examine any recent issue of the *American Journal of Agricultural Economics*. While theory provides the conceptual underpinnings for much of what we do, it remains the case that agricultural economists overwhelmingly continue in the rich tradition of validating, confirming, and testing theory by making creative and appropriate use of econometric methods and statistical techniques. Over time our methods have evolved, and we now have much richer data sets available for analysis than earlier generations. But even so, those of us at work today in the agricultural and resource economics profession continue as the intellectual heirs of those early and even more recent pioneers, all of whom have made lasting and often profound contributions to econometric and statistical methods.

The purpose of this article, then, is quite literally to celebrate our collective legacy in the development and application of statistical techniques and econometric methods, albeit in an abbreviated fashion. For the reasons indicated above, our task has not necessarily been easy. Nearly all other subdisciplinary areas of our profession make extensive use of sophisticated econometric methods and have, at times, been associated with important additions to our collective tool kit. The implication is that we cannot in any meaningful way cover in a few pages what might otherwise fill an entire volume. We thus have had to make hard choices about what to leave in and what to exclude. Undoubtedly, in the process of doing so we have made decisions with which some, perhaps many, readers will disagree—please accept our apologies in advance.

The plan of the article is as follows. In the next section we review the contributions of the early pioneers. We then turn to a discussion of contributions in various subareas including structural equations modeling, panel data and limited dependent variable methods, time series analysis, forecasting, productivity and efficiency modeling, Bayesian methods, nonparametric and robust regression analysis, and simulation and computational methods. The final section concludes and offers several conjectures regarding future developments in econometric theory and application *vis-à-vis* agricultural and resource economics.

## The Early Years

Mordecai Ezekiel, Henry Schultz, Gerhard Tintner, Frederick Waugh, the brothers Elmer and Holbrook Working, and the father and son team Phillip and Sewell Wright each made fundamental contributions to the advancement of econometrics during their careers. Their major contributions, and those of many others during the early decades of the profession, spanned economics, mathematics, and statistics. Here we offer only a brief overview of some of these early contributions; more in-depth treatments are provided by Fox (1986, 1989), Hotelling (1939), Houck (1991), and Stock and Trebbi (2003).

*Contribution #1: Developing the basic foundations of multiple correlation and regression analysis in economic models*

Mordecai Ezekiel was one of the first economists to develop and apply the methods of multiple correlation and regression analysis to linear and nonlinear economic models (Ezekiel 1924, 1925, 1926, 1927, 1928, 1929, 1930, 1933; Tolley and Ezekiel 1927).[1] His 1930 text *Methods of Correlation Analysis* and its revisions (Ezekiel 1941; Ezekiel and Fox 1959) served as standards for decades. Ezekiel was a strong advocate for structural models, arguing that applied researchers should develop the economic theory for cause and effect relationships prior to formulating empirical regression models. His empirical work often focused on the statistical analysis of price determination for agricultural products (e.g., Ezekiel 1927, 1928, 1933). He presented a pellucid and comprehensive development, analysis, and explanation of the cobweb theorem in Ezekiel (1938) as one way to model exogenous or predetermined variables in a structural econometric model. His estimates of the relationships among consumption, savings, and investment (Ezekiel 1937, 1942a, 1942b, 1944) are widely recognized as seminal empirical results.

Henry Schultz's outstanding career was cut short by a fatal automobile accident in the mountains near San Diego, California, in 1938.[2] Prior to his death, he contributed prolifically to the general economic theory of food and agricultural products, as well as the empirical analysis of the demand for and supply of food and agricultural products (Schultz 1924, 1925a, 1925b, 1927a, 1928, 1932, 1933, 1935, 1938). He was inspired by the seminal work of Henry Moore to derive demand curves from time series data. Shultz's empirical analysis of the demand for barley, corn, hay, and oats (Schultz 1933) stimulated Harold Hotelling's (1935) interest in the integrability conditions for consumer demand functions with a limited budget.

[1] Ezekiel and his colleague Louis Bean were among the early participants in seminars and conferences sponsored by the Cowles Commission in the mid-1930s. Moreover, both individuals were employed as analysts by the USDA.

[2] Indeed, Schultz's untimely demise precipitated the relocation of the Cowles Commission from Colorado Springs, Colorado, to the University of Chicago in 1939.

*Contribution #2: Pioneering the development and estimation of dynamic economic models*

Like Schultz, Gerhardt Tintner made numerous contributions to both theory and empirical methods in economics. Perhaps his most significant contribution was in pioneering dynamic economic models (Tintner 1936, 1937, 1938a, 1938b, 1939b), and he was also a strong advocate for their empirical application. In econometrics, his focus on dynamic models, expectations formation, risk and uncertainty, and time series data (Tintner 1938, 1939, 1940, 1941a, 1941b, 1942a, 1942b, 1944) led him to develop methods for estimation and hypothesis testing based on differencing the data. Subsequent refinements, extensions, and formalizations of these methods have become standard practice in time series econometrics for analyzing stationarity and cointegration. Tintner also made significant contributions to multicollinearity (Tintner 1945) and systems of equations, identification, estimation, and testing (Tintner 1946a, 1946b, 1950a, 1950b). A measure of his high standing and influence in the econometrics profession is his 1953 *Econometrica* article on the definition of econometrics, settling on "investigations which utilize mathematics, economics, and statistics" (Tintner 1953, p. 37).

*Contribution #3: Highlighting and developing techniques to solve the issue of identification in systems of simultaneous equations*

Frederick Waugh's empirical work on the impact of quality attributes on the market prices of vegetables (Waugh 1928, 1929) preceded the formal derivation of the economic theory and econometric analysis of hedonic price relationships by four decades. He also was a major early contributor to the methodology of multiple correlation and regression analysis (Waugh 1935, 1942, 1943). A less well known, albeit important, contribution by Waugh focuses on a debate at the time over structural versus reduced form modeling. Waugh advocated for the conditional mean interpretation of least squares as providing the best estimates (in the Gauss-Markov sense) of the only relevant parameters of interest (Waugh 1943, 1961). This put him at odds with his colleague in the Bureau of Agricultural Economics, Mordecai Ezekiel, and with many econometricians of the period. Even so, to us Waugh's logic on this point seems unassailable.

Fredrick Waugh was a major force behind the development of econometrics at the USDA and in the United States. Under his leadership, USDA's "studies of agricultural commodities established the groundwork for applied econometric work, not only in agricultural economics, but also in economics generally" (Abel 1988, p. 43). James Houck's inaugural Waugh lecture (Houck 1991) on Frederick Waugh's life and career is worthwhile reading for all agricultural economists, and we defer to that article in this *Journal* for anyone who is interested.

The brothers Elmer and Holbrook Working had profound influence on the application and interpretation of econometric estimates of supply or demand parameters, simultaneity bias, and identification (E. Working 1927; H. Working 1925a, 1927a; H. Working and Hotelling 1929). Holbrook Working also was a major early contributor to the econometrics of market prices (H. Working 1925b, 1926, 1927b) and is responsible for the universally applied Working's law for consumption expenditures (H. Working 1943) in the econometric analysis of consumer choice.[3]

Based on observed time series data, Henry Moore (1914) estimated demand equations for corn, hay, oats, and potatoes from the agricultural sector and pig iron from the industrial sector. The pig iron results motivated Elmer Working's (1927) classic paper "What Do Statistical Demand Curves Show?" He noted that Moore's results in the agricultural sector were "in accord with Marshall's 'one general law of demand' " (p. 213). However, with respect to the demand for pig iron, "Professor H. L. Moore finds a 'law of demand' which is not in accord with Marshall's universal rule. He finds that the greater the quantity of pig iron sold, the higher the prices will be" (p. 214). Working then showed that relative shifts in the demand and supply curves can account for a statistical demand curve for pig iron that looks like a theoretical supply curve.

The failure to account for relative shifts in demand and supply can be reformulated as a failure to achieve econometric identification. Two major forces in solving this problem at an early stage were the father and son team Phillip and Sewell Wright (P. Wright 1928, 1929; S. Wright 1925). James Stock and Francesco Trebbi (2003) argue that the identification and instrumental variables method was first solved in Appendix B of Phillip Wright's *The Tariff on Animal and Vegetable Oils* (P. Wright 1928). This appendix uses the method of path coefficients, which Sewell Wright had developed (S. Wright 1921, 1925, 1934). However, using the technique of stylometric analysis, Stock and Trebbi conclude that Appendix B was written by Phillip rather than Sewell Wright, although it appears quite likely that they collaborated closely on the project.

## Modeling Structural Equations

Modeling economic structure was at the heart of much of the early econometricians' work and remains today a major focus. The econometrician postulates a priori a theoretical relationship, which summarizes the autonomous or causal relationships behind observed economic phenomena. This ideal relationship is called a "structural" relationship (Haavelmo 1944; Girshick and Haavelmo 1947). This terminology was "adopted, via Haavelmo, by the Cowles Commission with their label structure. Frisch and Waugh's (1933) usage is the first" (Morgan 1990, p. 150).

The problem Moore (1914) found in estimating demand relationships required considerable creative thinking on simultaneous demand and supply equations to distinguish between relationships, summarize regularities in the data, and identify the structural parameters of the underlying demands and supplies. The early work by Wright (1928) solved this problem by including additional variables that shift one relationship (e.g., the demand equation), thereby allowing the parameters of the other equation (supply) to be identified.

This solution, labeled "instrumental variables" estimation, predates a huge literature in consistent and efficient estimation of structural relationships. In all cases, a priori theory is used to provide the identifying information (variables to be labeled endogenous, exogenous, and predetermined). In addition to traditional instrumental variables estimation methods, two-stage least squares (2SLS), three-stage least squares (3SLS), and the GMM have since the 1950s provided a rich set of structural parameters for demand, supply, and other economic relationships.

Even as this literature on a priori structure was developing, agricultural economists asked basic questions about endogeneity (Kuznets 1953). Solutions to these issues had to wait until formal testing methods were developed and applied; Thurman's (1986) work on endogeneity testing is particularly noteworthy in this regard.

[3] The Working brothers were also among the early participants in the summer conferences hosted by the Cowles Commission in Colorado.

More recent work on economic structure has turned to the experimental laboratory. Here internal validity (i.e., unbiased parameter estimation) is addressed by construction, as random assignment of treatments to subjects is used to break any dependence between omitted variables and the dependent variable of interest. Agricultural economists have contributed to the experimental literature, especially in food safety and resource economics (Coursey and Schulze 1986; Hayes et al. 1995). The strength in internal validity in the laboratory raises a challenging question on external validity: "Do the experimental results extend to real-world parallel settings?" Recent efforts on field experiments appear to be moving toward more satisfactory econometrics on structure (Herberich, Levitt, and List 2009).

## Panel Data and Limited Dependent Variable Econometrics

From the outset, much of the econometric analysis done in the agricultural and resource economics profession has employed data that have a time series dimension and data that are, moreover, typically aggregated to the national level. Even so, early empirical studies also made use of data on individual units of observation collected over relatively short periods of time or data collected on individual observational units without any time dimension. For example, Ezekiel (1926) used data on individual cows to estimate a production response surface for milk. Waugh (1928) employed data on sales of individual lots of vegetables over a relatively short period of time to estimate the effects of quality factors on the prices for these goods. Since those early days, agricultural and resource economists have continued to estimate econometric models with data that are either purely of a cross-sectional nature or have been collected for a large number of individuals (observational units) over relatively short periods of time (i.e., panel data). Cross-sectional data sets are the most common application of models with limited dependent variables, so we will discuss those in this section as well.

*Contribution #4: The development of models designed for analysis of panel data by using fixed effects*

Early pioneers in the development of panel data methods were Marc Nerlove, Irving Hoch, Zvi Griliches, Yair Mundlak, and Clifford Hildreth, among others.[4] In an early piece published as a Cowles Commission monograph, Hildreth (1950) considered an econometric model for the case of observations on a large number of observational units over multiple time periods. He also recognized that some of the variables in the model might not change across observational units, while others might be constant across time. Specifically, he considered the problem of a single equation of the form

$$(1) \qquad y_{it} + \gamma z_{it} + \mu = \omega_i + \lambda_t + \varepsilon_{it}, \quad i = 1, \ldots, N, \; t = 1, \ldots, T,$$

where the subscript $i$ denotes individuals and the subscript $t$ denotes time. In short, Hildreth (1950) identified an error component specific to individuals that does not vary over time ($\omega_i$), an error component that varies over time but not across individuals ($\lambda_t$), and a purely idiosyncratic error that varies across time and individuals ($\varepsilon_{it}$). He then proposed an maximum likelihood estimation procedure under the assumption that all error components are jointly normal. A few years later Irving Hoch completed a dissertation at the University of Chicago under the direction of D. Gale Johnson. The part of his research relevant here was published in *Econometrica* (Hoch 1962), wherein he estimated a Cobb-Douglas production function based upon input and output data for a collection of 63 farms in Minnesota over a six-year period. Of interest is that he included in his model fixed effects for both firms (farms) and for time. In short, this is one of the first applications of a fixed effects panel data model in the economics literature. Mundlak, who worked at essentially the same time as Hoch and received his Ph.D. in agricultural economics from UC Berkeley in 1957, adopted Hoch's basic approach in an analysis of 66 farms in Israel over a five-year period. Like Hoch, Mundlak (1961) included farm-level and time fixed effects. Moreover, he interpreted the estimates of farm fixed effects (relative to the ordinary least squares [OLS] model without fixed effects) as indicators of management bias. Hildreth (1950), Hoch (1962), and Mundlak (1961) are responsible for the next contribution.

[4] An excellent review of the general history of panel data models may be found in Nerlove (2002).

*Contribution #5: The development of models designed for analysis of panel data by using random effects*

The next big advance in this area was provided by Balestra and Nerlove (1966), who examined the demand for natural gas in 36 states over a six-year period. There are at least two highly notable aspects of their study. First, they introduced a lagged dependent variable (natural gas consumption) into the model specification. Heretofore, panel data models had been specified without dynamic terms. Secondly, they were the first to specify and estimate a basic random effects model. The error term in their model was specified to depend on two components: a term that varied with the observational unit (state) but not over time and a term that varied over both time and observational units. They considered several estimation strategies, including maximum likelihood. In a follow-up paper, Nerlove (1971) provided the necessary machinery, including transformations that could be used to reduce the covariance matrix to a diagonal form, to estimate a panel data model with a three-component error term. Others doing similar work in this area at approximately the same time as Nerlove include Fuller and Battese (1973, 1974), who examined linkages between fixed effects estimators and generalized least squares and maximum likelihood estimators for three-component random effects models. Mundlak (1978) illustrated that the random effects approach and the fixed effects approach will yield the same estimates of the slope parameters, and therefore concluded that fixed effects models are satisfactory in most applications. An estimation framework which has also been widely used in the context of panel data is the random coefficients model, due originally to Hildreth and Houck (1968).[5] The basic idea underlying their approach is that the regression model can be written as

(2) $y_i = x_i\beta_i + \varepsilon_i$, where

(3) $\beta_i = \beta + \upsilon_i$.

When combining (2) with (3), it is easy to see that the resulting model may be written as

(4) $y_i = x_i\beta + (x_i\upsilon_i + \varepsilon_i)$,

that is, a regression model with a two-component error term. By making suitable assumptions regarding the error terms in (4), it may be shown that the resulting model is rather similar to one with group-wise heteroskedasticity. Hildreth and Houck developed several consistent estimators for their model, although subsequent authors added additional refinements.

*Contribution #6: Development of more efficient estimation techniques for data with qualitative and limited dependent variables*

Of parallel interest are models for the case where either the dependent variable is discrete or its values must lie within a certain range. For ease of exposition, we classify these as limited dependent variable (LDV) and qualitative dependent variable (QDV) models.

Perhaps the first adaptation of these types of models in the agricultural economics literature was provided in the famous study by Griliches (1957). Beginning in the 1930s hybrid corn was made commercially available to farmers. While early hybrids improved yields dramatically, adoption rates differed across states and regions. Using state-level data, Griliches fit logistic functions, or logit models, specified as a function of time, to the adoption data. The logistic function was chosen over the standard normal for ease of estimation.

As time passed and computing power increased, more sophisticated applications of LDV and QDV models were considered. Many of these applications were in the resource and environmental economics literature, where, among other things, direct linkages between economic theory and the empirical specifications of QDVs provided a logical framework for model estimation as well as interpretation of results (Hanemann 1984). The most notable example of this is the random utility model, or RUM. For example, travel cost models exploit the features of the Poisson and negative binomial models, respectively, under stratification to estimate recreation demands (Englin and Shonkwiler 1995). In this spirit Grogger and Carson (1991) examined a class of maximum likelihood estimators for count data from truncated samples. They provided simulation results to infer the size of the bias associated with failing to account for overdispersion in the sample, as well as an application to fishing trips in Alaska. Herriges and Kling (1999) relaxed the common assumption of constant marginal utility of income in RUMs and

[5] The random coefficients model may be used, however, with nearly any data structure, including time series and cross-sectional data.

adapted a Markov chain Monte Carlo simulator for the purpose of obtaining welfare estimates. The framework was then used to obtain welfare estimates in the context of recreational demand for sport fishing in California. Phaneuf, Kling, and Herriges (2000) proposed a framework for directly estimating a structural model of recreational demand wherein the Kuhn-Tucker conditions were explicitly incorporated into the maximum likelihood estimation.

While these studies represent an extremely small sample of the applications of LDV/QDV methods appearing in the literature in recent years, there can be no doubt that these models will remain essential in the applied economist's tool kit for years to come and that additional refinements and extensions will likely continue.

## Time Series Econometrics

Time series analysis has been a key feature of advances in econometric methodology from its inception. For example, Nerlove (1964) illustrated how spectral analysis could be used to analyze the seasonal nature of high-frequency time series data. Likewise, Griliches (1961) explored the bias in estimating distributed lag models when the error terms are autocorrelated. In any event, for most purposes time series methods can be effectively categorized as univariate and multivariate, with the former finding applications in modeling economic agents' expectations and the latter in modeling series interactions through time. Both have been used for forecasting.

### *Contribution #7: The development and application of the adaptive expectations framework*

Developing appropriate theoretical and empirical models for agents' price expectations has been omnipresent in the agricultural and resource economics literature. Ezekiel (1938), for example, assumed that agents held naïve expectations, wherein the most recently observed price is simply assumed to prevail in future, which gave rise to the cobweb model which is discussed in Myers, Sexton, and Tomek (this issue).

While naïve expectations remained the dominant paradigm in the literature for years, in the late 1950s agricultural economists made substantive contributions to expectations modeling. Specifically, in a series of papers published in the late 1950s, Marc Nerlove first introduced the adaptive expectations model, which in turn is based upon a Koyck distributed lag (Nerlove 1958a, 1958b; Nerlove and Addison 1958). Prior to Nerlove's work, no formal conceptual justification had been provided for the Koyck distributed lag model. The adaptive expectations mechanism allowed analysts to consistently estimate both short- and long-run supply response in a single equation. Variants of the adaptive expectations model were used extensively in the agricultural and resource economics literature during the 1960s and 1970s to model short- and long-run behavior in both supply and demand equations. Noteworthy among these extensions is Just's (1974) model that incorporates second moments of expected price (under the assumption that producers are risk averse), again based on an adaptive expectations formulation. A thorough review of many (over 600) applications of Nerlove's model to agricultural supply estimation can be found in Askari and Cummings (1976).

### *Contribution #8: Developing models and appropriate estimation techniques for the inclusion of the future expectations of economic agent under rational and quasi-rational expectations*

At the same time, models with more general lag structures for both the dependent variable and any strictly exogenous variables were proposed, including Burt's (1980) nonstochastic difference equation, or NSDE. Burt's innovation is to use expected values (as opposed to realizations) of the lagged *y*-variable on the equation's right-hand side. The researcher is then free to estimate the model's parameters (including any autocorrelation parameters) without resorting to an instrumental variables approach. Numerous applications of Burt's nonstochastic difference equation to agricultural supply, investment, inventory, and product price models have appeared in the literature over the years, including, for example, Rucker, Burt, and LaFrance (1984) and Foster and Burt (1992).

An important alternative to the adaptive expectations hypothesis, the rational expectations hypothesis, was proposed at nearly the same time as Nerlove's framework. One of the first applications of rational expectations is by Eckstein (1984), who estimated a dynamic rational expectations model for cotton and wheat acreage, yield, and prices in Egypt. As well, Shonkwiler and Maddala (1985) examined rational expectations in the context of bounded prices, that is, where lower and/or upper price limits are enforced, perhaps through government policies, as was the case for many field crops in the United States during the second half of the twentieth century. They considered an application to the U.S. corn market. Several years later, Holt and Johnson (1989) showed that iterative techniques could be used to solve the nonlinear bounded prices model for the relevant price expectations. They, too, applied their framework to a model of the U.S. corn market, and found considerable empirical support for their approach.

An alternative approach to maximum likelihood estimation of a structural model with rational expectations is to use instrumental variables, most typically in a GMM framework. Goodwin, Grennes, and Wohlgenant (1990) were the first agricultural economists to use this approach to model price expectations. They argued that trade takes time and therefore that the "law of one price" (LOP) should hold only in terms of expected as opposed to observed prices. The model was applied to a set of homogeneous international commodity prices, with lagged prices and the contemporaneous exchange rate used as instruments. Once expected prices were used, considerable support was found for the LOP, a result that is, moreover, atypical.

Other recent advances in expectations modeling include modeling of rational expectations of first and second moments of price by using GARCH (generalized autoregressive conditional heteroskedastic) processes, by Holt and Aradhyula (1998), the quasi-rational expectations models of Nerlove, Grether, and Carvalho (1979), Nerlove and Fornari (1998), and Chavas (2000), who assumed that different expectation regimes could coexist simultaneously. The essential idea of quasi-rational expectations is to replace expectations based on the structural model's predictions with those obtained from the best fitting ARIMA (autoregressive integrated moving average) model. Nerlove and Fornari (1998) apply this framework to a dynamic model of the U.S. cattle industry and find considerable support for their specification. Quasi-rationality has also been tested (and not rejected) in laboratory settings with agents facing incentive compatible payoffs in Nelson and Bessler (1989).

*Contribution #9: Developing formal tests for whether or not the data should be first differenced*

The more general ARIMA representation that found applications in modeling quasi-rational expectations in agricultural supply was also helpful in generating simple forecasting models in the agricultural sector. Here an individual series was represented by a parsimonious number of lags of itself (the autoregressive [AR] component of the ARIMA representation) and current and past innovations (the moving average [MA] component of the representation). While clear tests were available to determine the order of the AR and MA components, no test existed for the integration component until Wayne Fuller and his student David Dickey presented a formal test of nonstationarity of time series data (Dickey and Fuller 1979). This work began an extensive literature on unit root testing.

## Multivariate Time Series Models

While univariate models have been useful for representing expectations and for forecasting, a substantial literature has developed in multivariate time series. Two *AJAE* papers published in 1984 were the first to use a vector autoregression (VAR) on aggregate time series data to study macro/financial issues in agriculture (Chambers 1984; Bessler 1984). Additional VAR work followed in time. The VAR summarizes the dynamic correlation patterns behind a set of theory-generated variables. Early VAR models were unrestricted in that every variable was permitted to affect every other variable in the model with lags. These "profligately" parameterized models were estimated equation by equation with OLS.

The use of VARs to inform policy analysis required the analyst to identify causal flows among contemporaneous VAR innovations. Here early work mechanically generated "orthogonal innovations" via a Cholesky factorization (a just-identified structure) of contemporaneous innovations (errors). The arbitrary nature of such orderings was discussed by Bessler (1984); the dynamic patterns one obtains from the VAR depended in a nontrivial manner on how one ordered contemporaneous innovations (which series is placed first, etc.). The study by Orden and Fackler (1989) was an early paper imposing prior theory-based overidentified structural orderings on contemporaneous innovations. Bessler and Akleman (1998) provided empirical evidence based on graph theory to generate overidentifying restrictions on contemporaneous innovations.

Early VAR work in agriculture made no explicit adjustment for individual nonstationarity in the underlying series; that is, early work made no explicit stationary inducing transformations (Nerlove, Grether, and Carvalho 1979; and Bessler 1984). More recent work in agricultural economics followed Engle and Granger (1987) by formally modeling cointegrated time series as error correction processes. This model has been particularly helpful in the study of LOP and other dynamic relationships implied by theory (e.g., Ardeni 1989).

For the most part, agricultural economists have studied cointegration in bivariate settings, following the Engle and Granger (1987) two-step procedure, or in multiple series settings using the maximum likelihood procedures as laid out in Johansen (1988). However, agricultural and resource economists have created additional tests better suited to particular situations or otherwise improving on the earlier work. Examples include the studies by Bewley et al. (1994), Dorfman (1995), and Wang and Bessler (2005).

## Forecasting

Forecasting is another area of econometrics where agricultural and resource economists have long been in the forefront. Because agricultural and resource economists often work with commodities with greater variability than do regular economists, it makes sense that agricultural and resource economists have been particularly interested in improving mechanisms for generating forecasts.

### *Historical Beginnings*

At least near the beginning, Frederick Waugh (1961) wrote a definitive paper which deserves more recognition today. In this piece he drew a clear distinction between forecasting and inference about structural parameters that economists would still benefit from studying. In response to a growing trend toward more sophisticated methods for estimating systems of equations (e.g., 2SLS, the just developing 3SLS), Waugh pointed out that such methods were appropriate only if the researcher's goal is unbiased estimation of the structural parameters. For forecasting purposes, OLS was still the best linear unbiased estimator for $E(y|X)$. This paper is really a bright line delineating the forecasting literature from the hypothesis testing literature and as such remains important today. Endogeneity, direction of causation, correlation of errors or sets of random variables, all these worries fade into the background if all that is desired is a conditional forecast. In another contribution to today's econometricians, Waugh also included a plea for more graphical data analysis in this paper.

Even earlier, Holbrook Working (1927b) tackled the problem of how to forecast the price of wheat. While he did not obtain forecasts per se, he did provide a roadmap of issues for future forecasters to consider. Following this map, Leuthold et al. (1970) tried several structural and time series approaches for forecasting hog prices and supplies. The structural model was superior as measured by the Theil inequality coefficient when out-of-sample performance was compared. Just and Rausser (1981) compared the performance of commercial, large-scale structural model forecasts with futures market forecasts for a set of agricultural commodity prices. They found some advantage to futures for soybeans, the commercial forecasts for livestock, and essentially a tie for other commodities. Just and Rausser also noted that futures are more unbiased while the commercial forecasts have smaller variance, implying that the choice for the optimal forecast source would depend on whether the user is risk neutral or risk averse.

*Contribution #10: Improved methods of making and evaluating forecasts of economic time series*

### *State Space Forecasting*

State space models became popular for a period in the forecasting arena, with many of the key advances due to agricultural and resource economists. Aoki and Havenner (1989) laid out the theory behind a form of state space model that is particularly well suited to forecasting. Cerchi and Havenner (1988) added a twist by showing how to estimate and forecast with a state space model that incorporates cointegration. Foster, Havenner, and Walburger (1995) used a state space model to forecast cattle prices, found cointegration of seven cattle price series from different markets, and provided strong statistical evidence that their model would allow arbitrage across those markets that would generate significant economic profits.

### *Qualitative Forecasting*

A key specialty within forecasting is the prediction of binary events. In economics, these are most often turning points in economic time series such as prices, output, and employment. Agricultural and resource economists have made significant contributions in this field. Kling (1987), an early contributor, extended an autoregressive model to include explanatory variables and incorporated coefficient uncertainty into his forecasts. LeSage (1990) and Zellner, Hong, and Min (1991) both use Bayesian techniques to forecast turning points.

### *Composite Forecasting*

Brandt and Bessler (1981) made a key advance in forecasting applications to agricultural and resource situations. They demonstrated, by using hog price data, that composite forecasts can be statistically superior to forecasts from individual models, with even simple average composites being preferred. Li and Dorfman (1996) developed a new way to form composite forecasts more suited to turning point forecasts. Since turning point forecasts (or any binary forecasts) are right or wrong, Li and Dorfman used logit models to forecast the probability that each component model would be correct in the next forecast period. The estimated probabilities were then used as the weights to form composite qualitative forecasts. In sum, this body of work by agricultural economists has expanded the boundaries of forecasting modeling and helped improve forecast performance for both the agricultural and the more general economics professions.

## Productivity and Efficiency Measuring and Modeling

Productivity and efficiency measurement is a field that has seen great strides, with many of the econometric refinements important to the field being made by agricultural and applied economists. Many of these advances are detailed in Chavas, Chambers, and Pope (this issue).

### *Contribution #11: Improving the realism and usefulness of both models and measurement of efficiency and productivity*

Major contributions by agricultural economists have been in three areas: theoretical consistency of the modeling process; improved methodologies for estimation, especially in terms of accounting for real-world features; and modification methods to incorporate situations with an undesirable output from the production process. Each of these areas will be taken in turn.

In the area of theoretical consistency, important papers are by Antle (1986), Stefanou (1989), and Kumbhakar (1990). Antle (1986) showed the dangers in trying to estimate technical change with aggregate data and developed the necessary restrictions on firm expectations to allow the use of aggregate data. In particular, he showed that if firms have rational expectations, estimation of factor demand, cost share, or profit share systems will yield biased estimates when aggregate data are used. Stefanou (1989) showed how to cast the cost function in a long-run context with dynamic adjustment costs and then use it to measure returns to scale and efficiency in production. Kumbhakar (1990) developed an econometric model that allowed for both technical and allocative inefficiency to be estimated simultaneously. This paper was an important extension to the literature because Kumbhakar was the first to allow the allocative efficiency measures to be both firm specific and time varying, implying that firm inefficiency is not necessarily constant over time.

Modifications of standard production theory to better fit real-world data have also been a province of agricultural economists. Morrison (1986) pioneered the inclusion of capacity utilization in efficiency modeling so that capital is more accurately measured. This paper showed that neglecting capacity utilization led to a false view of the reported productivity slowdown of the 1970s. Luh and Stefanou (1991) introduced adjustment costs, returns to scale, and quality-adjusted inputs to the measurement of productivity growth in a study of U.S. agricultural productivity and showed that most productivity gains in production agriculture are from technical change. Their paper also showed that neglecting the other factors led to biased estimates for such policy-relevant measures as the returns to research. Morrison (1997) also demonstrated an approach to estimating productivity in the presence of asset fixity and adjustment costs in an application to the U.S. food processing industry.

Kumbhakar, Ghosh, and McGuckin (1991) went beyond simply estimating inefficiency measures to parameterizing the inefficiency as a function of a set of firm-specific variables. In their application to U.S. dairy farms, they showed that farm operator education level and farm size were significant determinants of the farm's efficiency score. Kumbhakar (2001) showed that technical and allocative inefficiency are not statistically independent and then developed proper estimation techniques for both cross-sectional and panel data sets. This key paper also handled nonhomogeneous production functions, which are shown, using a panel of sixty Norwegian salmon farms, to be an important generalization of previous models. O'Donnell and Coelli (2005) presented a Bayesian approach to imposing curvature conditions on distance functions, allowing the researcher to estimate a distance function that meets theory's requirements of monotonicity and (quasi-)convexity. A final important paper on more realistic and flexible models is by Griffiths and O'Donnell (2005), who developed the econometric apparatus necessary for handling variable returns to scale and demonstrated the estimation of such a model using a numerical Bayesian approach with data on U.S. state-level agricultural production.

The third area of important contributions is in accounting for undesirable outputs. In both the environmental arena and production agriculture, we often confront settings where the productive process results in a by-product (air pollution, manure, etc.) that is undesirable. Reinhard, Lovell, and Thijssen (1999) authored an early paper in this area. Atkinson and Dorfman (2005) developed a different approach based on treating the bad output as a technology shifter, having shown that several alternative approaches to handling undesirable outputs are scale dependent, meaning that rescaling of the data could yield different productivity measures.

## Bayesian Methods

Agricultural economists have made a number of key advances in the use of Bayesian methods in econometric analysis. In fact, over the last five years, Bayesian applications in the agricultural and resource economics literature have greatly proliferated. However, due to space constraints, we discuss only papers with true methodological advances in either theory or application, not the many fine Bayesian applied econometrics papers being produced by today's agricultural and resource economists.

### *Contribution #12: Expanding the application of Bayesian econometrics within the discipline*

#### *Basic Methodological Advances*

Given his recent association with the UC Berkeley Department of Agricultural and Resource Economics and an early publication on fisheries, we claim Arnold Zellner as an agricultural economist and begin with him. Zellner, particularly through his 1971 book, did more than any other econometrician to popularize Bayesian econometrics. He developed many linkages with frequentist approaches, produced an improvement to 2SLS estimators in his MELO (minimum expected loss) estimator for systems of simultaneous equations (Zellner 1971), and did important work on the forecasting of turning points (e.g., Zellner, Hong, and Min 1991) which has long been a topic of interest for agricultural economists.

The second key contribution to Bayesian methods is the inclusion of Bayesian techniques in *The Theory and Practice of Econometrics* (Judge et al. 1985), the classic econometrics textbook from which at least twenty years of agricultural economists learned their econometrics. This inclusion can be credited mainly to George Judge and Bill Griffiths, two of the book's authors and two outstanding Bayesian econometricians. Griffiths and Judge (1992) also combined on an important paper on estimation of regression coefficients and testing equality of those coefficients in the presence of heteroskedasticity. This paper shows that in most situations, a Stein-rule empirical Bayes estimator is the superior choice. The paper built on a long series of papers that Judge wrote on Stein-rule estimators and how Bayesian priors can be used to shrink estimators in ways that improve performance (cf. Judge, Hill, and Bock 1990).

Dorfman (1995) developed the second Bayesian cointegration test in the literature, one that was considerably more general than the original and relatively easy to apply. Moving to Bayesian decision science, Lence and Hayes (1994) made a tremendous contribution by pointing out that using point estimators of structural parameters to then approximate a nonlinear function of those parameters could lead to greatly flawed decision making. They showed how to use the posterior distribution of the parameters to correctly solve such problems.

## Improving Applications

Agricultural economists were among early adopters of the Bayesian numerical methods that were invented beginning in the late 1980s. Chalfant, Gray, and White (1991) were the first to apply numerical Bayesian methods in agricultural economics and contributed importantly to applied econometrics by using the Bayesian numerical methods to impose inequality (curvature) restrictions from economic theory onto a system of Canadian meat demands. A concurrent use of numerical Bayesian methods to test net substitutability in demands was presented by Hayes, Wahl, and Williams (1990), who applied the Chalfant, Gray, and White approach in testing, although not in estimation. A more modern contribution to imposing economic theory is found in O'Donnell and Coelli (2005), who demonstrated how Bayesian estimation can be used to impose theoretically based curvature constraints on distance functions. Jim LeSage has been at work for nearly twenty years in bringing valuable advances in Bayesian methods to spatial econometrics; this work is well summarized in his recent book (LeSage and Pace 2009). Thurman, Fox, and Bingham (2001) presented an innovate use of Leamer's contract curve approach to show how a Bayesian prior can yield improvements in the policy arena by allowing a clear depiction of the trade-off between the model's goodness of fit to the data and the consistency of the estimated parameters with economic theory. Heckelei and Mittelhammer (2003) broadened the potential applicability of Bayesian methods by introducing a Bayesian bootstrap multivariate regression approach which replaced the traditional fully specified likelihood function with a "multivariate regression-structure likelihood" approximated via a bootstrap procedure that avoids the need to fully specify the likelihood function. Their approach is similar to a Bayesian method of moments but relies on bootstrap resampling of the data to produce an empirical approximation to the likelihood function.

## Nonparametric and Robust Regression Techniques

*Contribution #13: Developing estimation approaches that are more robust to specification error or require fewer assumptions to be made in specifying the model to be estimated.*

Work in this area begins with Day (1965), who used nonparametric tests on crop yield distributions to reject normality. Using the Wald–Wolfowitz runs test and the Wallis and Moore (1941) test based on phases (basically runs in the first differences) to reject trends, long cycles, and autocorrelation (both in the levels and in the differences), he also detected skewness in cotton and oats, but not in corn; kurtosis different from the normal distribution is found in all three crops. Rejecting the log-normal distribution, Day went on to estimate Type I Pearson distributions to fit the data and included a fascinating discussion of the relative merits and differences between maximum likelihood and method of moments estimation. All this effort is used to point out the danger of using mean response estimates derived assuming normality to make production decisions such as fertilizer application rates.

Buccola (1986) examined the normality of net returns data and found that wheat data he tested had departures from normality minor enough to leave net returns acceptably normal for use in mean-variance decision analysis settings. He pointed out that nonnormal distributions of prices and yields can dampen out in their product (revenue) if they are correlated.

Crop yields have been a fruitful area for advances in nonnormal modeling. Nelson and Preckel (1989) estimated conditional beta distributions for corn yield, improving the approximation to higher moments. Goodwin and Ker (1998) estimated nonparametric yield distributions and showed that these distributions lead to significantly different premium rates for crop insurance, and should therefore improve the actuarial performance of the crop insurance program. Just and Weninger (1999), moving somewhat against the trend and harkening back to Day (1965), pointed out the care that must be taken in testing for nonnormality. Once they detrended crop yield series and dealt with issues in aggregate data (as compared with farm-level yield data), they found normality in almost all data tested (across several counties and multiple crops).

Another topic in robust regression is that of methods to guard against model misspecification. Nonparametric methods are one approach to increasing the robustness of results, but semiparametric approaches bring added model flexibility while retaining some statistical power. Moschini (1991), for example, used a kernel estimator for the price parameters in a meat demand system. With model specification a key point in the argument over whether or not taste changes were occurring in meat demand, Moschini fashioned a robust approach that avoided strictly specifying the function that relates normalized prices to changes in consumption ratios while at the same time retaining a parametric specification of the preference change variables. This middle road allowed him to use standard statistical tests for the hypothesis of changes in taste, giving his approach more power than a purely nonparametric one.

Another approach is to estimate multiple models with different specifications and then average over the results. Bayesian methods are particularly well suited to this. The first example of this in the agricultural and resource economics literature was the study by Dorfman and Lastrapes (1996), in which multiple macroeconomic identifying restrictions were considered in a set of VAR models of the impacts of monetary policy on agricultural prices. By integrating over the model specification uncertainty, they avoided having to condition all their results on a single, tenuous macroeconomic theory.

## Simulations and Computational Methods

Economists began to utilize simulations and computational methods in the 1970s and 1980s as computational costs fell; Agricultural and resource economists were, moreover, right there at the start of this movement. Monte Carlo experiments were typically employed to generate large numbers of pseudo-data sets and to test the performance of competing estimation methods. Bootstrap methods also arose, an approach similar to the Monte Carlo experiment, but with the pseudo-data being generated from the actual data and then being used either to empirically approximate a statistic that the researcher cannot compute analytically or to obtain refinements on first-order asymptotic theory for testing purposes. In combination, these techniques allowed agricultural and resource economists to produce precision measures for nonlinear functions of estimated parameters, which expanded the value of our empirical work in the policy arena.

## The Future of Econometrics in Agricultural and Resource Economics

So what will be the future of econometrics in agricultural and resource economics? We are certain that agricultural and resource economists will continue to be distinguished by careful modeling of real-world issues. Our econometric efforts will thus continue to deal with familiar problems and issues such as heteroskedasticity, autocorrelation, trends, cycles, nonstationarity, regime switching, spatial dependence, LDVs, QDVs, and endogeneity.

We believe that robust estimation techniques are likely to increase in importance and use in coming years, including model averaging, non–least squares estimation approaches, modeling of nonnormality, and new approaches that we have no inkling of yet. Computational and simulational methods for quantifying the precision of policy-relevant functions of estimated parameters will continue to increase in prevalence to become standard practice. Because of the ever-falling costs of computer-intensive computations, as well as availability of better and more reliable software, Bayesian econometrics will likely expand in use to approximate parity with frequentist estimation within the next ten to twenty years.

Forecasting will continue to be an important area of research, especially approaches that allow conditional forecasts so that advice to policymakers on the likely impact of different values of specific exogenous variables can be provided. Panel data estimation will continue to grow in importance as more panel data sets become available. These data sets are already spreading in international development, in domestic rural development, and in farm production and management. Thus, new techniques for handling such data with the unique problems inherent to agricultural, natural resource, and environmental problems will be developed.

In summary, we are confident that agricultural and resource economists will, in the tradition of our profession, rise to these challenges and continue to provide both our discipline and the broader economics profession with important econometric advances over the decades to come.

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